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Returns to Education and Human Capital Externalities: Empirical Evidence from Indonesia

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature : ……………………

Date : …………………….

Dedicated to

My late father (you are all I aspire to become) and

my mother (I am what I am because of you)

And

My sisters and brothers

For their love and support

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This thesis is the result of the research I conducted during the three years I was enrolled as a PhD student at the School of Economics and Finance, Curtin Business School, Curtin University. I could not have completed this thesis without the help of some very important people, to whom I owe tremendous thanks.

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Abstract

This thesis investigates the return to schooling and human capital externalities in Indonesia. It approaches these issues from two different, but related perspectives. First, it examines the estimates of the returns to schooling and human capital externalities based on years of schooling. Second, it allows for non-linearity in returns to schooling by evaluating the estimates of the return to schooling and human capital externalities based on levels of education. In terms of estimation method, this study adopts two major approaches, namely Ordinary Least Squares (OLS) and Instrumental Variables (IV).

While there have been numerous studies on the returns to schooling and human capital externalities, there are few empirical studies from Indonesia. This study attempts to fill this research gap.

On the basis of conflicting empirical findings, there has been an ongoing debate on the magnitude of the private returns to schooling and human capital externalities. This study attempts to contribute to the current debate by investigating the returns to education and human capital externalities in Indonesia using recent and comprehensive data from the Indonesian Family Life Survey wave 4 (IFLS4). The work for this thesis is unique in four respects. First, as distinct from previous studies using Indonesian data, this study proposes to provide a comprehensive analysis of the returns to education and human capital externalities for every level of education. Second, this study also utilises an augmented Mincerian equation and an instrumental variable approach to overcome the ability bias problem, whereas previous studies generally used a simple correlation between years of education and wages. Third, the major novelty of this study is that it canvasses a wide range of potential instruments for use in the estimation of the private return to schooling in Indonesia. Fourth, in contrast to previous studies that only examine the benefit of education, this study adopts an alternative perspective - proposed by Oreopoulos (2003) - by taking into account foregone earnings to quantify the opportunity cost of dropping out from school. These estimates are argued to provide a more useful guide for private, and even public, investment in education.

Three empirical analyses are presented in this study. The first analysis examines the return to schooling based on years of schooling and level of education using the OLS approach. The results show the return to schooling in Indonesia ranges between 4.36 and 6.46 percent across the different samples and estimating equations. Furthermore, a notable finding of this study is the substantial non-linearity in returns to schooling in Indonesia: returns increase with the level of education. Female workers earn a higher return to schooling compared to their counterpart male workers.

The second analysis evaluates the return to schooling based on years of schooling using the IV approach. When the IV approach is applied, the returns to schooling vary from 4.59 to 8.92 percent across the different sample groups and estimating equations. Although adopting the IV approach has increased the return to schooling for Indonesia, the estimated returns remain low compared to other Asian countries and less developed countries.

The last analysis investigates human capital externalities in Indonesia. The results of this component of the study provide evidence that human capital spillovers exist in Indonesia. Furthermore, the finding supports the view that investing in education is even more important for aggregate economic performance than it is for the individuals who do so. This study also provides evidence of the existence of human capital externalities as high as, or even much higher than, the private return to schooling. Thus, there is clear role for the public sector fostering education and human capital development in order to seize the benefit of these externalities

Table of Contents

Appendix materials please see the enclosed CD.

List of Tables

Page

List of Figures

List of Abbreviations and Acronyms

$	United States Dollar
2SLS	Two-Stage Least Squares
ADB	Asian Development Bank
AFQT	Armed Forces Qualification Test
ALLBUS	*Bevokerungsumfrage der Soziali Wissenschaften* (German General Survey)
BAPPENAS	*Badan Perencanaan dan Pembangunan Nasional* (National Development Planning Agency)
BKB	*Bina Keluarga Berencana*
BPS	*Badan Pusat Statistik* (Central Bureau for Statistics)
CEL	Compulsory Education Law
CHIP	Chinese Household Income Project
CMA	Census Metropolitan Areas
CPPS	Center for Population and Policy Studies
CPS	Current Population Survey
CSAL	Compulsory School Attendance Law
DIY	*Daerah Istimewa Yogyakarta* (Special Region of Yogyakarta)
DKI	*Daerah Khusus Ibukota* (Jakarta Capital Region)
D1	*Diploma 1* (One year college/academy)
D2	*Diploma 2* (Two years college/academy)
D3	*Diploma 3* (Three years college/academy)
D4	*Diploma 4* (Four years college/academy)
EFA	Education for All
ESCAP	Economic and Social Commission for Asia and the Pacific
FEIV	Fixed Effect Instrumental Variables
GDP	Gross Domestic Product
GER	Gross Enrolment Ratio
GSOEP	German Socio-Economic Panel
GSSS	General Senior Secondary School
HCT	Human Capital Theory
HDI	Human Development Index
HIES	Household Income and Expenditure Survey
HILDA	Household, Income and Labour Dynamics in Australia
IBGE	*Instituto Brasileiro de Geografia e Estatisca* (Brazilian Institute of Statistics)
IFLS	Indonesia Family Life Survey
INPRES	*Instruksi Presiden* (Presidential Instruction)
IV	Instrumental Variable
JSS	Junior Secondary School
KB	Keluarga Berencana (Family Planning)
LDC	Less Developed Country
LIS	Luxembourg Income Study
LLM	Local Labour Market
LSE	*Schweizerische Lohnstrukturerhebung*
MA	*Madrasah Aliyah* (Islamic Senior Secondary School)
MDG	Millennium Development Goals
MI	*Madrasah Ibtidaiyah* (Islamic Elementary School)

MIDUS	Midlife in the United States Survey
MoMT	Ministry of Manpower and Transmigration
MoNE	Ministry of National Education
MoRA	Ministry of Religious Affairs
MoSA	Ministry of Social Affairs
MSA	Metropolitan Statistical Area
MTs	*Madrasah Tsanawiyah* (Islamic Junior Secondary School)
NER	Nett Enrolment Ratio
NGO	Non-Government Organisation
NLSY	National Longitudinal Survey of Youth
NTB	Nusa Tenggara Barat
OLS	Ordinary Least Squares
PNAD	*Pesquisa Nacional por Amostra de Domidilios*
POSYANDU	Pos Pelayanan Terpadu (Integrated Service Post)
PRSP	Poverty Reduction Strategy Paper
PS	Primary School
PUMA	Public Use Microdata Areas
PUMS	Public Use Microdata Samples
RA	*Raudlatul Atfal* (Islamic Kindergarten)
RLMS	Russian Longitudinal Monitoring Survey
Rp	Rupiah
SHIW	Survey of Household Income and Wealth
SMSA	Standard Metropolitan Statistical Area
SUPAS	Survey Penduduk Antar Sensus (Intercensal Survey of Indonesia)
SUSENAS	Survey Sosial dan Ekonomi Nasional (National Socioeconomic Survey)
S1	Strata 1 (Undergraduate programme)
S2	Strata 2 (Master degree programme)
S3	Strata 3 (Doctoral degree programme)
TK	*Taman Kanak-Kanak* (Kindergarten)
TPA	*Tempat Penitipan Anak* (Child care centre)
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organisation
UT	*Universitas Terbuka* (Open University)
VSSS	Vocational Senior Secondary School
WCS	Working Conditions Survey
WMS	Welfare Monitoring Survey

Chapter 1

Introduction

1.1 Background to the Study

Education is often considered as a key determinant of a person's economic and social achievement. It provides both direct and indirect benefits for the individual who receives the education and for the society with which this individual connects. At a national level, the effect of investment in human capital on productivity, technology and growth has long been emphasised by economists. Recognising these benefits, the Indonesian government has been making an effort to increase access to education, thereby improving children's school participation. Equalising and broadening access to education is one of the three pillars of the Ministry of National Education's (MoNE) current strategic plan.

Since the 1970s, enrolment rates have increased significantly as a result of the government's sustained drive to build schools across the country. The results have been impressive: the net primary school enrolment rate has increased from 72 percent in 1975 to nearly universal coverage by 1995. In 2005 the net primary enrolment rate was 91 percent. The net enrolment rate for junior secondary education showed an even more marked increase, rising from 18 percent in the 1970s to approximately 62 percent in 2005. The senior secondary enrolment rate has also been increasing, although at a more modest rate. However, education services still are not at the desired levels. Critical challenges remain to achieve the goals of 'Education for All' (EFA), particularly increasing enrolment in junior secondary schools, targeting the poor and improving the quality of teaching (Granado *et al.*, 2007).

Given the huge amount of resources devoted to education, both by government and parents, it is worth investigating whether these investments in education yield returns to individuals that justify the resources invested. In terms of policy making, estimates of the returns to education are useful in a number of ways. For instance, they provide an indication of the level of the education sector that the government should invest in. From a policy perspective, the challenge is to determine how best to allocate scarce resources across various types of education. Will the benefit be higher if resources are invested in schools, technical and vocational education, or universities? An analysis of returns to education can also help in the evaluation of broader economic policies. It is, for example, well established that human capital is crucial to economic development (Ranis *et al*., 2000).

Governments should therefore seek to adopt policies that are consistent with human capital development. To the extent that returns to education in a particular country may show a declining trend, it is necessary to evaluate the causes of such decline. If the returns associated with education are high but school enrolments are low, it is an indication that individuals are not investing optimally in education. Thus, a study on the returns to education has important policy implications (Kimenyi *et al*., 2006). A large number of studies from various parts of the world show that the returns for an additional year of schooling are positive, and range between 5 percent in developed countries to 29 percent in developing countries (Psacharopoulos, 1985 and 1994). For Indonesia, there are few studies on the returns to education. Duflo (2001) estimates that the economic returns to education in Indonesia range from 6.8 to 10.6 percent in 1995. In comparison, Byron and Takahashi (1989) reports that the return to education in Indonesia (Java) was as high as 17.0 percent in 1981.

Given the inconclusiveness of these studies, more accurate and up to date estimates of the returns to education are warranted for the purposes of policy making. Such an exercise is important because it appears that rates of return to education in Indonesia could have varied over time and, therefore, estimates based on dated data may not be useful in today's policy making.

When estimating the private returns to education, it is normally assumed that returns to an individual are independent of the education levels of others. This assumption, which dominates most of the previous studies, ignores a major aspect of human capital theory, namely human capital externalities. The existence of human capital externalities suggests that increasing the education level of one person will have some impact not only on the earnings of that individual but also on the earnings of other individuals (Weir and Knight, 2004).

There is an enormous literature devoted to estimating rates of returns to education and human capital externalities, but there are few empirical studies from Indonesia. This study attempts to fill this vacuum. On the basis of conflicting empirical findings, there has been an ongoing debate on the private returns to schooling and human capital externalities. Some authors find relatively high returns to education in developing countries and others find the opposite. Some authors find that the return declines with the level of schooling, while some find that it rises. Some authors find positive and robust human capital externalities, and some authors find no evidence of human capital externalities. This study attempts to contribute to the current debate by investigating the returns to education and human capital externalities in Indonesia using recent and comprehensive data from the Indonesian Family Life Survey wave 4 (IFLS4). As distinct from previous studies using Indonesian data, this study proposes to provide a comprehensive analysis of the returns to education and human capital externalities for every level of education. Moreover, this study also utilises an augmented Mincerian equation and an instrumental variable approach to overcome the ability bias problem, while previous studies generally used a simple correlation between years of education and wages.

1.2 Research Objectives

The aim of this study is to investigate the private rates of returns to investment and the human capital externalities of education for the Indonesian economy in terms of increased earnings for each additional year of study. The specific objectives are as follows:

1. To comprehensively estimate the importance and value of education to the individual, and to evaluate the returns on investment for the different levels of education in Indonesia.
2. To investigate how large are the human capital externalities of education in Indonesia.
3. To provide further evidence of the effects of education on earnings and to present this evidence in a framework for discussing the potential policy implications.

1.3 Significance of the Study

This study is significant for several important reasons. Firstly, it provides a detailed and comprehensive analysis of the returns to education and human capital externalities in Indonesia using a recent survey, the fourth wave of the Indonesia

Family Life Survey (IFLS 2007/2008). Secondly, it extends Mincer's human capital earnings function to allow for an evaluation of the returns to schooling based on the years of schooling or the level of education, to permit earnings discrimination on the basis of gender to be examined, and to yield a framework for the quantification of human capital spillovers. Furthermore, in estimating the private return to schooling as well as human capital externalities, in addition to the instruments that have been used in previous studies, this study employs variables that have not been employed to date in Indonesia, and which have received limited attention in the literature in general. Thirdly, it aims to foster debate on the issue of the impact of education on economic and social outcomes. Fourthly, although there is enormous literature devoted to estimating rates of return to schooling and human capital externalities, there are few empirical studies from Indonesia. This study helps to fill this gap. Finally, the comprehensive and precise estimation of returns to education and human capital externalities will be useful to formulate recommendations for education policies in Indonesia.

1.4 Outline of the Thesis

This thesis contains eight chapters, including the present one. The first chapter provides an introduction to the study's subject matter. The background to the study problem is presented, and the objectives and the significance of the study are discussed. The next chapter reviews the education sector in Indonesia. It presents an overview of the policies in the education sector, and the trend and patterns of student enrolment from pre-school to higher education levels.

The theoretical framework and empirical background relevant to the estimation of the return to schooling and human capital externalities are presented in Chapter 3. The purpose of the review is to highlight issues that require attention in the analysis of the impact of education on earnings and externalities. While much of the literature relates to developed countries, where possible the review covers studies of developing economies to provide a firmer basis for the analysis for Indonesia conducted in Chapters 5 to 7.

Chapter 4 covers methodological issues relating to the estimation of the theoretical models discussed in the previous chapter. Two methodologies are discussed: the

Ordinary Least Squares (OLS) and the Instrumental Variable (IV) approaches. These two methods are the main techniques used in the analysis of the payoff to schooling, as well as in the empirical assessment of the externalities of schooling. They can be applied to the data set to be used in this thesis.

Chapters 5, 6 and 7 constitute the main part of the thesis. The empirical findings from the analyses of the economic return to schooling and human capital externalities are presented in these three chapters. Chapter 5 discusses the estimates of the private return to schooling obtained using the OLS approach. The presentation of the results commences with estimates from the standard Mincerian model that employs years of schooling in the earnings function. Then the return to schooling based on more detailed information on educational attainment is examined. Following this the discussion turns to estimates of the return to schooling obtained after additional control variables are included in the earnings functions. In order to check for the possibility of selectivity bias in the analysis, this section also presents estimates of Heckman's two-step model. Separate estimations for males and females are undertaken for all specifications.

Given the evidence on the apparent role of ability bias for other countries it is of practical importance to see whether ability bias impacts the estimate of the return to schooling in Indonesia. This issue is considered in Chapter 6 by adopting the Instrumental Variable (IV) approach.

Chapter 7 provides estimates of human capital externalities in Indonesia. In particular, this study attempts to evaluate the existence and the magnitude of local human capital externalities for Indonesia, taking the province as the territorial unit of analysis. Both OLS and IV methods are used. Separate estimates of human capital externalities are obtained for males and females.

In the concluding chapter, the key findings from the previous three chapters are summed up. Using the evidence revealed in this thesis, the policy implications for educational practitioners and policy makers are discussed. This chapter also presents the limitations of the study and explores the scope for further research.

Chapter 2

Overview of Education Sector in Indonesia

2.1. Introduction

This chapter presents a brief overview of the Indonesian economy. It also provides a brief outline of the Indonesian education sector. In particular it discusses the Indonesian education system, early childhood care and education, basic education, secondary education, tertiary education, and the human capital profile of the population. This information provides a foundation for the discussion in subsequent chapters.

The chapter is organised as follows: Section two presents a brief background to Indonesia, covering a range of economic and social indicators, such as geography, population, religion, and economic growth. Section three provides an overview of the education sector in Indonesia. Section four discusses the Indonesian human capital profile followed by Section five, which concludes the chapter.

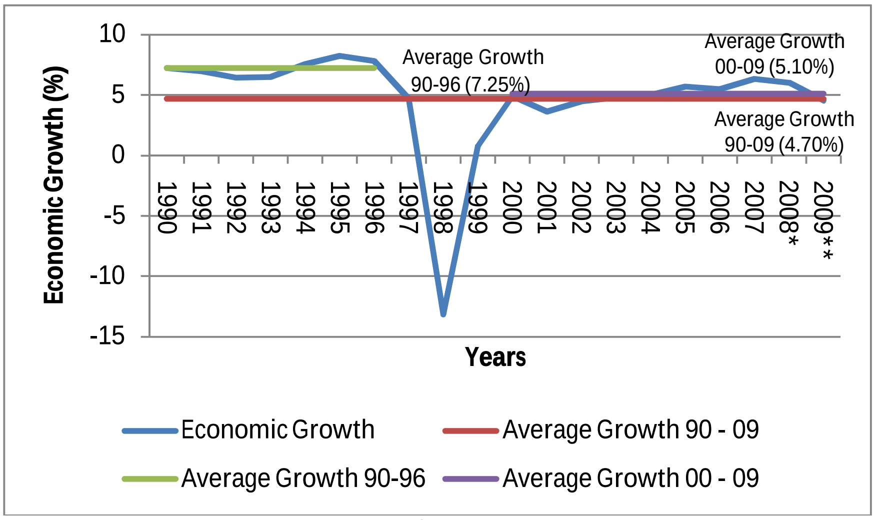
2.2. Brief Country Profile

Indonesia is the largest archipelago in the world, stretching from Sabang to Merauke, and comprises 17,670 islands, of which 6,000 are inhabited. Together the islands have a total area of 1.9 million square kilometres, cover three time zones, and extend from the Indian Ocean into the Pacific for about 5,000 kolimetres. The five largest islands are Sumatra, Java (the most populous), Kalimantan, Sulawesi, and Papua. Indonesia lies between two continents, Asia and Australia, and in 2010 was inhabited by a population of about 237.56 million that comprises of more than 300 ethnically distinct groups who speak about 583 local languages and dialects and practice some of the major religions (Islam, Protestant, Catholic, Buddhism, Hinduism, and Confucianism). The geography, size and diversity of Indonesia are also reflected in the political and public administration system. There are currently 33 provinces and over 440 districts. Population density across these provinces varies widely, from around 14,469 people per square kilometre in Jakarta to 8 people per square kilometre in West Papua. The average population density is around 124 per square kilometre.

Currently, Indonesia is the fourth most populous country, after the People's Republic of China, India, and the United States. Although the population is widely dispersed throughout the archipelago, the heaviest concentrations are located in the fertile islands of Java and Bali, where the population density is 3,277 and 673 per square kilometre, respectively.

Indonesia ranks as a low or lower-middle income country, with a real Gross Domestic Product of Rp 2,082,315.90 billion in 2008 (approximately US $208.23 billion).[1] Manufacturing is the largest contributor to GDP. Since 2002, Indonesia's economy has grown slowly, with growth still below the pre-crisis level (Figure 2.1). Economic growth in the post-crisis period has averaged about 5 percent per annum. More recently, economic growth has started to recover. Thus the GDP growth rate in 2007 was 6.35 percent per annum, the highest rate since 1996.

Figure 2.1: Average Annual GDP Growth, Indonesia, 1990 to 2009



Source: Author's calculation based on data from BPS, August 2010 (BPS, 2010).
Notes: * Preliminary figures. ** Very preliminary figures.

With a GINI index of 34.3 in 2007/2008, Indonesia does not have particularly large disparities in income distribution. However poverty rates still remain significant, despite encouraging economic recovery since the 1997 economic crisis. Education development plays a key role in Indonesia's poverty reduction strategies, through expanded access to post-basic education opportunities and subsequent paid or private employment. Beyond basic education, Indonesia places attention on its system of labour-market oriented technical and vocational education in order to better prepare

[1] Gross Domestic Product at 2000 constant market prices by expenditure.

the huge number of labour market entrants for jobs. This type of life-skills orientation also helps to achieve Indonesia's Poverty Reduction Strategy Paper's (PRSP) basic right to employment opportunities (Asian Development Bank, 2006). Poverty eradication programmes through education channels are implemented by providing education and training in entrepreneurial skills, providing technical assistance, and by promoting entrepreneurial networks and partnerships supported by local organisations, local governments, the private sector and universities. Life skills and entrepreneurship in education programmes consist of village level life-skills programmes, including income generating activities. The Government conducts these programmes through small block grants to community groups. At the same time, senior secondary vocational schools have also been expanding income generating activities through small scale production units and expansion of afternoon and evening classes for adults. Furthermore, since 2006 The Directorate General of Non-formal Education has introduced professional development courses. The objective of these programmes is to provide young people with relevant skills, and entrepreneurship training in rural villages and urban areas.

Issues of gender inequality in earnings can be found in Indonesia. Permana (2006) reported that based on education, experience, rural-urban location, province, and socio-demography-economic characteristics, there are significant gender disparities in earnings in Indonesia. Furthermore, Permana (2006) describes that the male-female earnings gap decreases with the level of education, reaches a plateau at the "post-secondary level" and then tapers off. In other words, the profile of earnings disparity by gender has a "reversed U" shape.

2.3 Education Sector in Indonesia

The scale and structure of Indonesia's education system reflect the size and cultural traditions of the country. The Indonesian education system is complex due to, at least, three factors. These are the sparse distribution of population, the considerable ethnic diversity, and the complex social structure. These become challenges to the efforts to improve the quality of education as well as to expand the education sector, if both equality and equity measures are to be taken into consideration. Efforts in improving the education sector in Indonesia have encountered various obstacles such as: limitations in learning facilities; inadequate quantity, quality, and welfare of teachers;

and an inadequate budget for education. Further description of the education system in Indonesia is provided below in order to provide a more comprehensive understanding of the issues that it needs to confront, and to provide a basis for the policy recommendations that will flow from the empirical analysis in this thesis.

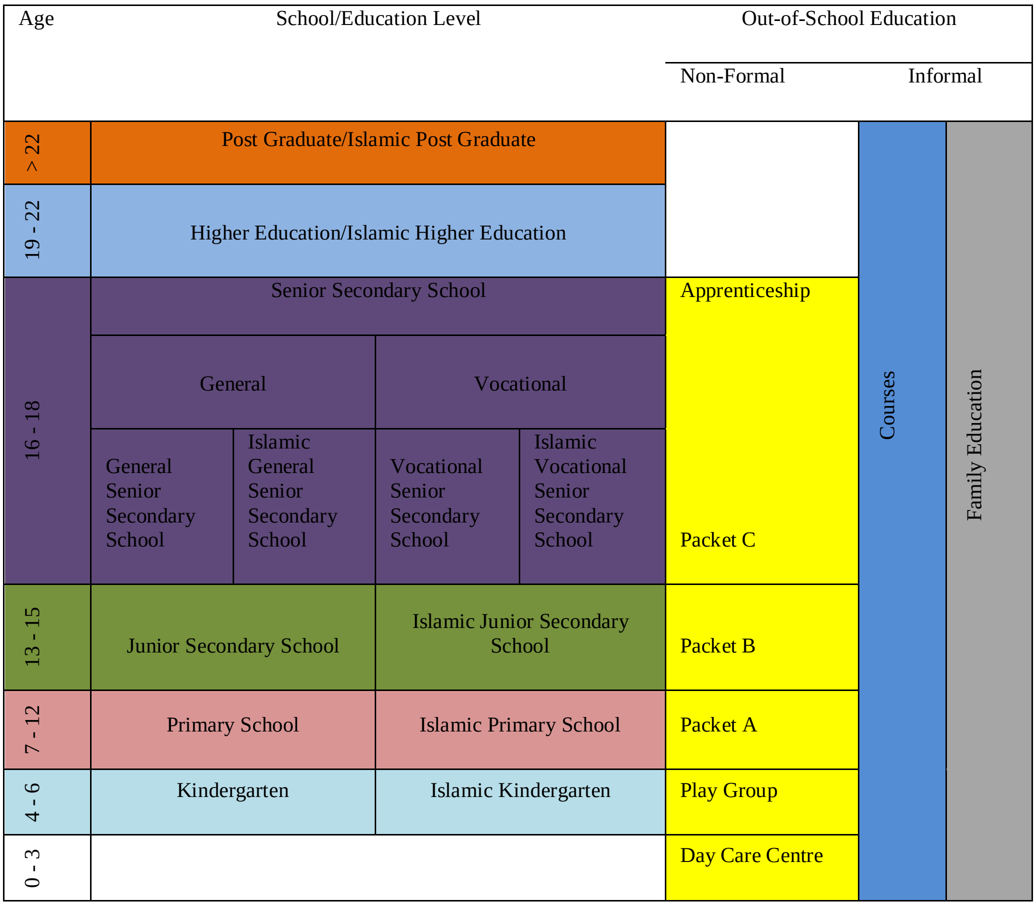
2.3.1 Indonesian Education System

Indonesia's national education system is enormous and complex. With over 46 million students enrolled in all levels of education and 2.7 million teachers in more than 250,000 schools, it is the third largest education system in the Asian region and the fourth largest in the world (behind only China, India and the United States) (National Development Planning Agency, 2010). Two ministries are responsible for managing the education system, with 84 percent of schools under the Ministry of National Education (MoNE) and the remaining 16 percent under the Ministry of Religious Affairs (MoRA).

Based on the 1999 decentralisation legislation and the education Law 20/2003, the government has designed specific strategies and programmes to implement the education policy through three strategic pillars. These three strategic pillars consist of ensuring expanded access and equity, improving quality and relevance, and strengthening governance, accountability and the public image (MoNE, 2007).

The Indonesian National Education System is organised into three different paths, namely formal, non-formal and informal education (Figure 2.2). Formal education is conducted in schools through teaching and learning activities that are gradual, hierarchical, and continuous. Non-formal or out-of-school education is a substitute programme designed to eradicate illiteracy in reading/writing and numerals and the Indonesian language. This programme also provides individuals with an opportunity to develop the knowledge and skills required to work and generate an income, to enable individuals to proceed to a higher level within the formal education system, and to fulfil the needs of persons, families, and communities that cannot be met by the formal education system. Education within the family, or what is called informal education, is an essential part of out-of-school education and provides cultural, religious and moral values and family skills.

Figure 2.2: Education System in Indonesia



Source: MoNE (2007).

According to the *Indonesian Education Act* number 20 (2003), the national formal education system consists of three main levels of education, basic education, middle or secondary education, and higher or tertiary education. Apart from the levels of education mentioned above, pre-school education is also provided to a small proportion of children. Pre-school is the lowest level required to enter elementary school. However, the government makes every effort to encourage parents to send their children to pre-school education before entering elementary school.

Basic education consists of six years of Primary/Elementary Schools (PS) and three years of Junior Secondary Schools (JSS), which was declared as Nine Years of Compulsory Education by the President of the Republic of Indonesia on May 2, 1994. Children start formal schooling at the age of seven.

The types of secondary education include General Senior Secondary School (GSSS) and Vocational Senior Secondary School (VSSS). General education gives priority to expanding knowledge and developing students' skills and preparing them to continue their studies to a higher level of education. Vocational secondary education focuses on expanding specific occupational skills and puts emphasis on the preparation of students to enter the world of work and on developing their professional attitude. Middle or secondary education consists of three years of schooling at GSSS or three to four years at VSSS.

Higher education is offered through diploma (D1, D2, D3, and D4) and bachelor degree courses (S1). Higher education also includes post-graduate programmes (S2) and doctoral programmes (S3). Open universities provide distance learning higher education programmes (UT).

Parallel to the formal system is a set of non-formal programmes known as Packet A Learning Programme (*Kejar Paket A*), a non-formal programme equivalent to primary education; Packet B Learning Programme (*Kejar Paket B*) for junior secondary education; and Packet C Learning Programme (*Kejar Paket C*) for senior secondary education.

Similar to most countries, there are public and private schools in Indonesia. Both types of schools follow the national curriculum developed by the MoNE. There are also Islamic schools, called *Madrasah*. *Madrasah Ibtidaiyah* (MI) is equivalent to elementary school, *Madrasah Tsanawiyah* (MTs) is equivalent to junior secondary school, and *Madrasah Aliyah* (MA) is equivalent to senior secondary school. Different from regular schools, *Madrasah* follow the curriculum developed by the MoRA and, as the name suggests, use Islam as the curriculum's foundation. Similar to regular schools, there are also public and private *Madrasah*.

2.3.2 Early Childhood Care and Education

Although early childhood education is not part of the formal education system in Indonesia, the government devotes attention to early childhood education programmes. This is because children are essential social capital for the development of a nation's human resources potential. Indonesia has committed itself to providing a better future for all of its children, which includes (National Coordination Forum Education for All, 2003):

a. improving children's health and nutrition;

b. ensuring that all children receive adequate education to reach their full potential;
c. providing children with an opportunity to find their identity;
d. instilling awareness of their spiritual values; and,
e. ensuring a secure and supportive environment within a stable family environment.

Pre-school education is aimed at stimulating the physical and mental growth of pupils outside the family environment before entering primary school or out-of-school educational programmes. Early childhood education and development programmes are designed to generate a synergy of good health, good nutrition, and appropriate cognitive stimulation for healthy development in the early years, which in turn is vital for achieving high levels of education and human capital formation later in life. National Education System Law 20/2003 recognises early childhood education as a stage preceding basic education and stipulates that it can be organised formally, non-formally or informally. Five main early childhood services can be identified in Indonesia. A summary of their profile is provided in Table 2.1.

Among the types of pre-school education available are *Taman Kanak-kanak* (TK) or kindergartens, *Kelompok Bermain* (KB) or playgroups, and *Tempat Penitipan Anak* (TPA) or child care centres. TK is the main centre-based pre-primary education service catering for children aged 4-6 years. The objective of TK is to help establish the foundation for the development of the attitude, behaviour, knowledge, skill and creativity of children for further development and growth.

Raudlatul Atfal (RA) is similar to TK, but with emphasis on Islamic teaching. In RA the Islamic atmosphere is very strong and becomes the spirit of the overall teaching and learning process. RA falls under the supervision of the MoRA.

Table 2.1: Profile of Key Early Childhood Services

	Kindergarten (TK) / Islamic Kindergarten (RA)	Playgroup (KB)	Childcare Centre (TPA)	Integrated Service Post (POSYANDU)	Mother's Programme (BKB)
Child age	4-6	2-6	3 months -6	0-6	0-5
Target	Child	Child	Child	Child and mother	Mother
Focus	- Pre-primary education. - Child development and school readiness. - Religious teaching in RA.	- Play-based education. - Mental and emotional development.	Care service for children of working parent, combined with a child development component.	Health service for mothers and children, combined with parenting education.	Parenting education; activities for children also offered during meetings.
Opening hours	2 hours, daily.	2 hours, 3 times/week.	8-10 hours, daily.	2 hours, 3 times/month.	2 hours, 3 times/month.
Required qualification level for teachers	2 years teacher training college diploma (D2).	Senior secondary education with related special training, including apprenticeship.	Senior secondary education with related special training, including apprenticeship.	Junior secondary education with related special training, including apprenticeship.	Junior secondary education with related special training, including apprenticeship.
Responsible government agencies	Ministry of National Education. Ministry of Religious Affairs - supervision and monitoring of RA.	Ministry of Social Welfare - supervision. Ministry of National Education - curriculum.	Ministry of Social Welfare - care and social service component, supervision. Ministry of National Education - guideline development.	Ministry of Health - technical support, supervision. Ministry of Home Affairs - initiated the service in partnership with the Family Welfare Empowerment Movement.	Ministry of Women's Affairs - policy. National Family Planning Coordination Board - delivery and supervision.

Source: UNESCO (2005).

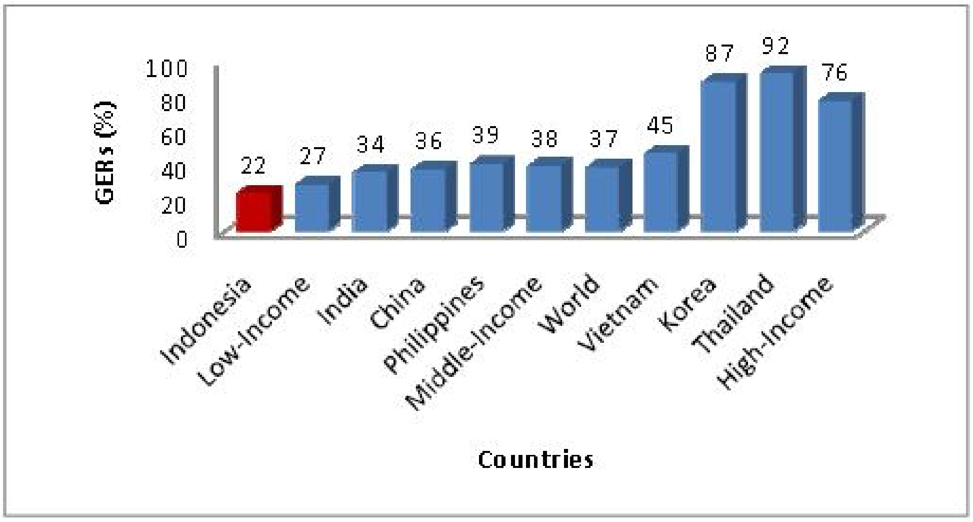
Playgroup is a type of educational service given to children from the age of 3 until they are ready for primary education. Its activities aim at developing the children's potential to the optimum appropriate to their developmental stage through playing while learning and learning while playing activities. Playgroups are generally organised by a foundation or a Non-Governmental Organisation (NGO). Only a few of these NGOs are organised by the government. Playgroups are supervised by the Ministry of Social Affairs (MoSA) and its regional offices, and the Ministry of National Education and its regional offices.

TPA caters for children aged 3 months to 6 years while their parents (especially mothers) have to go to work or, for other reasons, have to be away from home so that they cannot provide the necessary care to their children.

Bina Keluarga Berencana (BKB) is an activity that is carried out by the society with the purpose of providing the necessary knowledge and skills to parents and other family members on how to promote optimal infant growth and monitor their growth and development.

Pos Pelayanan Terpadu or *Posyandu* is a welfare facility for mother and child that functions as a centre providing integrated health and nutrition services, especially for expecting mothers and children aged 0-5 years. *Posyandu* is an activity "from the community, for the community, and by the community" with supervision from medical personnel.

Figure 2.3: Gross Enrolment Ratios in Pre-primary Education, 2004



Source: World Bank (2006)

Low participation in early childhood services is a problem in many developing countries; it is especially pronounced in Indonesia. The country's participation rate in early childhood services, especially in education services, is one of the lowest in the world. Inequitable access to early childhood services is another problem experienced by Indonesia. According to World Development Indicators 2006 (World Bank, 2006), Indonesia's gross enrolment rate of children ages 4-6 years in educational early childhood services was 22 percent in 2004. This number indicates that Indonesia still lags behind many developing countries in the region. The global average enrolment rate for low-income countries was 27 percent, higher than that of Indonesia (Figure 2.3).

2.3.3 Basic Education

Human resources development is one of the strategic efforts for national development in Indonesia. The basic education programme is a major part of this. This programme was implemented to build an Indonesian nation with at least basic knowledge and skills. Such basic competence should enable graduates to either continue their schooling or start earning a living in the society.

Presidential Instruction Decree No. 10 of 1973 initiated Indonesia's programme of compulsory education and, by 1984, the government of Indonesia had fully implemented six-years of compulsory school attendance for primary school age children (7-12 years). The result of this policy was significant, in that the participation rate in primary schools sharply increased from 79 percent in 1973 to 92 percent in 1993. After this programme came fully into effect, the Indonesian government launched the Nine Years Basic Education Programme on 2 May 1994, extending compulsory school attendance to the 13-15 year-old population.

Another vital policy related to basic education program conducted in the period of 1973-1974 was the construction of *Sekolah Dasar* (Primary School) INPRES (Presidential Instruction). The *Sekolah Dasar* INPRES program was launched in 1973-1974. More than 61,800 new primary schools were constructed, and this represented about one school per 500 children aged 5 to 14. This program was reported as the fastest primary school construction program ever undertaken in the world (Duflo, 2001).

Education for All (EFA) national and Millennium Development Goals (MDG) international targets for Indonesia are to ensure that, by 2015, all Indonesian children are able to complete primary and junior secondary education (basic education). A number of policy and regulatory measures have been adopted to achieve this target. In 2005, the Presidential decree set out mutual responsibilities for government and parents regarding primary and junior secondary school attendance. The school operational block grants are designed to eliminate direct cost barriers for parents. As part of quality assurance, MoNE has issued minimum standards for school and student performance and related standards for school infrastructure, textbooks and teacher deployment and qualifications provision (MoNE, 2007).

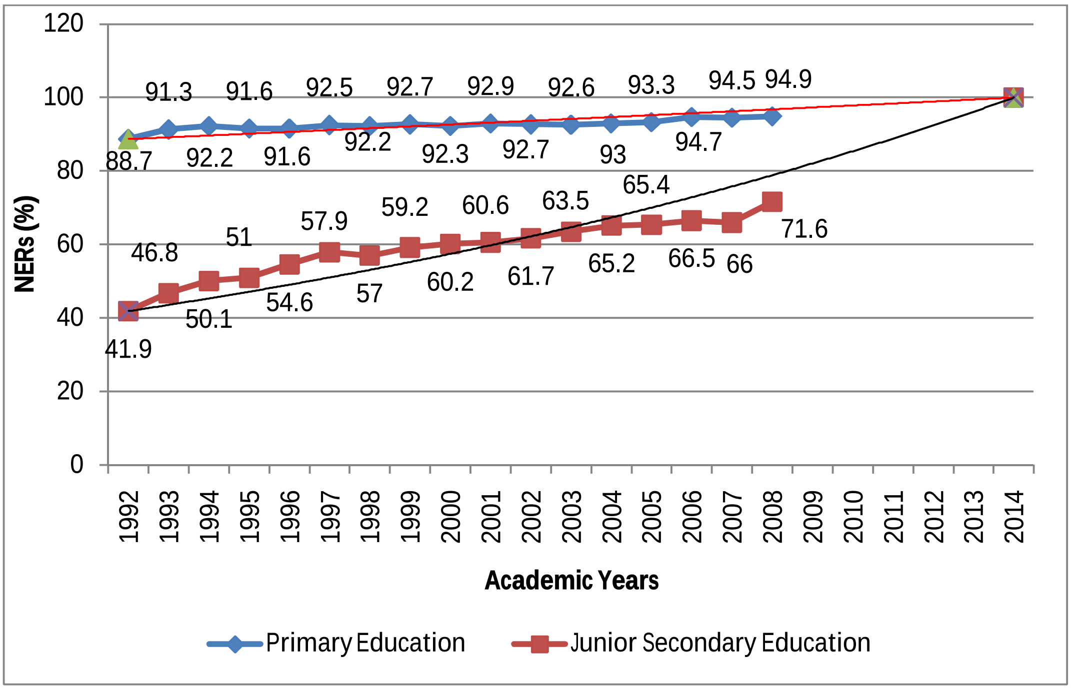
There has been significant progress in gross enrolment rates and net enrolment rates at the primary level over the period 1992-2008.[2] Net enrolment rates have grown from about 88 percent to about 95 percent. Primary gross enrolment rates have increased from around 110 percent to around 115.5 percent. These data show that there is a significant gap between the gross enrolment rate and the net enrolment rate. This pattern indicates two phenomena: first, the high level of 5 and 6 year olds (under-age) enrolling in the first grade of primary school; and second, a number of over 12 years old (over-age) enrolments in primary schools (Government of Indonesia and United Nations System, 2004; MoNE, 2007). Under-age children can enrol in primary schools, a trend that has increased, especially in urban areas. Over-age students may be a result of late enrolment and repeating grades.

The net enrolment rates for primary school in 2006 were 94.7 percent (Figure 2.4). In other words, Indonesia is close to achieving universal primary education, though it needs to be noted that there remain pockets of low enrolment, with the enrolment rate varying from 96 percent in Central Kalimantan to 78 percent in Papua. Unfortunately, many children do not perform well in primary school. Either they have to repeat classes or they drop out. Currently, for example, around 9 percent of children have to repeat grade 1, and at each grade around 5 percent of children drop out. As a result, around one-quarter of children do not graduate from primary school (Stalker, 2007).

[2] The gross enrolment rate (GER) is a comparative figure for the number of students at a certain stage of education as compared to the number of people of school age among the population, expressed as a percentage. Net enrolment rate (NER) is the ratio of children of official school age who are enrolled in school to the population of the corresponding official school age.

This suggests there is still much room for improvement in the provision of primary education.

Figure 2.4: Primary and Secondary Education Net Enrolment Rates and MDG Target

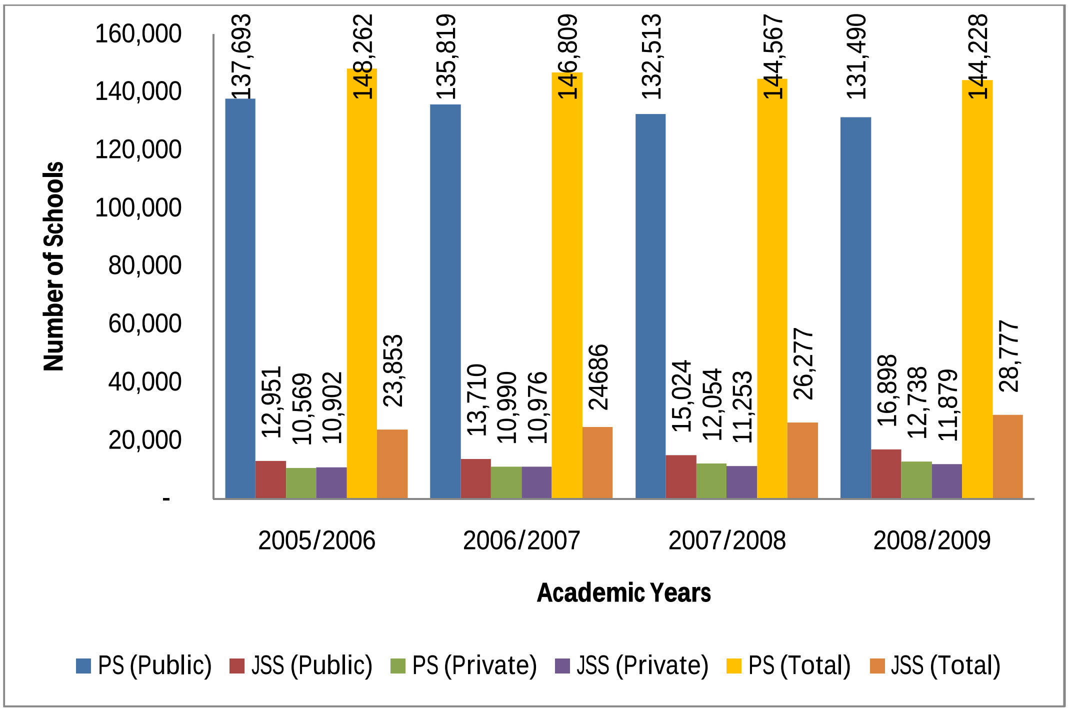


Sources: 1992-2006 data: Stalker (2007); 2007-2008 data: Pusat statistik Pendidikan (2007f, 2008f).

Access to junior secondary education has increased significantly since the Nine Years Compulsory Basic Education Programme was launched in 1994. This policy led to positive results. The transition rate from primary to junior secondary education climbed from 82 percent in 2000 to 92 percent in 2006. The net enrolment rate of junior secondary education rose from 58 percent to 71.60 percent over the period 2000-2008. There has been an encouraging increase in junior secondary education gross enrolment rates, from 75 percent in 2000 to 92.32 percent in 2008.

Figure 2.5 shows the trend in the number of primary and junior secondary schools from 2005/2006 to 2008/2009. The total number of primary schools tends to slightly decrease year by year. In 2005/2006 the number of primary schools was 148,262. Three year later - 2008/2009 - the number of primary schools had fallen to 144,228, a decrease of approximately 3 percent. One of the reasons for this phenomenon is that in certain areas some schools have to be closed or merged due to the low school age population.

Figure 2.5: Number of Primary Schools and Junior Secondary Schools, 2006/2007-2008/2009



Sources: Statistik Sekolah Dasar, Pusat Statistik Pendidikan (2006b, 2007b, 2008b, 2009b), Statistik Sekolah Menengah Pertama, Pusat Statistik Pendidikan (2006e, 2007e, 2008e, 2009e).

Unlike the case of primary school where there has been a modest downward trend in the number of schools, the number of junior secondary schools has increased each year, from 23,853 in 2005/2006 to 28,777 in 2008/2009. During the three years period of 2005/2006-2008/2009 the number of junior secondary schools increased by about 21 percent.

In terms of status of the school, Figure 2.5 shows that primary schools and junior secondary schools are mostly public schools, with 131,490 public primary schools, or 91.17 percent of all primary schools in 2008/2009, and 16,898 public junior secondary schools, or 58.72 percent of all junior secondary schools in 2008/2009. Although the total number of primary schools decreased continuously during the period under review, the number of private schools at this level of education increased by 3.98 percent, 9.68 percent, and 5.67 percent in 2006/2007, 2007/2008, and 2008/2009, respectively. Similarly, the number of private schools at the junior secondary level increased by 8.96 percent during the period of 2005/2006-2008/2009.

2.3.4 Senior Secondary Education

As mentioned above, middle or senior secondary education consists of three years of schooling at GSSS or three to four years of schooling at VSSS. General secondary education gives priority to expanding knowledge and developing students' skills, and preparing them to continue their studies to the higher level of education. Vocational secondary education focuses on expanding specific occupational skills and puts emphasis on the preparation of students to enter the world of work and on developing their professional attitude. The concept of vocational education is to create a work/study programme through the participation of industry and commerce. Therefore, VSSS is expected to be able to meet the challenge of the development of the country. Thus, in the 2005-2009 strategic plan of MoNE, there was a focus on the development of vocational schools. The expansion of access to VSSS/GSSS is more directed towards the expansion of vocational schools rather than general senior high schools in order to reach a balanced composition in the number of general high schools and vocational high school students (MoNE, 2005). Table 2.2 shows the target student ratio in these schools.

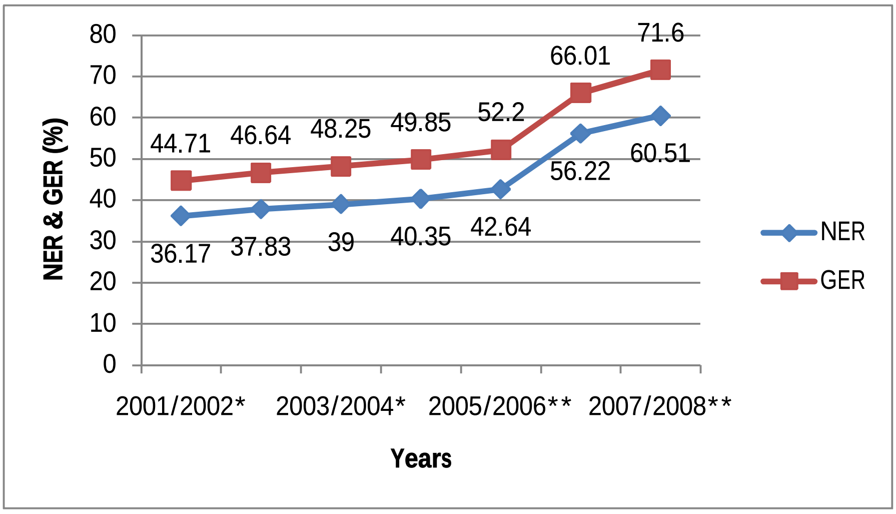
Table 2.2: Ratio of Students of VSSS:GSSS

Year	Target* VSSS : GSSS	Actual** VSSS : GSSS
2004	30 : 70	30 : 70
2005	32 : 68	39 : 61
2006	34 : 66	40 : 60
2007	36 : 64	42 : 58
2008	38 : 64	45 : 55
2009	40 : 60	n/a

Sources: * Strategic Plan, Ministry of National Education, The Republic of Indonesia 2005-2009, MoNE (2005); ** Author's calculation based on data from Statistik Sekolah Menengah Atas, Pusat Statistik Pendidikan (2006c, 2007c, 2008c, 2009c); Statistik Sekolah Menengah Kejuruan, Pusat Statistik Pendidikan (2006d, 2007d, 2008d, 2009d).

The government's target is to increase the ratio of students in VSSS/GSSS schools from 30:70 in 2004 to 40:60 by 2009. Due to an extensive VSSS infrastructure programme, the ratio reached 39:61 by 2005, and by 2006 the final target of 40:60 had actually reached.

Figure 2.6: Senior Secondary Education Net Enrolment and Gross Enrolment 2001/2002-2007/2008

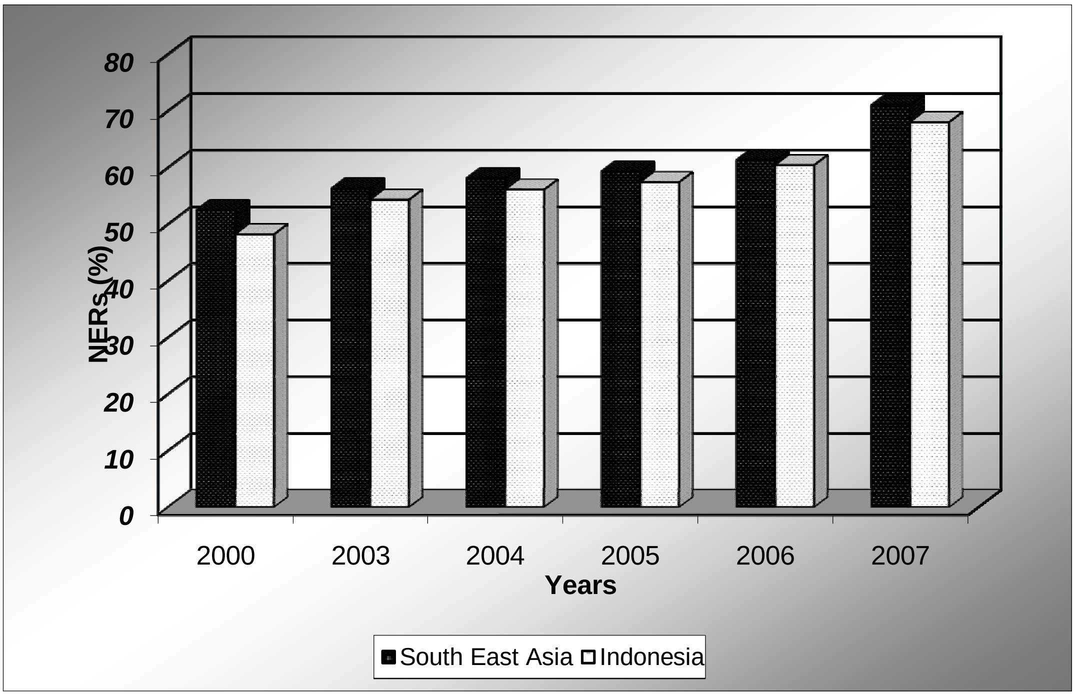


Sources:* Ikhtisar Data Pendidikan Nasional Tahun 2005/2006 Pusat Statistik Pendidikan (2006f); ** Ikhtisar Data Pendidikan Nasional Tahun 2007/2008, Pusat Statistik Pendidikan (2008f).

Indonesia has made noticeable improvement in terms of the secondary education (junior and senior secondary school) net enrolment ratio. Between 2001/2002 and 2007/2008 Indonesia recorded a 19.8 percentage point increase in the secondary education net enrolment ratio (Figure 2.6). This change seems to cover two distinct periods. The first, from 2001/2002 to 2005/2006, was a period of gradual growth. Thus, in 2001/2002 approximately 36.17 percent of 16 to 18 year old students were enrolled in senior secondary school. Four years later the number had increased by 6.47 percentage points. The second period, from 2005/2006, was a period of more rapid growth, with the net enrolment rate rising by around 18 percentage points in the space of just two years.

Figure 2.7 presents a comparison of secondary education net enrolment rates between Indonesia and South East Asia. This shows clearly that Indonesia's secondary education net enrolment rate grows steadily, year by year. However, Indonesia still lags behind neighbouring countries. For example, compared to the average net enrolment rate in South East Asia, that of Indonesia was always slightly lower in the period 2000-2007. In 2006, Brunei Darussalam and Thailand achieved a net enrolment level of 90.1 percent and 71 percent, respectively, while Indonesia had a secondary education net enrolment rate of 60.4 percent. These comparisons show there is still ample scope for improvements in Indonesia's efforts in terms of participation in secondary education.

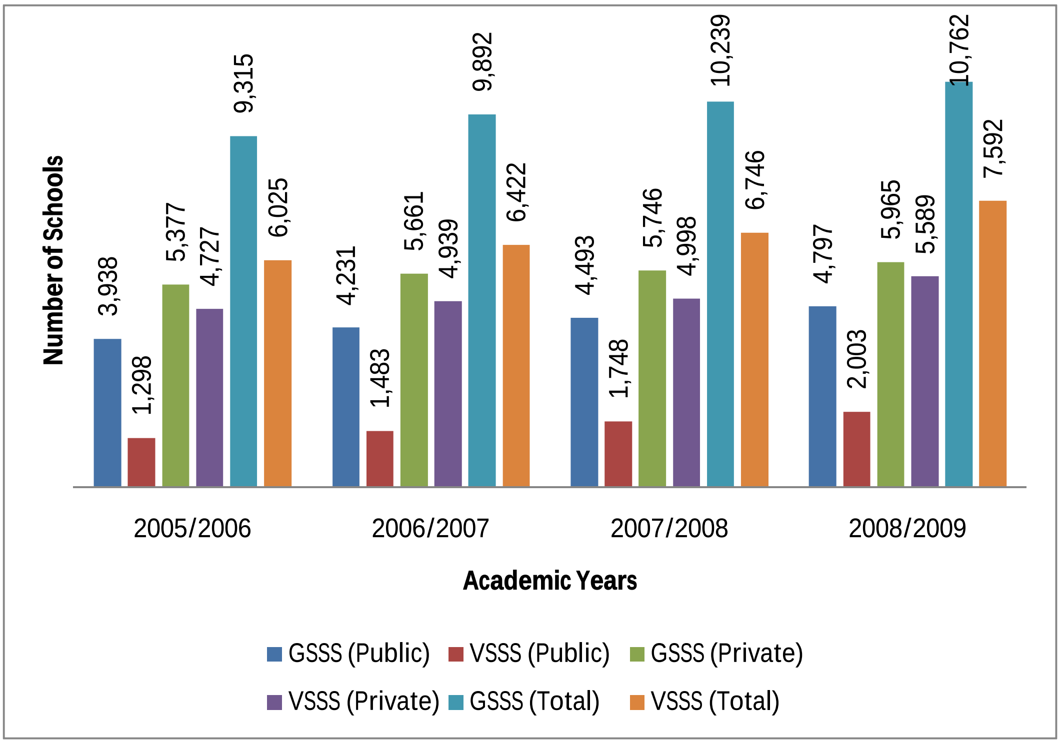
Figure 2.7: Secondary Education Net Enrolment in Indonesia and South East Asia



Note: Data related to Secondary School consist of Junior Secondary School and Senior Secondary School.
Sources: 2000-2006 = Statistical Yearbook for Asia and the Pacific 2008, ESCAP (2008); 2007= UNESCO Institute for Statistics.

Figure 2.8 shows the trend in the number of public and private general senior secondary and vocational senior secondary schools from 2005/2006 to 2008/2009. The number of public and private schools, both for general senior secondary and vocational senior secondary, increased during 2005/2006 to 2008/2009. From 2005/2006 to 2008/2009, on average the number of general senior secondary schools grew by around 7 percent and 4 percent for public and private schools, respectively. The growth in the number of vocational senior schools during the period of 2005/2006 -2008/2009 was about 16 percent per year for public schools and about 6 percent per year for private schools.

Figure 2.8: The Number of General Senior Secondary Schools and Vocational Senior Secondary Schools, 2006/2007-2008/2009



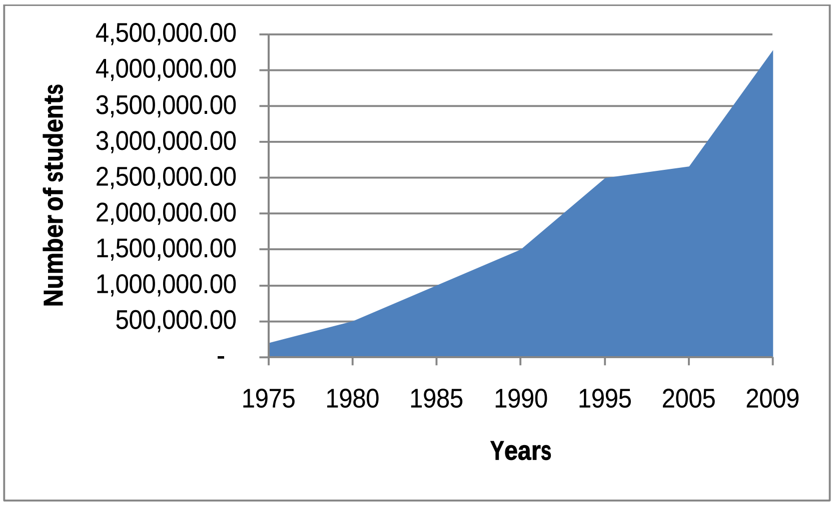
Sources: Statistik Sekolah Menengah Atas, Pusat Statisti Pendidikan (2006c, 2007c, 2008c, 2009c). Statistik Sekolah Menengah Kejuruan, Pusat Statisti Pendidikan (2006d, 2007d, 2008d, 2009d).

2.3.5 Tertiary/Higher Education

The first institution of higher education in Indonesia was established by the Dutch colonial government in 1851, when Netherlands East Indies established a medical school as part of an ethnic policy to educate prospective indigenous doctors. Before the Second World War, there were only about 200 students enrolled in this university, thus serving only a very elite segment of society (Nizam, 2006). In 1920, a private group of Netherlanders established an engineering college (*Technische Hogeschool*) in Bandung, West Java. This was subsequently followed by the establishment of *Landbouwkundige Hogeschool*, an agricultural school in Bogor, and the law school *Rechtskundige Hogeschool* in Batavia (Jakarta). The establishment of higher education at that time was to prepare professionals to address the lack of civil engineers, lawyers, medical doctors and other professionals due to shortages caused by World War I. The number of universities significantly increased from 4 in 1950 to 133 by 1960 (Fahmi, 2007). Nizam (2006) records that in the 1960s the government was successful in achieving its target of having at least one public university in each province. During that period, about 23 new universities, institutes, and teacher training colleges were established.

Higher education in Indonesia has steadily expanded since the enactment of the Education Act in 1961. This expansion has been reasonably uniform across the past four decades. Thus the number of students grew continuously from around 200,000 students in 1975 to more than 4 million students by 2009 (see Figure 2.9). Of the current enrolment, more than 1.7 million students attend the 82 public higher education institutions and 2.5 million students attend the 2,892 private higher education institutions. According to Nizam (2006), the rapid growth in the enrolment rate was driven by economic growth and an increase in the international trend towards mass participation in higher education.

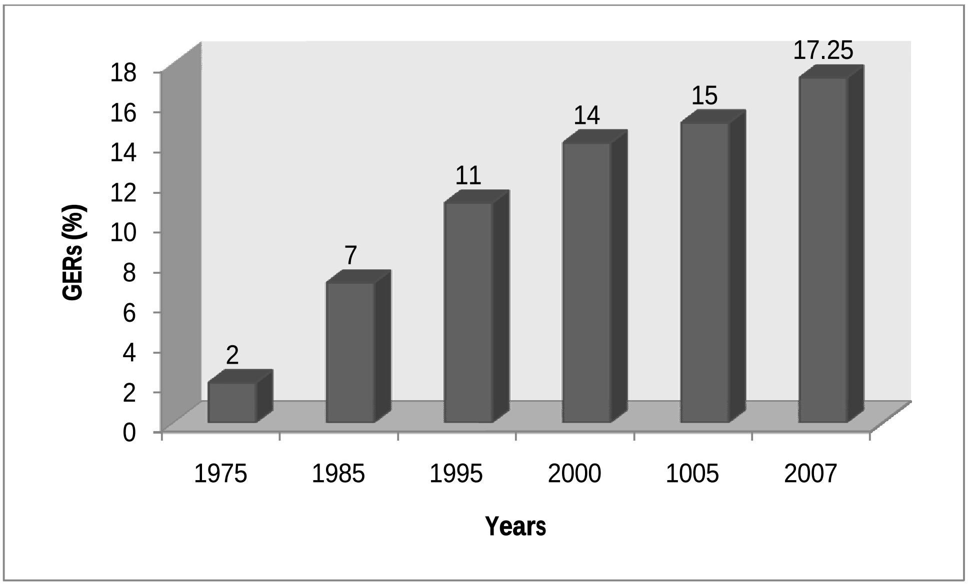
Figure 2.9: Higher Education Expansion in Indonesia, 1975-2009



Sources: 1975-1995: Nizam (2006); 2005-2009: Statistik Perguruan Tinggi, Pusat Statistik Pendidikan (2009a).

Similar to the trend in the higher education student numbers, the gross enrolment rates for higher education have gradually increased since 1975. During the period of 1975-1995, the gross enrolment rate rose from 2 percent to 11 percent. Then, in the era of the 2000s, enrolment in higher education steadily increased from about 14 percent in 2000 to about 17.25 percent in 2007 (see Figure 2.10). Although the gross enrolment rate for higher education has a positive trend, the growth in this sector has been sluggish compared to gross enrolment rates for lower education levels - primary and secondary education.

Figure 2.10: Indonesian Higher Education Gross Enrolment Rate 1975-2007



Sources: Lee and Healy (2006); Ikhtisar Data Pendidikan Nasional Tahun 2007/2008, 2008 Pusat Statistik Pendidikan (2008f).

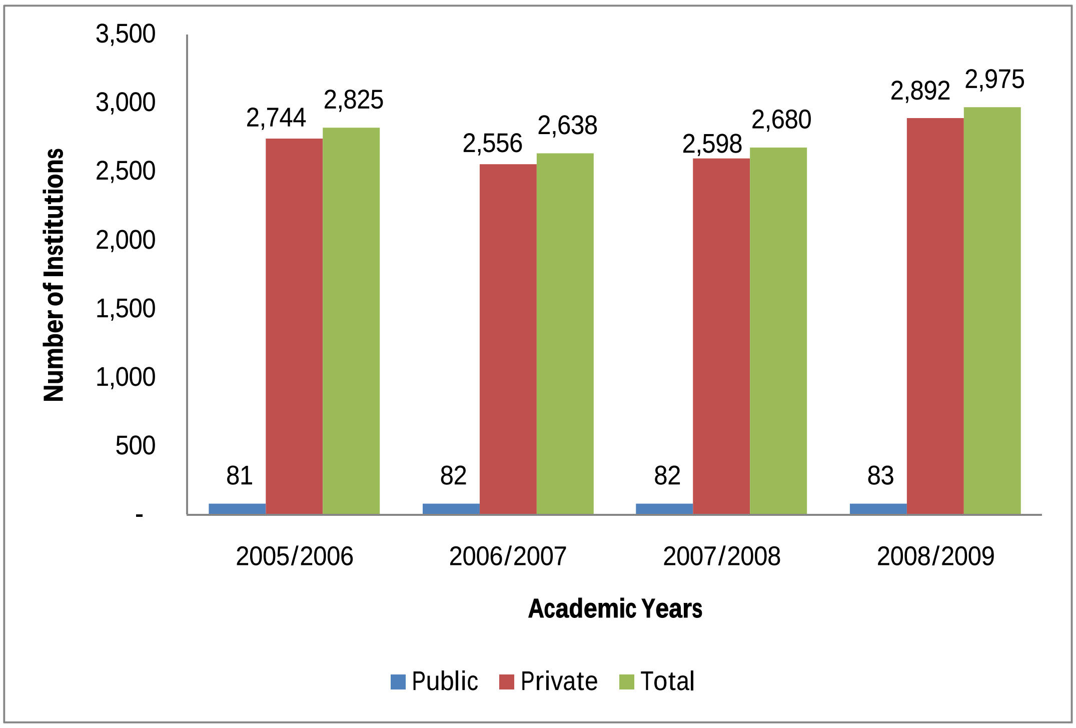
As with the discussion of the secondary education sector, it is useful to put Indonesia's higher education enrolment data in an international perspective in order to better assess its performance. Thus, Table 2.3 presents data on the gross enrolment rate in higher education for South East Asian Countries in 1999 and 2007. The rate for enrolment in Indonesian higher education is higher than that of some countries, such as Brunei Darussalam, Cambodia, and Lao PDR. However, the rate for enrolment in Indonesian higher education is considerably lower than that of Malaysia, the Philippines, and Thailand. These comparisons therefore show that Indonesia has had credible improvement in its higher education enrolment rate. They also show, however, particularly with reference to Thailand, that much more can be achieved in this area.

Table 2.3: Higher Education Gross Enrolment Rates in South East Asian Countries

Country	Gross Enrolment Rate (percent)		Country	Gross Enrolment Rate (percent)	
	1999	2007		1999	2007
Brunei Darussalam	12.3	15.4	Myanmar	7.4	n/a
Cambodia	2.1	5.3	Philippines	28.7	28.5
Indonesia	14.4	17.0	Thailand	33.0	49.5
Lao PDR	2.4	9.1	Timor-Leste	9.6	n/a
Malaysia	23.0	28.6	Vietnam	10.6	n/a

Source: Statistical Yearbook for Asia and the Pacific 2009, ESCAP (2009).

Figure 2.11: The Number of Indonesian Higher Education Institutions, 2006/2007-2008/2009



Sources: Statistik Perguruan Tinggi, Pusat Statistik Pendidikan (2006a, 2007a, 2008a, 2009a).

Figure 2.11 shows that higher education institutions are mostly privately owned, with 2,556 institutions or 96.89 percent of the total, 2,598 institutions or 96.94 percent of the total, and 2,892 institutions or 97.21 percent of the total of all institutions in 2006/2007, 2007/2008, and 2008/2009, respectively. On the other hand, only 82 institutions or 3.11 percent in 2006/2007, 82 institutions or 3.06 percent in 2007/2008, and 83 institutions or 2.79 percent of all higher education institutions in 2008/2009 are public institutions.

2.4 Human Resources Profile of Indonesia

In terms of the Human Development Index (HDI)[3], Indonesia's ranking remains disappointing at 109 out of 179 countries in 2008. Table 2.5 presents Indonesia's HDI by province from 2005 to 2008. Nationally the HDI of Indonesia increases slightly year by year, from 69.6 in 2005 to 71.17 in 2008. During this period, the highest HDI belongs to the province of Daerah Khusus Ibukota (DKI) Jakarta, with values of 76.1, 76.3, 76.59, and 77.03 in 2005, 2006, 2007, and 2008, respectively. In contrast, Papua

[3] Human Development Index (HDI) is a composite index of four indicators: life expectancy rate, literacy rate, average length of school participation, and per capita expenditures.

is the province that has the lowest HDI among the 33 provinces, with values of 62.1, 62.8, 63.41, and 64 in 2005, 2006, 2007, and 2008, respectively.

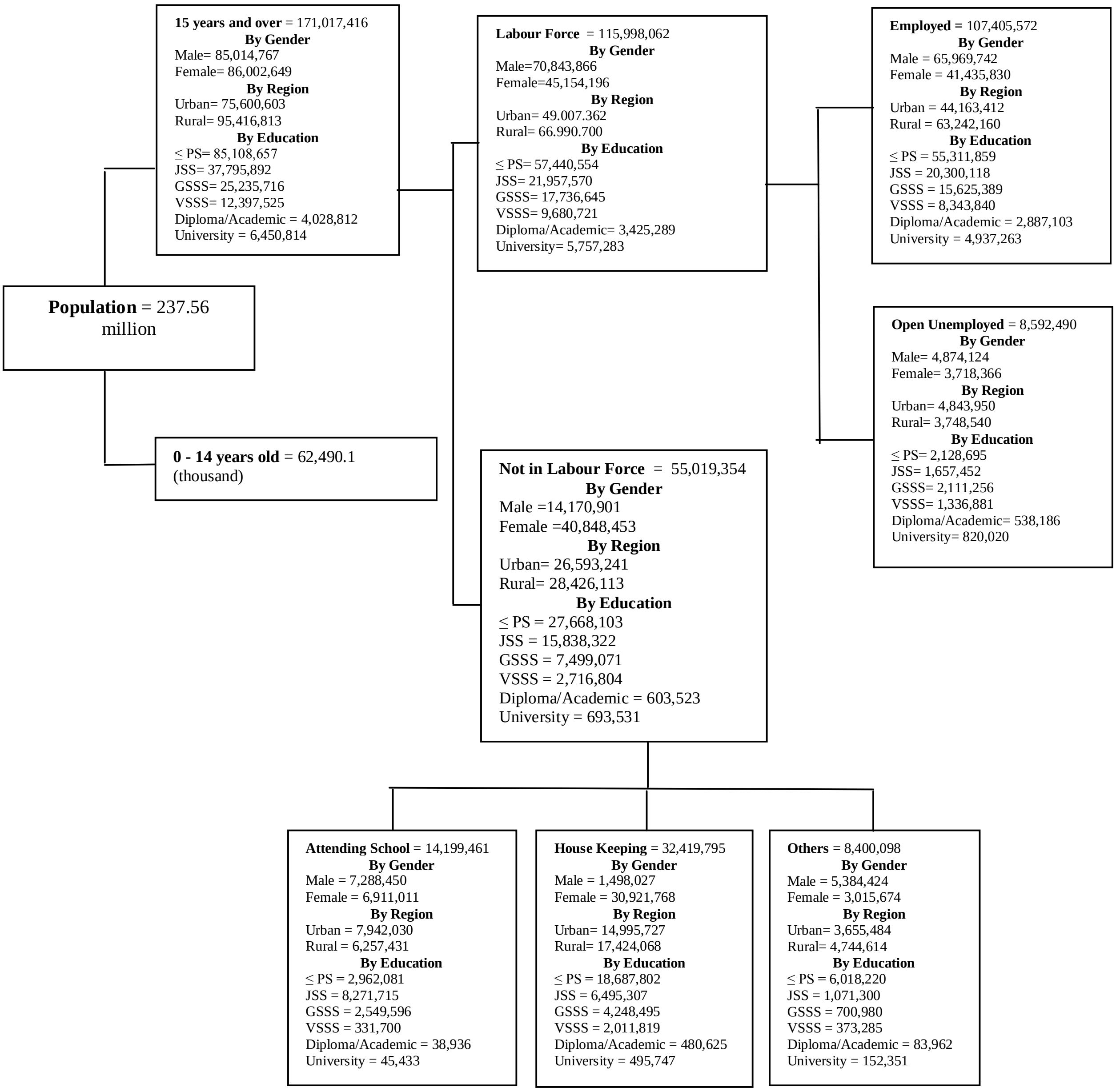
Table 2.4: Human Development Index by Province, 2005-2008

No	Province	2005	2006	2007	2008
1	Nangroe Aceh Darussalam	69.00	69.40	70.35	70.76
2	Sumatera Utara	72.00	72.50	72.78	73.29
3	Sumatera Barat	71.20	71.60	72.23	72.96
4	Riau	73.60	73.80	74.63	75.09
5	Kepulauan Riau	72.20	72.80	73.68	74.18
6	Jambi	71.00	71.30	71.46	71.99
7	Sumatera Selatan	70.20	71.10	71.40	72.05
8	Bangka Belitung	70.70	71.20	71.62	72.19
9	Bengkulu	71.10	71.30	71.57	72.14
10	Lampung	68.80	69.40	69.78	70.30
11	DKI Jakarta	76.10	76.30	76.59	77.03
12	Jawa Barat	69.90	70.30	70.71	71.12
13	Banten	68.80	69.10	69.29	69.70
14	Jawa Tengah	69.80	70.30	70.92	71.60
15	DI Yogyakarta	73.50	73.70	74.15	74.88
16	Jawa Timur	68.40	69.20	69.78	70.38
17	Bali	69.80	70.10	70.53	70.98
18	Nusa Tenggara Barat	62.40	63.00	63.71	64.12
19	Nusa Tenggara Timur	63.60	64.80	65.36	66.15
20	Kalimantan Barat	66.20	67.10	67.53	68.17
21	Kalimantan Tengah	73.20	73.40	73.49	73.88
22	Kalimantan Selatan	67.40	67.70	68.01	68.72
23	Kalimantan Timur	72.90	73.30	73.77	74.52
24	Sulawesi Utara	74.20	74.40	74.68	75.16
25	Gorontalo	67.50	68.00	68.83	69.29
26	Sulawesi Tengah	68.50	68.80	69.34	70.09
27	Sulawesi Selatan	68.10	68.80	69.62	70.22
28	Sulawesi Barat	65.70	67.10	67.72	68.55
29	Sulawesi Tenggara	69.20	67.80	68.32	69.00
30	Maluku	67.00	69.70	69.96	70.38
31	Maluku Utara	62.80	67.50	67.82	68.18
32	Papua	62.10	62.80	63.41	64.00
33	Papua Barat	64.80	66.10	67.28	67.95
	Indonesia	**69.60**	**70.10**	**70.59**	**71.17**

Source: Trends of the Selected Socio-Economic Indicators of Indonesia, August 2010, BPS (2010)

Figure 2.12 provides a summary of the human capital profile of Indonesia in 2010. The total population of Indonesia was estimated to be 237.56 million (119.51 million males and 118.05 million females) as of 2010. At the same time, the size of the economically active population aged 15 and over was estimated to be 116 million, which consists of 70.84 million males and 45.15 million females. Among this labour force, 42.2 percent come from urban areas and 57.8 percent from rural areas. More Indonesian women are now entering the labour market. As of 2010, the number of working women reached 41.44 million, or about 38.58 percent of all workers.

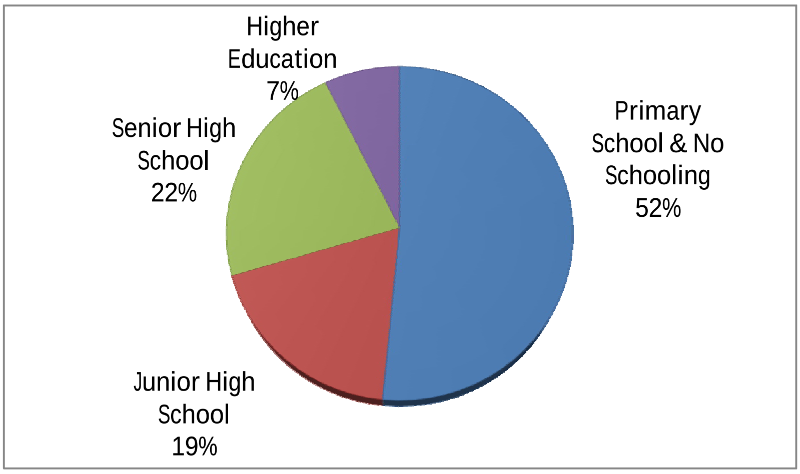
Figure 2.12: Human Resources Profile of Indonesian, 2010



Source: Trends of the Selected Socio-Economic Indicators of Indonesia, August 2010, BPS (2010)

The education profile of the labour force is dominated by the labour force having only, at most, a primary education, with 57,440,554 workers in this category in 2010 (or 52 percent of all workers). The proportion of the labour force who attended senior secondary education is 22 percent, whereas 19 percent have junior secondary education, and only 7 percent have graduated from higher education institutions. The share of workers with high school and university degrees, however, has been rising in urban areas, but less-well educated workers are still a majority even in the cities. Much of this profile is an historical legacy of previously limited access to secondary or post-secondary education. The challenge is therefore to provide life-long learning opportunities to those in the labour force who need to upgrade qualifications and skills in response to changing work force skill requirements.

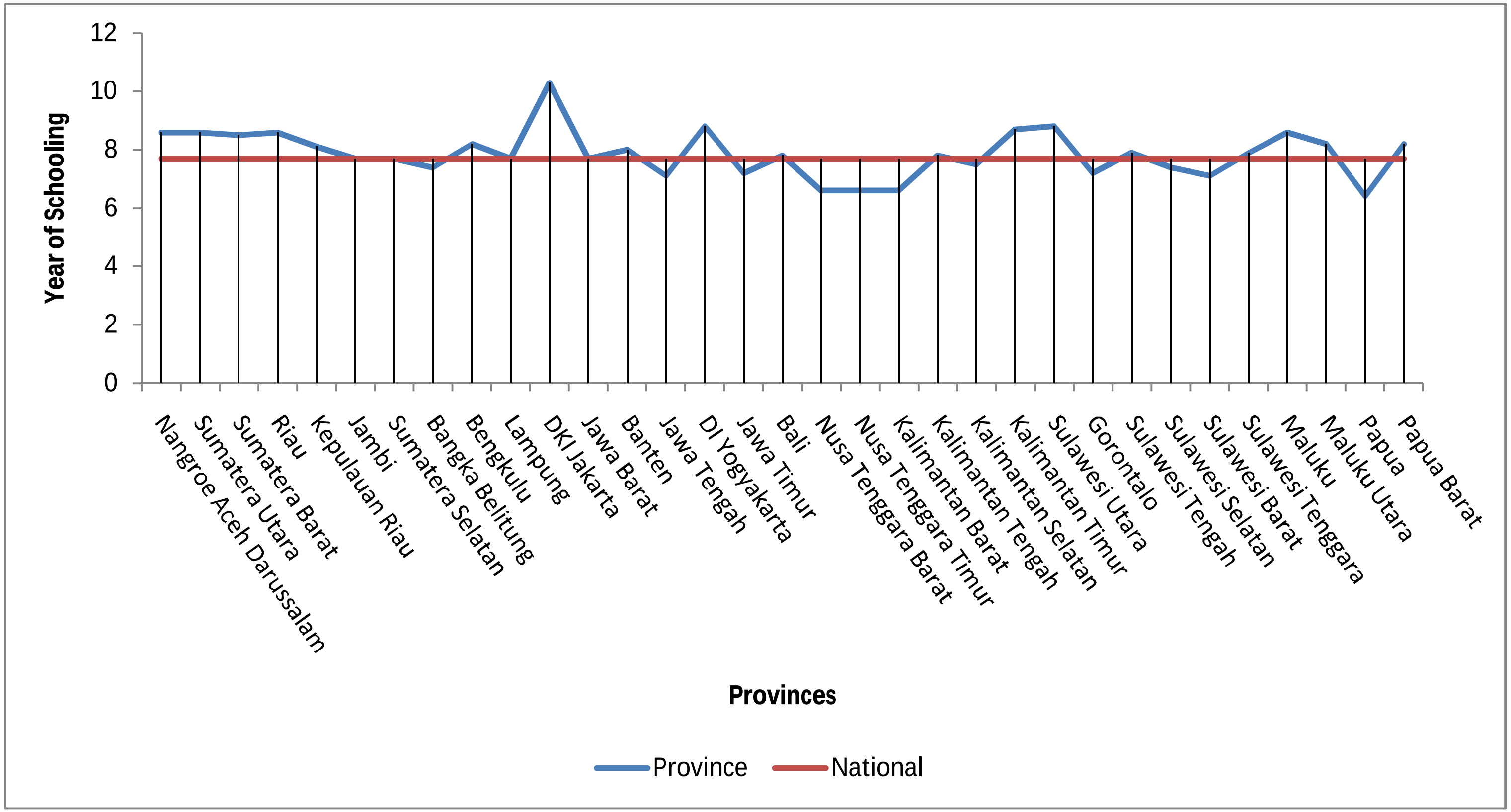
Figure 2.13: Percentage of Population Working by Educational Attainment 2010



Source: Author's calculation based on data from Trends of the Selected Socio-Economic Indicators of Indonesia, August 2010, BPS (2010).

Turning to the average years of schooling for the population 15 years of age and over in 2009, from Figure 2.14 it can be seen that this is 7.7 years. This implies that, on average, adult Indonesians attend elementary education only. Among 33 provinces, 18 provinces, or 54.5 percent, have a higher average years of schooling compared to the national average, and 11 provinces, or 33.3 percent, have lower figures compared to the national average. Most of the provinces with lower average years of schooling are located in central and eastern Indonesia. DKI Jakarta is the province with the highest average years of schooling for its adult population, with 10.3 years. On the contrary, Papua province has the lowest figure, with just 6.4 years.

Figure 2.14: Average Years of Schooling, Population 15 Years of Age and Over, by Province, 2009



Source: Trends of the Selected Socio-Economic Indicators of Indonesia, August 2010, BPS (2010).

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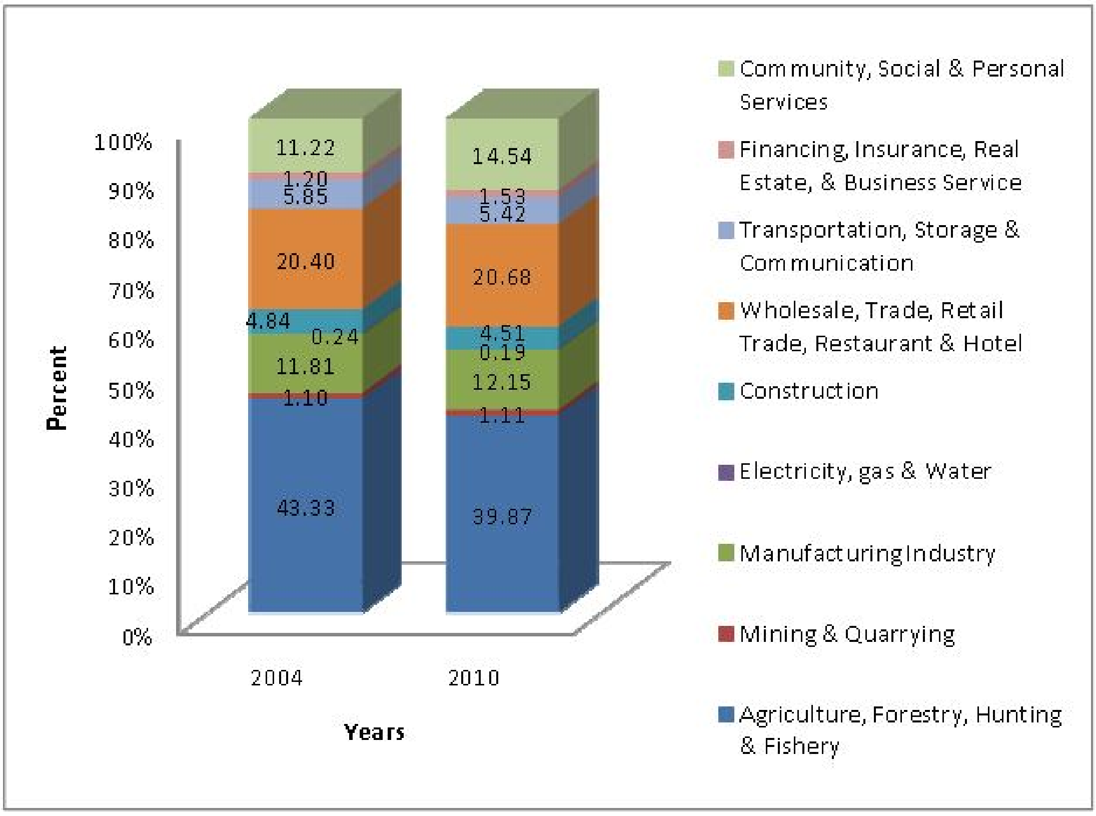
Despite the shift towards manufacturing and labour-intensive industries over the previous three decades, agriculture remains the main sector of employment in 2010 (Figure 2.15). Thus, in the 1980s, agriculture's employment share declined from 55 percent in 1985 to 50 percent in 1990. It then fell further, to around 44 percent by the late 1990s and by 2010 the agricultural sector's share of employment had dropped to 39 percent. This means that even at present around 43 million Indonesians work in the agricultural sector.

Figure 2.15: Population 15 Years of Age and Over Who Worked During the Previous Week by Main Industry, 2005 and 2010



Source: Author's calculation based on data from Trends of the Selected Socio-Economic Indicators of Indonesia, August 2010, BPS (2010).

The second largest sector in terms of the number of workers is the wholesale, trade, retail trade, restaurant and hotel sector, with more than 22 million workers, or about 20 percent of the work force. The share of this sector has increased slightly over time, from 20.40 percent in 2004 to 20.68 percent in 2010.

During the period of 2004-2010 the highest increase in the number of workers was in the community, social and personal services sector. Employment in this sector increased from about 11 million in 2004 to about 16 million in 2010. The community, social and personal services sector is thus an important sector in terms of absorbing a significant number of workers.

The second fastest employment growth has occurred in the manufacturing sector, where employment increased by about 2 million people, representing a 0.34 percentage point increase in the employment share, during the period. Other sector that have experienced growth are financing, insurance, real estate and the business services sector, where the employment share increased by 0.33 percentage point, the wholesale, trade, retail trade, restaurant and hotel sector, with a 0.28 percentage point increase in the employment share, and the mining and quarrying sector, though the employment share there expanded by only 0.01 percentage point. There were four sectors that experienced declines in their worker share during the period of 2004-2010, namely the agriculture, forestry, hunting, and fishery sector (3.46 percentage point fall), transportation, storage and communication sector (0.43 percentage point fall), construction sector (0.33 percentage point fall), and electricity, gas, and water sector (0.05 percentage point fall).

2.4 Conclusion

This chapter aims to present a background to the education sector and the human resources profile of Indonesian. As documented in this chapter, schooling in Indonesia has been characterised by rapid development. Indonesia has a particularly impressive record of expansion of primary education. In the case of secondary and tertiary education, however, while there has been much improvement, Indonesia is still struggling with its objective of increasing the participation rate and the opportunity to learn, while at the same time improving the quality of the education experience at all levels of education. The aim of documenting these features of the education sector in this chapter is to identify some factors that may be relevant to earnings function estimation, among others: the composition of the average years of schooling, level or type of education, industrial sector, number of higher education institutions, and the nature of Indonesia's compulsory education policy.

Chapter 3

Returns to Schooling and Human Capital Externalities: Review of Theoretical and Empirical Literatures

3.1 Introduction

This chapter examines the theoretical and empirical literatures on the return to education and human capital externalities. The purpose of the review is to highlight issues that require attention in the analysis of the impact of education on earnings and externalities. While much of the literature relates to developed countries, where possible the review covers studies of developing economies to provide a firmer basis for the analysis for Indonesia conducted in Chapters 5 to 7.

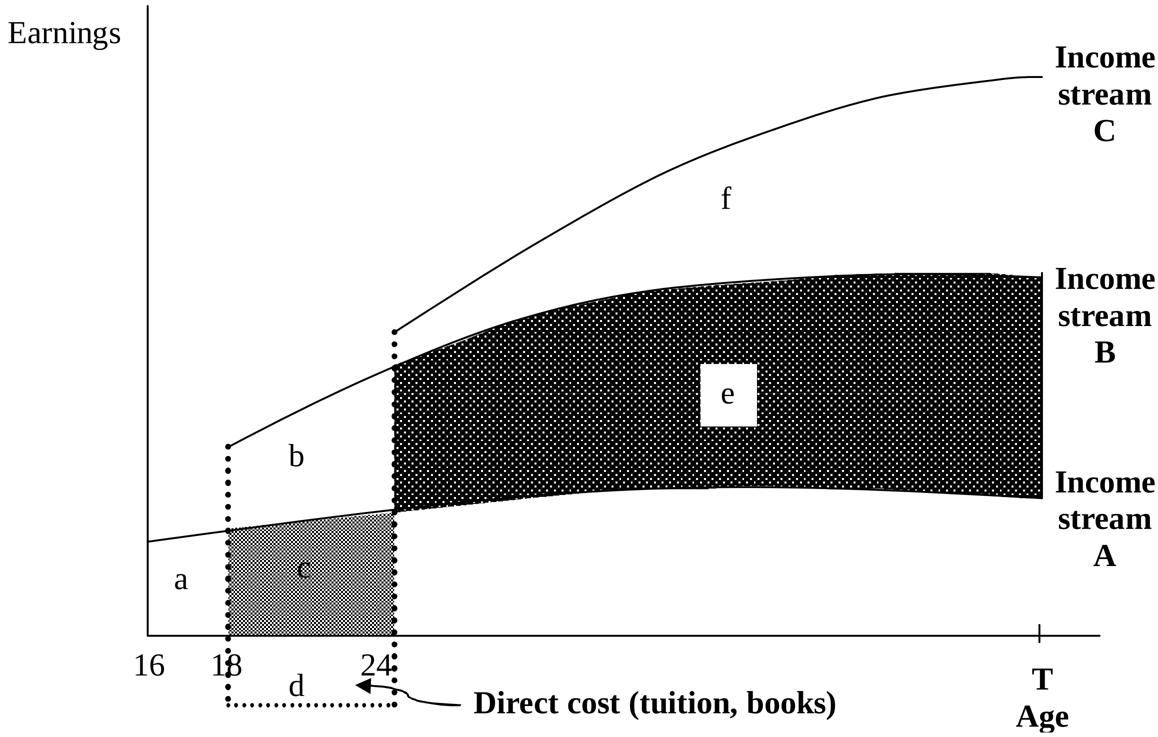
The rest of the chapter is organised as follows. Section 3.2 discusses the theoretical human capital literature, followed by a discussion of the foundation of the earnings function in Section 3.3. Section 3.4 presents a review of the theoretical literature relating to human capital externalities, followed by an analysis of findings from the empirical literature in Section 3.5. The final section provides a conclusion and relates this to the focus for the present study.

3.2 Human Capital Model

The human capital model is the model most widely used to explain the relationship between education and labour market outcomes. It was first introduced by Adam Smith in 1776 in his book, *The Wealth of Nations*. However, the recent popularity of the model is due largely to the developments by Schultz (1961), Becker (1962), and Mincer (1974).

The core of Human Capital Theory (HCT) is the idea that investments are made in human resources in order to improve productivity, and therefore employment prospects and earnings. These investments involve two types of costs; namely direct costs (e.g. tuition fees, cost of books) and opportunity costs through foregone earnings. This is illustrated in Figure 3.1. This figure shows the cost of education and income streams associated with three levels of education. The lowest income stream is for individuals who leave school at an early age (16 years). The middle income stream is for individuals who complete high school (school leaving age of 18 years). It is assumed that there are no direct costs of completing high school. However, the completion of high school is associated with foregone earnings of area "a". Finally, the highest income stream is for tertiary graduates (completed education at 24 years). Tertiary education is associated with direct costs of area "d" in this diagram. The completion of tertiary studies is also associated with foregone earnings of area "b + c" if the comparison group is viewed as high school graduates. This diagram is drawn to reflect the fact that the opportunity cost - the income foregone by not working - is the main component of the cost of obtaining human capital.

Figure 3.1: Education and Alternative Income Streams



Source: Benjamin *et al.* (2007: 258)

Figure 3.1 also illustrates the benefits of the investment in education. For high school graduates the extra earnings they receive is represented by area "b + e". For tertiary graduates, the increase in earnings power compared with high school graduates is given by area "f".

The shapes of the earnings streams indicate two key factors (Benjamin *et al.*, 2007). First, the lifetime earnings profile of more educated individuals lies above the equivalent earnings profile of less-educated individuals. This feature is associated with the proposition that education provides skills that increase the individual's productivity and thus earnings power in the labour market.

Second, for each profile, earnings increase with age, but at a decreasing rate. This upward slope reflects the fact that individuals generally continue to make human capital investments, in the form of on-the-job training and work experience, once they have entered the labour force. The concave shape reflects the concentration of their investments early in the career, and the depreciation of skills in later years. Mincer (1974) argues that this concentration occurs because of: (i) rising opportunity cost of investment in education with additional labour market experience; (ii) a finite lifetime (T in Figure 3.1) which reduces the benefits of later investment; and (iii) diminished learning capacity at older ages.

Figure 3.1 also illustrates a further typical feature of age-earnings profiles: the profiles for the better educated are steeper than those for the less-well educated. This pattern is usually held to reflect complementarities between formal education and on-the job training. That is, workers with higher education tend to undertake more on-the-job training and gain a higher return to such training.

Because the costs and benefits of education occur in different time periods, it is necessary to discount them into present value terms. For the tertiary education outcome depicted in Figure 3.1, this involves the investment decision: invest if

$$\sum_{t=7}^{T-17} \frac{f}{(1+r)^t} > \sum_{t=1}^{6} \frac{b+c+d}{(1+r)^t} \tag{3.1}$$

where r is the discount rate.

There are many factors that can impact this investment decision. These include uncertainty (Riddell, 2006) and the individual's background and ability (Becker, 1964). As these are not the primary focus of this thesis their potential impact will not be reviewed.

An alternative way of looking at the investment decision is to compute the internal rate of return. This involves solving

$$\sum_{t=7}^{T-17} \frac{f}{(1+\rho)^t} = \sum_{t=1}^{6} \frac{b+c+d}{(1+\rho)^t} \tag{3.2}$$

for ρ. The investment decision is then: invest if ρ exceeds the cost of funds (r). Much of the empirical literature in this field has aimed to quantify the rate of return to investment in education. The main method used in this regard is outlined in the next section.

In summary, HCT is based on four major arguments. First, investments in human resources are made in order to improve an individual's productivity and therefore their earnings. Second, it is an investment because costs are incurred, both in terms of direct costs (fees) and indirect costs (opportunity costs). Third, the optimal choice is dependent on the balance between benefits and costs. Fourth, investment in education will benefit both the individual and the society. One measure of the benefits is provided by the rate of return on the investment.

3.3 The Human Capital Earnings Function

The causal link between schooling and earnings has been illustrated in Figure 3.1. The primary means of assessing the value of the educational investment is the internal rate of return. The key question is: how much is the return to education? A number of methodologies have been proposed to answer this question, but the one that has become a cornerstone in empirical research is the human capital earnings function proposed by Mincer (1974) in his study, *Schooling, Experience, and Earnings.* Reflecting the discussion of Figure 3.1 above, Mincer argues that the investment in human capital takes two complementary forms: formal schooling, measured by years of school completed, and on-the-job training, which can be measured by potential years in the labour force subsequent to the completion of schooling.

Mincer's basic model is:

$$\ln(E_i) = \beta_0 + \beta_1 S_i + \beta_2 EX_i + \beta_3 EX_i^2 + \varepsilon_i \tag{3.3}$$

where E_i denotes the earnings or wages of individual i, S_i denotes years of schooling, EX_i denotes years of labour market experience, and ε_i denotes the error term, which embodies the effect of all of the determinants of wages or earnings besides schooling and experience.

Equation (3.3) states that the natural logarithm of earnings or wages depends linearly on years of schooling, experience and experience squared. The use of natural logarithms allows the interpretation of β_1 as the percentage effect of an additional year of schooling. This coefficient provides a measure of the private internal rate of return to schooling discussed in the previous section.

The model developed by Mincer (1974) has several distinct characteristics that make it particularly attractive (Chiswick, 2000). First, the functional form is an equation based on the optimising behaviour of individuals and represents the outcome of a labour market process.[4] Second, it converts the monetary cost of the investment in human capital into years of schooling and years of labour market experience. In other words, it converts the 'immeasurable' into the 'measurable'. Third, the function is adaptable to inclusion of other variables that affect earnings. Examples include ability, individual's characteristics, family background, and quality of schooling. Fourth, it allows comparisons across time and demographic groups, since the coefficients of the regression model have economic interpretations. For this reason it has, for example, been used extensively in studies of gender wage discrimination and immigrant wage adjustment. Fifth, although earnings are positively skewed and the inequality of earnings rises with the level of schooling, by using the natural logarithm of earnings as the dependent variable, the residuals are closer to being normally distributed and homoscedastic. Sixth, the functional form generates a commonly used measure of relative inequality, the variance of the natural logarithm of earnings, thereby facilitating the study of earnings and income inequality across time and space.

3.4 Human Capital Externalities

The discussion above has focussed on the benefits an individual obtains from additional schooling. However, it is widely accepted that education is beneficial to society as a whole as well as to the individual. That is, an individual's educational

[4] Mincer derives his earnings function using two key assumptions: all potential earnings capacity is allocated to human capital investments during formal schooling and in the post-school period the investment profile declines linearly over the working life.

attainment affects not only the individual's productivity but also that of others in the society. Workers benefit from being close to a dense, skilled, labour market where, through different channels, they can learn from others without compensation. Such productivity-enhancing external benefits of labour markets are called human capital externalities, knowledge spillover effects, learning externalities, or labour market local agglomeration economy[5] (Fu, 2007). Moretti (2004) argues that there are two separate reasons why an increase in the share of educated workers may increase total wages over and above the private return to schooling. Firstly, if educated workers and uneducated workers are imperfect substitutes, an increase in the share of educated workers will raise the productivity of uneducated workers. Secondly, the human capital externality raises the productivity of uneducated workers through the learning effects noted above.

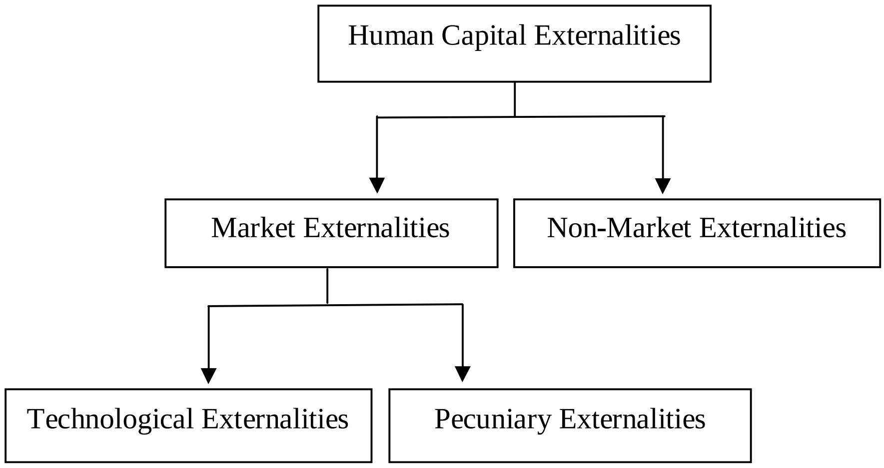
Education externalities need not be limited to the market externalities discussed above. A wide range of other potential externalities have been discussed in the literature (see, for example, McMahon, 2007), such as more informed voting and better parenting practices. Given the array of potential externalities, it is useful to have a formal categorisation in mind when discussing them. In general, the human capital externalities can be categorised into two main groups, namely market externalities and non-market externalities. The former can be divided into technological externalities and pecuniary externalities (Halfdanarson *et al.*, 2008; Heuermann *et al.*, 2010).

Various theoretical explanations of market externalities have been constructed. Romer (1986) and Lucas (1988) elaborate on technological externalities (non-pecuniary externality). They explain that the process of sharing or exchanging of knowledge and ideas, and learning by doing, in turn nurtures technological progress, and this is more likely to occur in an area with a higher average level of education. Technological human capital externalities arise if educated workers increase the

[5] Fu (2007) proposes that human capital externalities penetrate through four channels. Workers can learn from their occupational and industrial peers, who are in the same local labour market, through the depth (quality) of the human capital stock in the local labour market; Marshallian labour market externalities, or specialisation and peer competition effects; Jacobs labour market externalities or the diversity of the local labour market in terms of occupations and industries; and the thickness (density) of the local labour market, or labour market pooling effects.

productivity of other workers, for example through processes of informal learning, without being compensated (Halfdanarson *et al.*, 2008).

Figure 3.2: Types of Human Capital Externalities

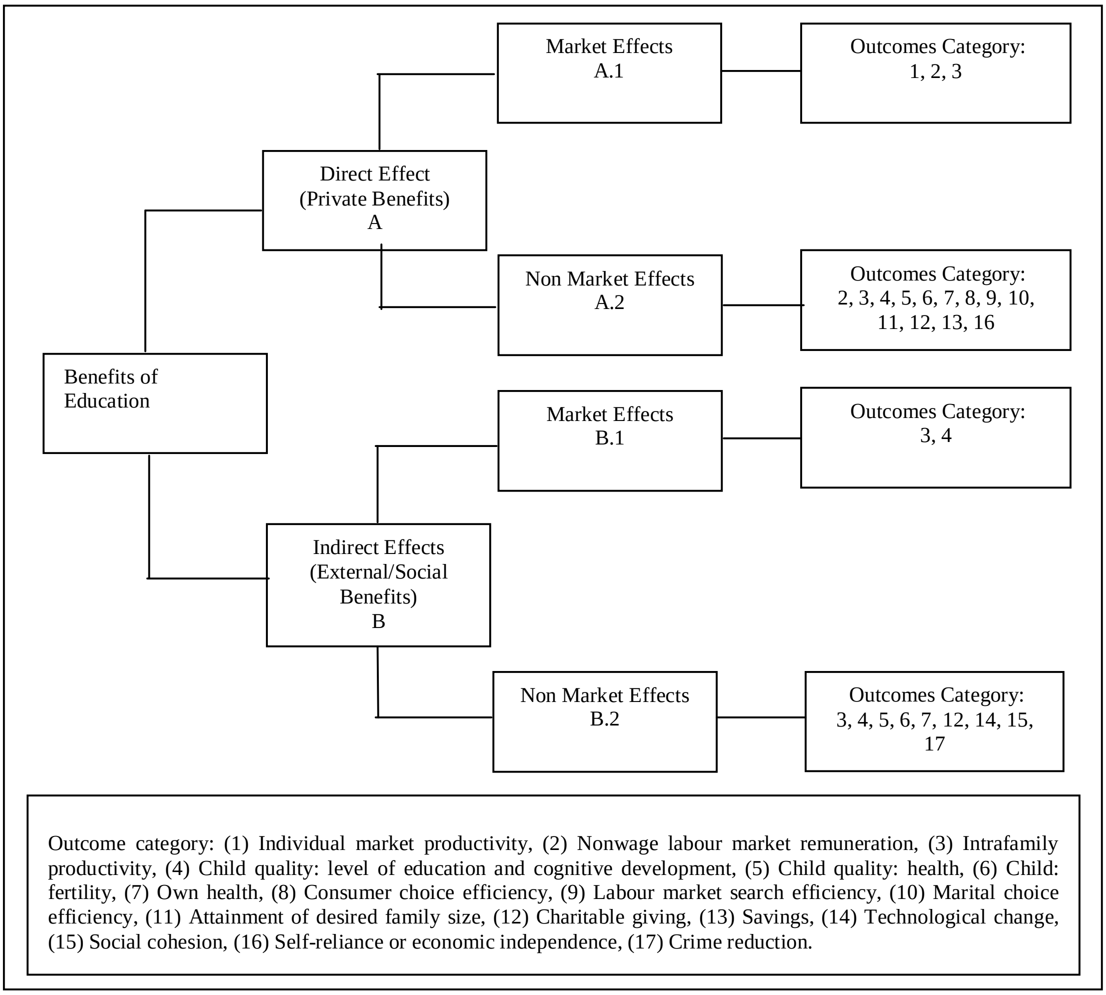


Source: Halfdanarson *et al.* (2008).

Pecuniary externalities feature in the works of Krugman (1991). This type of education externality is not created through technological channels, but rather through market interaction processes between firm and worker. Before entering the job market workers need to invest in human capital, such as schooling, training, and the acquisition of general knowledge. The length of schooling and the type of education chosen will generally depend on the available job types, skill required, and type of tool and equipment they expect to use. On the other hand, firms will decide the types of jobs and physical capital based on the skills and education of the labour force. An increase in workers' education could push firm to invest more. Thus the firms could increase their R&D investment to introduce skill-complementary technologies and so increase the productivity of skilled workers in the long-run. Although some of the workers do not increase their human capital, they will work with more physical capital and receive higher earnings (Acemoglu, 1996).

The final type of human capital externality in Figure 3.2 is non-market externality. In order to explain this type of externality it is necessary to distinguish between non-market private effects and non-market externalities of human capital. Figure 3.3 reviews the different benefits of education.

Figure 3.3: Benefits of Education and the Outcome Category



Source: Author's schematisation based on McMahon (2004, 2007); Wolfe and Haveman (2002).

Figure 3.3 indicates that education has direct and indirect effects. Both of these have two dimensions. The first dimension relates to market effects (private market benefits and social market benefits). The second dimension covers non-market effects (private non-market benefits and social non-market benefits). The direct effects of education are the higher earnings, better employment prospects and more prestigious jobs generally associated with extra years of schooling. Indirect effects occur as education works through other intervening variables to generate either market or non-market effects. The indirect effects are externalities because the education of one person benefits others in the family, the community, and/or in future generations. The benefits of these indirect effects are not enjoyed by the individual as the direct result of his or her education investment, but are freely available to all (McMahon, 2004 and 2007).

Based on Figure 3.3, it can be identified that there are four sets of education outcomes that can be linked back to the categories discussed above. The first set comprises individual market productivity (which is associated with higher earnings), nonwage market remuneration, and intrafamily productivity. These are the private market benefits (category A.1). The second set includes, among others, all forms of nonwage labour market remuneration (e.g. more flexible working hours, more prestigious positions), child quality, child health, fertility, own health, etc. Together these are referred to as private non-market benefits (category A.2). The third set of outcomes covers the enhancement of children of the more highly educated, through better education and cognitive development. This set of outcomes forms the external/social market benefits of education (category B.1). The last set of outcomes consists of matters such as crime reduction, lowering poverty, and improving the civic senses of individuals, strengthening civic institutions and so on. Collectively, these are the external/social non-market benefits of education (category B.2).

Most economists agree that social benefits of education of the types noted above exist, but they disagree on the size of these externalities. In addition, most conventional estimates of the social rate of returns do not take into account the non-monetary externalities, as these are difficult to measure. This is why the literature on the non-market externalities of education is rather sparse.

In order to evaluate the presence of human capital externalities, the standard Mincerian wage equation of Equation (3.3) can be augmented in a number ways. The most common approach is to attempt to capture regional human capital externalities as follows:

$$\ln(E_i) = \beta_0 + \beta_1 S_i + \beta_2 EX_i + \beta_3 EX_i^2 + \beta_4 Z_i + \varepsilon_i \tag{3.4}$$

where E_i denotes the earnings or wages of individual i, S_i denotes years of schooling, EX_i denotes years of labour market experience, Z_i denotes a vector of variables that are held to capture the presence of human capital externalities, including measures of the average level of human capital in a worker's local labour market, and ε_i denotes the error term, which again embodies the effect of all of the determinants of wages or earnings besides schooling and experience and the regional human capital externalities.

3.5 Empirical Evidence on the Returns to Schooling and Human Capital Externalities

3.5.1 Returns to Schooling

The empirical literature on the rate of return to education is divided into two eras: before the early 1970s and after the early 1970s. The assessment of the returns to education during the first era began in the late 1950s. The estimation procedure used in these early studies was the elaborate or full method that was outlined above in Equation (3.2). In the early 1970s the returns to education literature progressed to using the earnings function outlined in Equation (3.3) above (Psacharopoulos, 1981). This Mincer earnings function continues to dominate the current literature.

Psacharopoulos (1977) argues that the empirical analysis of the relationship between earnings and individual worker characteristics using regression analysis can be classified into two broad categories. The first category covers studies based on exploratory earnings functions that do not have a specific theoretical base. These studies treat the dependent variable (earnings) either in absolute or a log form. Some include age or labour market experience in linear form rather than as a quadratic. The second category comprises the wider set of studies based on human capital theory. These studies follow Equation (3.3) and specify the dependent variable (earnings) in log form. In addition, to distinguish between the biological and human capital effects of time, the human capital theory based regression equations use experience instead of age as an independent variable.

Most research in developed countries, particularly that over the past three decades, has been undertaken using the Mincer Equation. In the case of developing countries, however, studies of the profitability of education have used various methods, such as: cost-benefit measure and net present value (see Equation 3.1), the internal rate of return approach of Equation (3.2), and recently, similar to developed countries, the Mincer earnings equation.

This section reports summaries of selected research on the relationship between earnings and individual worker characteristics. The selection in this regard aims to convey the main methodological issues that empirical studies of the returns to schooling have addressed, as well as indicate the range of findings. Eight of the empirical studies covered here focus on developed countries and the other ten focus on developing countries. A summary of the returns to schooling studies at a microeconomic level is provided in Table 3.1. This table contains additional details on the eighteen studies discussed in the following paragraphs, as well as brief comments on a number of additional studies of interest.

With regard to the developed countries, the focus in the first instance is on establishing the conventional wisdom with respect to the magnitude of the return to schooling. Then studies that addresses major methodological issues are reviewed. The eight studies covered are: Hartog *et al.* (2004), who report returns to educational attainment in eight developed counties and a Central European "transition economy" using a standard Mincer equation; Rummery *et al.* (1999), Callan and Harmon (1999), Uusitalo (1999), and Leigh and Ryan (2008), who apply the IV approach to estimate the returns to schooling; Ashenfelter and Krueger (1994) and Miller *et al.* (2006) who exploit samples of twins in their analysis; and Bronars and Oettinger (2006) who make use of sibling data.

Hartog *et al.* (2004) present information on the returns to educational attainment in eight developed countries and a Central European "transition economy" (Poland) using the Luxembourg Income Study (LIS) database. The eight developed countries reviewed are US, Australia, Netherlands, Canada, Spain, Finland, Germany, and Italy. They apply a standard Mincer wage equation, utilising years of schooling and dummies for educational level as independent variables. When years of schooling are used as an independent variable, the estimation results imply that the rate of return for each additional year of schooling ranges from 4.4 to 12.3 percent. When the estimation was based on dummies for educational level as independent variables, the coefficients on these variables were the smallest for the lowest education category and they increased with each subsequent level of education. It appeared that the returns to education increase with the level of schooling in most countries.

Rummery *et al.* (1999) study the returns to education for Australian youth using data from the 1985 wave of the Australian Longitudinal Survey. Both OLS and a rank-order instrumental variable (IV) approach are applied in this study, with the IV approach being used in an attempt to address the endogeneity of the schooling variable. This arises where the schooling decision (i.e. how many years of schooling to complete) depends on the earnings gains attributable to the extra schooling.[6] The results show that, after taking into account the endogeneity of schooling, each additional year of schooling is related to an increase in wages of about 8 percent. Rummery *et al*. (1999) concluded that there is no strong evidence that the adjusted estimate of the payoff to schooling obtained using the rank-order IV method is significantly different from the OLS estimate.

Using OLS and IV methods, Callan and Harmon (1999) estimate the return to schooling for Ireland. Parental education and social class variables are exploited as instruments with the IV method. This study utilises data from the Survey of Income Distribution, Poverty and Usage of State Services, conducted by the Economic and Social Research Institute in 1987. OLS estimates of the return to schooling vary from around 7 to 9 percent. The IV estimate is about 10 percent. Different from other findings for the UK, the results from this study show that OLS estimates are not significantly downward biased. In other words, the differences the between estimates of the rate of return using OLS and IV approaches are not statistically significant.

Uusitalo (1999) reports evidence on the returns to schooling using an individual level data set from the 1970, 1975, 1980, and 1985 Finnish longitudinal census. In this study the author has a focus on ability as an omitted variable in the estimating equation.[7] There is an attempt to correct for the ability bias in the earnings equation by utilising ability test scores as an individual's ability proxy. Furthermore, to deal with the measurement error and/or endogeneity in school choices, IV estimation is adopted, using family background as the instruments. The OLS results indicate that, without controlling for ability differences, the return to schooling is 8.9 percent. Introducing three ability test scores measuring mathematical, verbal, and analytical abilities into the wage equation decreases the estimated effect of years of schooling on earnings from 8.9 to 7.4 percent. Taking into account the endogeneity of schooling

[6] The estimation without controlling for the endogeneity of education may generate biased estimates of the return to schooling. By controlling for the endogeneity of education using either an IV approach or natural experiments, it can be expected that the estimate of the returns to schooling will be higher. The extent of the bias depends on the structure of the particular model specified as well as the true values of the parameters of this underlying model.

[7] The exclusion of a relevant explanatory variable from the earnings equation may bias the estimated coefficients of the included variables. The extent of the bias will depend on: (i) the partial impact of the excluded variable on earnings; and (ii) the correlation between the excluded variable and the particular included variable. Including explicit measures that proxy for the unobserved effect and using twins or siblings are ways to minimise the problem of omitted variable bias.

through using the instrumental variable approach yields an estimate of the return to schooling of 12.9 percent.

Leigh and Ryan (2008) apply three different econometric approaches (OLS, instrumenting schooling with month of birth, and instrumenting schooling with changes in school leaving laws) to estimate the return to schooling in Australia. The data used are from The Household, Income and Labour Dynamics in Australia (HILDA) Survey. The naive OLS estimate of the return to an additional year of schooling (controlling for age and gender) is around 13 percent. The implied ability bias is 9 percent when instrumenting with changes in school-leaving laws, 10-28 percent from estimating a fixed effects model with identical twins, and 39 percent when instrumenting with their month of birth.

Ashenfelter and Krueger (1994) take advantage of data on identical twins to investigate the economic returns to schooling in the US in 1991. Identical twins have the same genes and so have the same "ability". Moreover, if the twins are raised together they will have the same family background. Ashenfelter and Krueger (1994) relate the difference in the earnings of identical twins to the difference in their levels of education as this difference in earnings approach should provide an estimate of the return to schooling that is not affected by omitted variables (ability and family background) bias. They similarly relate the differences in earnings of non-identical twins to the difference in their level of schooling to obtain an estimate of the return to schooling that is free of family background bias (though which has omitted ability variable bias). Both of the returns obtained from the study of twins can be compared with the estimated return obtained from the study of individuals (conventional), which suffers from both ability and family background bias. Numerous measurements of schooling levels were utilised in this study to evaluate the effect of reporting error on the estimated private returns to education. For example, the co-twin's report on educational attainment is used as the instrument for the twin's self-reported educational attainment in IV estimation. Ashenfelter and Krueger (1994) do not find upward bias of the estimated return to schooling created from omitted ability variables. In contrast, they find a significant downward bias in standard estimates of the returns to education caused by measurement error in self-reported schooling differences.[8] The estimation results after correcting for measurement error imply that each additional year of schooling raises wages by 12 to 16 percent. The study provides no evidence that conventional estimates of the return to schooling are misleading.

Applying Ashenfelter and Krueger's (1994) approach, Miller *et al.* (2006) explore the natural experiment of twins in labour market analysis for their analyses of the return to schooling of young Australian twins. The estimations in this analysis are undertaken using both OLS and IV. The estimation results from the analyses of the incomes of individuals and for the within-twins analyses for identical twins imply that the economic return to schooling ranges between 1.8 and 6 percent. Based on the estimates of a number of models of the determinants of annual earnings for non-identical twins, the economic return to schooling is between 3.6 and 7.7 percent. It is concluded that, when considering both genetic and family effects, the economic return to schooling in Australia among a sample of young twins is approximately between 5 and 7 percent. These estimation results are close to those obtained using conventional models.

Bronars and Oettinger (2006) use sibling data instead of data on twins in their examination of wage outcomes in the US. They employ wage data and aptitude test scores from the 1979 National Longitudinal Survey of Youth (NLSY79) to obtain OLS, family fixed effects, and fixed effects instrumental variable estimates of the return to schooling. They find that controlling for aptitude test scores has a substantial impact on the estimated returns to schooling. Adding aptitude test scores residuals as an independent variable in a log wage regression decreases the estimated return to schooling. This finding creates a doubt on the assumption that unobserved ability is a pure family factor. They also find that older brothers have a higher return to schooling than younger brothers, and women have a higher return to schooling than men. The former finding has a major implication: In the standard wage equation specification in sibling studies, the returns to schooling (and other characteristics) are assumed not to vary by birth order. But the result noted above supports the argument that parents overeducate their sons, and specifically their younger sons, relative to the

[8] Ignoring the measurement error may result in a downward biased estimate of the return to schooling. Many advocate the use of instrumental variable estimators to alleviate the problem of measurement error.

allocation of educational investment that would maximise the aggregate earnings potential of their children. Moreover, this indicates that parental preferences or other factors typically omitted from recent sibling models of the return to schooling influence the educational attainment of children, or that the quality of schooling (e.g. curricular content) may vary systematically by sex and birth order within families. Then, when the multiple sibling reports of schooling in the NLSY79 are utilised to estimate over identified FEIV models, the over identifying restrictions cannot be accepted. This finding suggests that sibling reports of schooling from the NLSY79 data are correlated with wage residuals. Hence these variables are not valid instruments for self-reported schooling in within-family estimates.

Turning to developing countries, it is observed that there is now a large body of literature that has investigated the returns to education in developing countries. In general, the estimated returns to education are larger in developing countries than in developed countries. Comprehensive overviews are provided in Psacharopoulos (1985, 1994). The review in this following section will briefly cover studies for Africa, Brazil, Russia, Bangladesh, China, and Indonesia.

A number of studies on the link between education and earnings in Africa find that the private rate of return to an additional year of schooling is quite high. The average private returns to education in Africa are 45 percent for primary education, 26 percent for secondary education, and 32 percent for higher education (Psacharopoulos, 1985). Moreover, Psacharopoulos (1981, 1985, and 1994) shows that for countries in Africa it was commonly reported in the early literature that the private returns to investment in education are highest at primary level and thus primary education should be the number one investment priority. However, a number of later studies on education in Africa have found that the private rates of return are not only relatively lower than suggested in the earlier literature, but contrary to the conventional pattern they also increase with the level of education (Kifle, 2007). There is also evidence that the returns to education vary within a country. Thus Kimenyi *et al*. (2006) report that in rural areas in Kenya the returns to university education are lower than the returns to secondary and college education, whereas the opposite pattern was observed in urban areas in that country.

Using a comprehensive micro dataset of full-time workers from the Welfare Monitoring Survey (WMS) of 1994, Kimenyi *et al.* (2006) analyse the returns to education in Kenya. Several OLS regressions based on the Mincer (1974) equation for the entire sample, and for the sample disaggregated by gender and region, were presented. The results suggest that generally the private returns to schooling rise with the level of education. At the national level, the rates of return to primary education, secondary education, college, and university are 7.7, 23.4, 23.6, and 25.1 percent, respectively. Rural areas have lower returns to schooling. Furthermore in these areas workers who graduated from university have lower returns to education compared to workers who graduated from college and secondary education.

Cohen and House (1994) examine the relevance of the human capital approach to the explanation of the variance in workers' productivity and earnings in the labour market of urban Khartoum, Sudan. A key finding is that the returns to primary education are lower than the average for other developing countries, while the returns to college education are higher. The results are opposite to the popular view observed by Psacharopoulos (1994). Based on this empirical evidence, Cohen and House conclude that the patterns of returns to education at different levels of education remain inconclusive.

Using household survey data collected in 1989 by the Brazilian Institute of Statistics (IBGE), Griffin and Edwards (1993) evaluate the rates of return to education for Brazil by using standard and augmented Mincerian earnings equations. The augmented Mincerian earnings equation was utilised to obtain the wage effects of changes in the educational structure of the labour force. This was accomplished by adding labour market condition controls, such as region and sector of employment, into the earnings equation. The basic Mincerian regression yielded results that suggested that the rate of return to an additional year of schooling is 15.1 percent. When region and industry variables were included in the earnings equation, the rate of return to an additional year of schooling declined to 12.5-12.8 percent.

Lam and Schoeni (1993) investigate the effect of family background on the earnings of male workers in Brazil. The inclusion of measures of family background in the earnings equation allowed the authors to examine the impact of omitted family background variables on the estimate of the return to schooling in Brazil as well as to identify the direct effect of family background on earnings. The data used in this study are from the 1982 household survey - *Pesquisa Nacional por Amostra de Domidilios* (PNAD) - conducted by the Instituto Brasileiro de Geografia e Estatistica (IBGE). A number of wage equations were estimated. First, Lam and Schoeni (1993) estimate a wage equation with the schooling of workers as an independent variable. Second, they successively add family background variables, such as: the schooling of the worker's parents, wife, and parents-in-law. The main conclusion of the study is that the family background bias in the returns to education is fairly small and need not imply returns to family connections.

Cheidvasser and Silva (2007) use a representative sample of the Russian Federation, the Russian Longitudinal Monitoring Survey, to estimate the return to education. The authors complement the OLS regression approach with an IV approach. Changes in the educational system in the ex-Soviet Union in the 1950s and 1960s are employed as instrument variables. Estimates using the IV approach suggest that the exogeneity of the education variable cannot be rejected. Hence, this justifies the focus on OLS estimates in this study. Using standard regression techniques and the Mincerian earnings function, they report that the returns to education in Russia are quite low compared with those reported in the literature on countries throughout the world. The returns to schooling range around 1-2.3 percent for men and about 3.7-5.9 percent for women.

Asadullah (2006) investigates labour market returns to education in Bangladesh using data from the national Household Income and Expenditure Survey (HIES) 1999-2000 of the Bangladesh Bureau of Statistics. This study adopts the standard Mincer human capital earnings function, which was estimated by using OLS. In order to address a potential sample selectivity problem, the author applies the sample selectivity correction framework suggested by Heckman (1979). The average return to education obtained for the full sample is 7.1 percent. Returns to schooling for urban workers are 8.1 percent and 5.7 percent for rural workers. An interesting finding from this study is that there is no significant evidence of sample selection bias in the analysis. In other words the OLS estimates are robust to potential non-random selection into waged work.

Applying Mincer's equation, Qian and Smyth (2008) draw on a survey of urban Chinese workers in 2005 from China's Institute of Labour Studies (ILS) to estimate the private returns to schooling. This study finds that, on average, an additional year of schooling led to an increase in earnings of 12.06 percent in 2005. Estimates of the marginal returns to completing each additional level of schooling result in the following pattern: Individuals with junior secondary education earn 39.57 percent more than primary school graduates; those possessing senior secondary education obtain 24 percent more than a graduate of junior secondary education; and workers completing a college or university degree earn 48 percent more than those holding senior secondary education or having a polytechnic education. The authors argue that the measurement of the years of schooling should have special attention for future research, as this has the potential to bias the estimate of the private returns to schooling. They explain that most studies using data for China convert the number of years of schooling by using the common number of years it takes to obtain a degree. However, this measure ignores the number of years of schooling obtained by individuals who pursue further study but do not complete the next degree. Thus, this measurement of years of schooling tends to create an upward bias. To overcome this problem, Qian and Smyth (2008) suggest utilising both the highest degree attained and the individual's actual years of schooling.

Deolalikar (1993) estimates the return to schooling for Indonesian adults who have completed their schooling. He uses data from the 1987 round of the National Socioeconomic Survey (SUSENAS) and the Village Potential (Potensi Desa) module of the Economic Census 1986. Instead of years of schooling, this study employs nine dichotomous variables for the different schooling categories, namely some primary schooling, primary schooling, general lower secondary schooling, vocational lower secondary schooling, general higher secondary schooling, vocational higher secondary schooling, diploma 1 or 2, diploma 3, and university. Similar to other studies on the return to schooling, this paper faces a sample selectivity bias problem. To correct for sample selectivity Deolalikar follows the Heckman (1979) framework. This involves the estimation of a probit model of the probability of wage labour participation of individuals over 15 years of age in order to construct the sample selection correction term (lambda). Three sets of estimates of the log earnings function are obtained: selectivity-corrected estimate of the standard earnings function, uncorrected estimate of the standard earnings function[9], and an expanded earnings function, which includes marital status, non-labour income and spouse's age, in addition to the variables in the standard earnings function. The selection of correction term in the selectivity-corrected equation is highly significant. In contrast to Asadullah's (2006) research for Bangladesh, this implies that sample selectivity is important in influencing log earnings. The signs and significance of the schooling coefficients are mostly similar across the first equation and the third equation. However, the magnitudes of the schooling coefficients appear to be larger in the first equation than in the third equation. The schooling coefficients ranged from 0.116 to 1.406 for the first equation, from 0.022 to 1.378 for the second equation, and from 0.011 to 1.323 for the third equation. Generally the results suggest that adult female workers have significantly higher returns to schooling than males at the secondary and tertiary levels. Another interesting result from the earnings function estimates is that there appears to be an important age-cohort difference in the returns to schooling. Specifically, the older cohorts gain higher return to schooling, particularly at the secondary and tertiary levels, than younger cohorts.

Duflo (2001) studies the impact of the INPRES[10] program on the relationship between educational attainment and wages in Indonesia. She utilises data from the 1995 intercensal survey of Indonesia (SUPAS), and concentrates on adult males born between 1950 and 1972. She links the individual-level data on education and wages with district-level data on the number of new *Sekolah Dasar* (Primary Schools) INPRES built between 1973-1974 and 1978-1979 in the worker's region of birth. The author compares the educational attainment and the wages of individuals who had little or no exposure to the INPRES program (they were 12 to 17 years old in 1974) to those of individuals who were exposed the entire time they were in primary school (they were 2 to 6 years of age in 1974), in "high program" and "low program" regions. The number of schools built in the individual's region of birth and the individual's age when the program was launched are used to determine the exposure

[9] A semilog earnings function is estimated in which the independent variables are dichotomous variables for the nine different schooling categories recorded in the survey, a quadratic in age, and a disturbance term.

[10] In 1973, the Indonesian government launched a major school construction program, the Sekolah Dasar (Primary Schools) INPRES program. INPRES stands for Instruksi Presiden (Presidential Instruction). Between 1973-74 and 1978-79, more than 61,000 primary schools were constructed, an average of two schools per 1,000 children aged 5 to 14 in 1971.

of an individual to the program. Interactions between dummy variables of individual's age in 1974 and the intensity of the program in his region of birth are employed as instruments in the wage equation. Duflo confirms that these instruments have good explanatory power and the individuals born in the regions that benefitted from the program were more likely to stay longer at school and to earn more once they entered the labour force. The returns to education are estimated in a selected sample. The author focuses on men born between 1950 and 1972. There are 152,989 individuals in the sample, with an average level of 7.98 years of completed education. There are 60,633 individuals who work for a wage, meaning only 45 percent of the individuals in the sample is working for a wage, with most remaining individuals being self-employed. The probability of working for a wage is potentially affected by education. To evaluate this issue, a 2SLS (two stage least square) approach is applied. The results show that, on average, the program led to an increase of 0.25 to 0.40 in years of education and an increase of 3 to 5.4 percent in wages. Combining the effect of the INPRES program on years of schooling and wages generates 2SLS estimates of the economic returns to education ranging from 6.8 to 10.6 percent. The estimated coefficients in the 2SLS estimations are close to, and not significantly different from, those of the OLS estimations. Based on this evidence Duflo (2001) concludes that OLS coefficients do not appear to be biased upwards, as argued by Behrman (1990) in the context of developing countries.

Using a standard Mincerian earnings function, Comola and Mello (2010) explore the determinants of employment and earnings in Indonesia. They use data from the 2004 Indonesian labour market survey (Sakernas). The authors aim to address two main problems: selection bias and the endogeneity of educational attainment in the wage equation. The former problem is tackled by employing a full-information maximum likelihood system of equations. Earnings are observed for salaried employees, and the selection into the different labour market statuses is modelled in a multinomial choice setting. The authors follow Hill (1983) in describing the Indonesian labour using three categories: people may be inactive, people may work as wage-earners or people may work in non-salaried jobs. A binomial selection equation (where individuals are either employed or not employed) is also considered. The endogeneity of educational attainment problem is handled by instrumenting years of schooling in the equations by exposure to Sekolah Dasar INPRES, measured as the intensity of school construction in an individual's district of birth and his/her age when the program was launched. This paper thus uses a similar identification strategy as Duflo (2001). In this study the authors compare wage determinants estimation using OLS, binomial selection (Heckman selection), and their multinomial selection model. Estimates are obtained which treat educational attainment as exogenous, and for when educational attainment is instrumented by program exposure. Comola and Mello (2010) control the workers' sector of activity in the third set of results. The estimate of the return to education from a Mincerian wage equation for 2004 obtained by standard OLS ranged from 9.49 percent to 10.32 percent. Under the binomial selection procedure using Heckman's (1979) approach, the estimate of the return to education ranged between 10.79 and 11.61 percent. The return to education obtained using the multinomial selection procedure ranged between 10.21 and 11.21 percent. These estimates of the returns to education are comparable to the interval of 6.8-10.6 percent reported by Duflo (2001). The estimated coefficients were very similar whether or not the educational attainment is treated as endogenous. This supports Duflo's conclusion that OLS estimates are not likely to be biased upwards (Duflo, 2001).

Table 3.1: Summary of Selected Studies on the Private Returns to Education

No	Author and Year	Data Set	Country/countries	Econometric Technique(s)	Conclusion(s)
1	Comola and Mello (2010)	The 2004 Indonesian labour market survey (Sakernas).	Indonesia	OLS, IV	The return to education ranges from 9 to 10.8 percent.
2	Qian and Smyth (2008)	2005 survey of urban Chinese workers.	China	OLS	The study finds that, on average, an additional year of schooling led to an increase of earnings of 12.06 percent in 2005.
3	Andini and Pereira (2007)	Portuguese male workers from the European Community Household Panel, from the wave of 1994 to the wave of 2001, and focusing on a sample of former working students.	Portugal	Random-Effects estimator (RE), Between-Effects estimator (BE), OLS, and Quantile-Regression estimator (QR)	The conditional average earnings return to one year of part-time schooling is much lower than the analogous return to one year of full-time schooling.
4	Kifle (2007)	363 employees (salary and/or wage earners) working in public and private sectors of the Eritrean economy 2001-2002.	Eritrea	OLS	The rates of returns to education increase with the increase in levels of education.
5	Cheidvasser and Silva (2007)	The 1992-1999 Russian Longitudinal Monitoring Survey (RLMS).	Rusia	OLS, IV	The returns to schooling are around 2.6 percent for men and approximately 5.9 for women.
6	Asadullah (2006)	The 1999-2000 Household Income and Expenditure Survey (HIES).	Bangladesh	OLS	The average returns to education obtained for the full sample is 7.1 percent.
7	Kimenyi *et al*. (2006)	1994 Welfare Monitoring Survey (WMS).	Kenya	OLS	The results suggest that generally the private returns to schooling rise with the level of education.
8	Miller *et al.* (2006)	Young Australian twins.	Australia	OLS, IV	The economic return to schooling in Australia among a sample of young twins is between 5 and 7 percent when account is taken of genetic and family effects.
9	Hartog *et al*. (2004)	Luxembourg Income Study (LIS).	US, Australia, Netherlands, Canada, Spain, Finland, Italy, Germany, and Poland	OLS	The estimation results imply that the rate of return to education for each additional year of schooling ranges from 4.4 to 12.3 percent.
10	Trostel *et al.* (2002)	International Social Survey Programme data, 1985-1995.	28 countries	OLS, IV	Conventional OLS estimates suggest a worldwide average rate of return to schooling of about 5 percent for men, and 6 percent for women. There is no evidence for a worldwide rising rate of return to education from 1985 through 1995. In general, instrumental-variable estimates are over 20 percent higher than OLS estimates.
11	Duflo (2001)	The 1995 intercensal survey of Indonesia (SUPAS).	Indonesia	OLS, 2SLS	The economic returns to education range from 6.8 to 10.6 percent.

No	Author and Year	Data Set	Country/countries	Econometric Technique(s)	Conclusion(s)
12	Tsakloglou and Cholezas (2000)	Household Budget Surveys HBSs (1974, 1988 and 1994).	Greece	OLS	Returns to education increase as the level of education rises.
13	Liu *et al*. (2000)	1990 Taiwan "Human Resource Utilization Survey".	Taiwan	OLS	Returns to schooling increase with the level of education. The effect of father's schooling is larger than the effect of mother's schooling in the wage function. However, the effect of wife's schooling is even larger.
14	Lauer and Steiner (2000)	The 14 waves of the German Socio-Economic Panel (GSOEP).	Germany	OLS	The return to schooling is around 8 percent for men and 10 percent for women.
15	Rummery *et al.* (1999)	The 1985 wave of the Australian Longitudinal Survey.	Australia	OLS, IV	Taking into account the endogeneity of schooling, the results show that an additional year of schooling is associated with an increase in wages of about 8 percent.
16	Callan and Harmon (1999)	The 1987 Survey of Income Distribution, Poverty and Usage of State Services.	Ireland	OLS, IV	There is no difference between estimates of rates of return using OLS and IV.
17	Bedi and Gaston (1999)	May 1990 survey of Honduran households.	Honduras	OLS, IV	The IV estimates are significantly higher than the OLS estimates. The higher rate of return estimates are driven by the greater schooling attainment and the higher marginal returns for individuals from more privileged family backgrounds.
18	O'Donoghue (1999)	The German Socio-Economic Panel, the Irish Survey on Income Distribution, Poverty, and the Usage of State Service Research Institute and the Survey of Italian Households, UK Family Expenditure Survey.	Germany, Ireland, Italy and the United Kingdom	OLS	Private returns are higher than social and fiscal returns to education. This implies that individuals gain more from education than society in general and more than the public finances do.
19	Uusitalo (1999)	1970, 1975, 1980, 1985 and 1990 censuses.	Finland	OLS, IV	Cognitive abilities are found to have a significant effect both on the choice of the length of schooling and on subsequent earnings. Instrumental variable estimates that utilise family background variables as instruments produce estimates of the return to schooling that are approximately 60 percent higher than the least squares estimates.
20	Ashenfelter and Krueger (1994)	New survey of identical twins.	US	OLS, GLS, IV	The estimation results indicate that each additional year of schooling raises individual's wage by 12 - 16 percent.
21	Deolalikar (1993)	The 1987 round of the National Socioeconomic Survey (SUSENAS).	Indonesia	OLS, Probit	Generally the results suggest that adult female workers have significantly higher returns to schooling than males at the secondary and tertiary levels.
22	Lam and Schoeni (1993)	1982 household survey - *Pesquisa Nacional por Amostra de Domidilios* (PNAD).	Brazil	OLS	The main conclusion of the study is that the family background bias in returns to education is fairly small and need not imply returns to family connections.

Source: Author's compilation.

The empirical studies from the various countries discussed in this section provide two essential messages. The first message concerns the magnitude of the return to schooling. The rate of return to schooling ranges from approximately 5 to 16 percent. These figures confirm that schooling is an important determinant of earnings.

The second main message relates to technical aspects of the earnings function. Three kinds of estimation bias may exist in this function, namely omitted variable bias, measurement error bias, and endogeneity bias. Many studies attempt to deal with these three potential biases using various approaches. The omitted variables bias (e.g. ability, family background) can be solved by adding explicit measures that proxy for the unobserved effect. Some studies use IQ, aptitude test, and other related test scores as a proxy for unobserved ability (Griliches and Mason, 1972; Bronars and Oettinger, 2006). However, this approach is not without its problems. It has been criticised because is very difficult to develop reliable ability measures (Ashenfelter *et al.*, 1999). The second approach to overcome the omitted variable bias is by using twins or siblings (see Ashenfelter and Krueger, 1994; Miller *et al.*, 1995 and 2006; Bronars and Oettinger, 2006). Empirical studies utilising twins or siblings approaches provide varying results. However, many of the within-twin studies indicate that ability bias is relatively small (Ashenfelter *et al.*, 2000). The second problem is measurement error. Many studies deal with this problem by applying an IV approach (see Uusitalo, 1999; Ashenfelter and Krueger, 1994). The endogeneity bias problem can be overcome using two methods: utilising natural variation in data caused by exogenous influences on the schooling decision or applying an IV method (see Rummery *et al.*, 1999; Callan and Harmon, 1999; Uusitalo, 1999; Leigh and Ryan, 2008; Duflo, 2001; Comola and Mello, 2010). The results from IV studies are varied. Some studies point towards the presence of a downward bias in OLS estimates, while others report that the results from IV and OLS are close.

The discussion above shows that to measure the relationship between earnings and schooling we can employ some relatively sophisticated methods such as: using proxies for unobserved variables, utilising natural variation in schooling outcomes, and exploring twins or siblings methods, or we can apply a simple (standard) method. However, many of the previous studies provide evidence that there are no significant differences between results obtained from innovative methods and those from the standard OLS approach. Thus, the majority of the empirical studies confirm that the standard (OLS) method is a reasonably robust way to assess the link between schooling and earnings.

3.5.2 Human Capital Externalities

In Section 3.4 the significant aspect of human capital externalities has been discussed from the theoretical perspective. This Section complements that earlier discussion by presenting the main finding from selected empirical studies on human capital externalities. The first part of the section covers empirical evidence on market externalities. The second part reviews empirical studies on non-market externalities.

3.5.2.1 Market Externalities

There is a vast body of research on human capital externalities at the macroeconomic level, gained largely through investigating the determinants of economic growth. These studies typically show that education is an important contributor to the growth of nations. However, fewer researchers have studied human capital spillovers at the microeconomic or individual level (Rakova and Vaillancourt, 2005; Liu, 2007), particularly in the case of less developed countries (LDCs). This section provides summaries of some of this research. Ten papers are reviewed in this section. The first seven estimate human capital externalities in developed countries and the three others cover less developed countries.

Rauch (1993) and Morreti (1998, 2004) investigate human capital externalities in the US at the metropolitan areas (cities) level. Acemoglu and Angrist (2000) and Rudd (2000) study human capital externalities in the US at the state level. The next two papers are similar studies conducted for other developed countries. The first of these covers Canadian cities, and the second one covers Italian local labour markets. The three studies for less developed countries cover Iran (manufacturing sector), Kenya (district level), and China (city level). A summary of human capital externalities studies at a microeconomic level is provided in Table 3.2. This table contains additional details on the ten studies discussed in the following paragraphs, as well as brief comments on a number of additional studies of interest. In terms of Figure 3.2, all of the studies reviewed in this section represent the category of market externalities, either technological externalities or pecuniary externalities. Moreover, all the studies can be seen to correspond to panel B.1 of Figure 3.3, that is external/social market benefit.

Using the augmented Mincerian model of Equation (3.4), Rauch (1993) estimates average-schooling externalities in a cross section of US cities in 1980. He uses US individual data from the Public Use Microdata Sample of the 1980 Census of Population, together with data for the Standard Metropolitan Statistical Areas (SMSA), to assess the effect on the wages of individuals of the average level of human capital in their region of residence. He finds that the SMSA average education and the SMSA average experience are both significant in raising individual wages. An additional average year of schooling means an increase of 5.1 percent in the wage, and an additional average year of experience means a 0.46 percent increase in the wage of the typical individual. These appear to be economically important magnitudes.

Moretti (1998) similarly analyses the external return to education to individuals who work in cities in the US. The empirical analysis of this study uses individual micro data from the 1970, 1980 and 1990 Censuses. In particular, he exploits the Metropolitan Statistical Area (MSA) as a local labour market and the 1989 March Current Population Survey (CPS) to determine average education by city. The estimation results show that a 1 percent increase in the share of college educated workers raises high-school drop-outs' wages by 2.2 percent, high-school graduates' wages by 1.3 percent and the wages of workers with a college degree by 1.1 percent. Again, these externalities appear to be quite large.

In a further study, Moretti (2004) explores several data sets. The focus of the study is the existence of unobservable characteristics of individuals and cities that correlate with the share of college graduates and which could raise individual wages, thus biasing the coefficient of the aggregate human capital measure. In order to tackle the problem of unobservable characteristics this study employs an Instrumental Variable (IV) method of estimation. The two instrumental variables that are used are the (lagged) city demographic structure and the presence of a land-grant college. He concludes that there is an externality at the city level because a greater share of college graduates in cities leads to an increase in their wages in both 1980 and 1990.

Acemoglu and Angrist (2000) extend the static approach of the above studies to a panel of US states and account for state-fixed effects as well as for the endogeneity of average and individual schooling. This study uses a sample of white men aged 40-49 from the 1960-1980 US Censuses. They employ the variation in educational attainment associated with compulsory schooling laws and child labour laws in the US to examine whether there is evidence of external returns to higher average schooling. Instead of the metropolitan area level, Acemoglu and Angrist (2000) measure aggregate human capital by the average years of schooling at the state level. The main findings of this research suggest that a small external return of about 1 percent (mostly ranging from 1 to 3 percent) is possible, but that there is little evidence of sizeable external returns to education.

Rudd (2000) investigates whether the average level of human capital in a state affects the earnings of an individual residing in that state in a manner external to the individual's own human capital. He uses data from the 1978-1991 March Current Population Survey (CPS). His results show that there is little evidence of an external effect of human capital at the state level in US. The main difference between Rudd (2000) and Moretti (1998, 2004), and Raunch (1993) seems to be in the level of disaggregation: to the state level in Rudd (2000) and finer regional disaggregation in the other studies. This suggests that the design of the study may affect the empirical results.

Rakova and Vaillancourt (2005) estimate the externalities resulting from the local concentration of human capital that raise labour productivity of all workers in Canadian metropolitan areas. They use the 1991 and 2001 Canadian Censuses of Population. In order to assess the presence of human capital externalities, Rakova and Vaillancourt (2005) utilise a sample of individuals aged 15 years or more who had a job in the reference year (the year prior to the census year) and who were not full time students. They propose four alternative measures of human capital: (i) a combination of average education and average experience variables; (ii) the share of workers with university degrees; (iii) the share of workers with postgraduate degrees; and (iv) the share of scientists and engineers. The results of their estimation of the impact of the aggregate human capital at the level of Canadian Census Metropolitan Areas (CMA) on the individual labour productivity over different samples and in different time periods indicate the existence of human capital externalities. Using 1990 and 2000 data and employing the share of workers with university degrees, share of workers with a postgraduate degree and share of scientists and engineers as measures of human capital, the results suggest that an increase of 1 percent in each of these three measures of human capital increases the labour productivity of other workers by 0.6 to 1.3 percent, by 1.5 to 5.8 percent and by 2.1 to 3.1 percent, respectively.

Dalmazzo and Blasio (2007) examine the effects of local human capital on household-level rents and individual-level wages for a sample of Italian local labour markets (LLM). In this research a LLM is defined as "a territorial unit resulting from the organisation of social and economic relations in that its boundaries do not reflect geographical particularities or historical events" (Dalmazzo and Blasio, 2007, pp 366). They exploit data from the 1993, 1995, 1998, and 2000 Survey of Household Income and Wealth (SHIW). The authors adopt three strategies. The baseline model in their study included local human capital, a set of dummies that control for time effects in the years of the surveys, and the basic Mincerian set of individual characteristics. First, they check the robustness of the baseline estimates by including additional household/individual controls such as: a dummy for branch of activity of the company for which each individual works and a dummy for firm size. Second, they test whether the estimated effects of local schooling are robust to the inclusion of additional territorial variables. Third, they deal with a reverse causality problem by instrumenting local schooling. The results show that there is an economically important correlation between local human capital and average wages after controlling for individual characteristics. This implies that human capital generates positive externalities at the local level.

Naderi and Mace (2003) employ multilevel models to examine the existence of human capital externalities in the manufacturing sector of Iranian industry. They use data about the characteristics of 15,755 full-time male employees working in 35 manufacturing firms in Iran. This empirical study provides evidence for the pecuniary externality effects of human capital. A worker working in a firm that has a higher average accumulation of human capital embodied in workers earns more than a worker working in a firm with less human capital.

Table 3.2: Summary of Selected Studies on Human Capital Externalities at a Microeconomic Level

No	Study	Data Set	Country/countries	Econometric Technique(s)	Conclusion(s)
1	Canton (2009)	Dutch survey data and Working Conditions Survey (WCS) from the Dutch Ministry of Social Affairs and Employment 1992-2006.	Netherlands	Fixed Effects estimation	The regional fraction of high-skilled workers or the region's average educational attainment appears with a positive and statistically significant coefficient in an augmented Mincer specification. However, the impact on individual wages completely vanishes when the firm's human capital stock is included as an additional control.
2	Kirby and Riley (2008)	United Kingdom Labour Force Survey (LFS) 1994-2004.	UK	OLS estimation and Feasible GLS estimation	A one year increase in industry average schooling raises the wages of workers within that industry by 2.6 to 3.9 percent, giving a social return to schooling that is significantly above the private return.
3	Muravyev (2008)	Russia Longitudinal Monitoring Survey 1992-1994.	Russia	OLS and Random Effects estimation	A one percentage point increase in the share of people with higher education in a city results in an increase of city residents' earnings of about 1 percent.
4	Wirz (2008)	Linked employer-employee data from for the year 1996 from the *Schweizerische Lohnstrukturerhebung (LSE)*.	Switzerland	Weighted least squares	There is clear empirical evidence for education spill-over effects on individual wages within occupational groups (about 4 percent) and at the firm level (about 2 percent).
5	Dalmazzo and Blasio (2007)	1993, 1995, 1998 and 2000 from the Survey of Household Income and Wealth (SHIW).	Italy	OLS and IV	The results show that human capital generates positive externalities at the local level.
6	Liu (2007)	1988 and 1995 Chinese Household Income Projects (CHIP).	China	OLS and IV	OLS estimates of the external returns range from 4.9 percent to 6.7 percent. 2SLS estimates suggest that a one-year increase in city average education could raise individual earnings by between 11 and 13 percent.
7	Ciccone and Peri (2006)	Public Use Microdata Samples (PUMS) of the US Census (US Bureau of Census, 1970, 1990).	US	2SLS	Empirical results yield no evidence of statistically significant average schooling externalities at the city level or the state level.
8	Kimenyi *et al*. (2006)	Welfare Monitoring Survey (WMS) of 1994.	Kenya	OLS	In the rural areas male average human capital at the district level has a negative and significant effect on earnings while female average human capital at the district level has a positive but insignificant effect. On the other hand, in the urban areas, the effect of the district level average education for males and females on earnings is positive and statistically significant. At the national level, the female average human capital has a positive, statistically significant effect on earnings of workers while the average male human capital has a positive but insignificant effect.
9	Isacsson (2005)	1993 and 1998 Statistics for Sweden.	Sweden	OLS, Fixed Effects	The cross-sectional models suggest, in general, that externalities

No	Study	Data Set	Country/countries	Econometric Technique(s)	Conclusion(s)
					are positive and significantly different from zero. However, after accounting for individual fixed effects and dummy variables for the county in which the individual works, the results indicate no statistically significant external effects of education on earnings in Sweden.
10	Rakova and Vailancourt (2005)	1991 and 2001 Canadian Census of Population.	Canada	OLS	Empirical results indicate there is a positive human capital externality.
11	Morreti (2004)	The 1979-1994 Metropolitan Statistical Area (MSA), the 1970, 1980 and 1990 Census, the National Longitudinal Survey of Youth (NLSY), Public Use Microdata Areas (PUMAs).	US	OLS and IV	The results indicate that an increase in the supply of college graduates raises high school drop-outs' wages by 1.9 percent, high school graduates' wages by 1.6 percent, and college graduates' wages by 0.4 percent.
12	Naderi and Mace (2003)	15,755 full-time male employees working in 35 manufacturing firms in Iran.	Iran	Multilevel Modelling	The estimation results provide evidence for the pecuniary externality effects of human capital in the manufacturing sector in Iran.
13	Rudd (2000)	Individual data on a period from 1978 to 1991.	US	2SLS	Most of the results were found to be insignificant.
14	Morreti (1998)	Individual data from the 1970, 1980 and 1990 Census and the Current Population Survey (CPS).	US	OLS and IV	Empirical results suggest the existence of a positive human capital externality.
15	Maani (1996)	The 1991 New Zealand Census of Population and Dwellings.	New Zealand	OLS	The estimates of the social rates of return to education are positive and significant, indicating that investments in education result in positive economic returns.
16	Rauch (1993)	Cross-sectional micro-data for the year 1980 from the United States Census of Population.	US	GLS	Wages increase, ranging from 2.8 to 5.1 percent and from 0.2 to 0.7 percent, after one year increase in average education and average experience, respectively.

Source: Author's compilation.

Kimeny *et al.* (2006) apply the augmented Mincer equation to analyse returns to education and the social externality of education at the district level in Kenya. The data used in this study come from the Welfare Monitoring Survey (WMS) of 1994 undertaken by the Central Bureau of Statistics (Ministry of Finance and Planning, Government of Kenya). The estimation results provide evidence of human capital externalities in the urban areas. At the national level, women's education has a significantly larger impact on male earnings compared to the impact that is associated with men's schooling on female earnings. Another important point from the results is that public policies that provide wide opportunities for disadvantaged people benefit the whole society in term of earnings and productivity improvement.

Liu (2007) investigates the external returns to education using city average education in the standard earnings equation. The study utilises data from the Chinese Household Income Project 1988 (CHIP88) and the Chinese Household Income Project 1995 (CHIP95). The focal point of this study is on urban individuals between 16 and 65 years of age who had full-time jobs, and reported complete information on wage earnings, schooling, work experience, gender, and employment. Several approaches to estimate the impact of human capital externalities are employed, such as OLS estimation using city average education for city-level education, OLS estimation using the fraction of college-educated workers for city-level education, IV estimation, and estimation of the external returns by education group. The estimates show that a one year increase in city average education raises individual earnings by 11 to 13 percent. The social returns to education, which consist of the private and external returns, were able to reach 16 percent in the mid-1990s in urban China. The study also finds evidence that the economic reforms of the late 1980s and early 1990s increased the external returns to education in Chinese cities.

Based on the literature surveyed in this section, there are several points that can be highlighted. First of all, it appears from all previous studies that the importance of human capital externalities depends on the level of disaggregation. Significant results are obtained when the aggregate human capital is measured at the city or district level. In studies where the level of analysis is extended to a wider geographical area, such as state level, the human capital externalities are generally not significant. Second, several measure of human capital that are commonly utilised are the average of the years of schooling, the proportion of workers with college or higher degrees, and the average of work experiences. All of the studies discussed in this section indicate that human capital externalities are important regardless of the human capital measure of externalities. Third, most of the studies suggest that when estimating human capital externalities there should be consideration of a potential endogenity problem. Instrumental Variable estimation is recommended to tackle this problem. Fourth, some studies measure the effect of human capital externalities separately for various groups, such as male/female, rural/urban area, and occupational group. These studies reveal that the measures of human capital based on these criteria have different magnitude of effect on earnings.

Although there is enormous literature devoted to estimating the rates of return to schooling and human capital externalities, there are few empirical studies for Indonesia. The information learned from the studies discussed in this section will provide a valuable foundation for examination of the issue for Indonesia.

3.5.2.2 Non-market Externalities

In comparison to the literature on market externalities covered in the previous section, empirical studies on the non-market externalities of education are rather sparse. One of the reasons for this is that it is extremely difficult to measure this type of externality. This section reviews five papers that discuss non-market externalities of education. The two first papers cover education non-market externalities in terms of the intergenerational transmission of education. The third and fourth studies provide brief discussion on the health benefits of education. The last paper examines the impact of schooling on civic participation and attitudes. Covering just these five studies is sufficient to convey the typical approach in this field of enquiry, and to illustrate the types of finding established. A summary of studies on non-market externalities of education is presented in Table 3.3. This table contains additional details on the five studies discussed in the following paragraphs, as well as brief comments on a number of additional studies of interest.

Daouli *et al.* (2010) report on an empirical study of education non-market externalities in terms of the intergenerational transmission of education among Greek women. These intergenerational educational correlations are investigated using the educational attainments of parents and their daughters. The authors make use of data from the 1981, 1991, 2001 Greek censuses and the 2004/2005 Greek Household

Budget Survey. They find that there was substantial intergenerational educational mobility during the last three decades in Greece. The results support the existence of non-market externalities of human capital.

Using the 1986, 1994, and 2001 waves of the Canadian General Social Survey, Sen and Clemente (2010) assess the correlation between the educational attainments of different generations in Canada. They estimate the effects of parental post-secondary educational attainment on the child achieving any type of post-secondary education. This study finds evidence of an intergenerational spillover from parental education. The results show that children belonging to a father (mother) with post-secondary education are approximately 0.2 (0.17) more likely to attend university than children belonging to parents with only a high school education.

Lundborg (2008) studies the health returns to education. This study had two objectives. The first objective was to estimate the causal effect of education on health employing data from the first wave of the Midlife in the United States (MIDUS) survey collected in 1995. The second objective was to explore some of the mechanisms through which the effect occurs. He evaluates the effect of education on a variety of lifestyle factors, occupational hazards, and health insurance coverage to investigate potential mechanisms. A sample of identical twins was used to assess the health returns at different levels of education. The study finds strong evidence of a positive link between education and health. Higher education levels were positively correlated with self-reported health and negatively correlated with the number of chronic conditions. Regarding the second aim, the author provides the following remarks: (i) The results imply that lifestyle factors, such as smoking behaviour and being overweight, make only a modest contribution to the education/health gradient. (ii) There is no evidence that job risks have an impact on the education/health gradient. (iii) Using the pooled twins sample, the results suggest that education is associated with a greater likelihood of being covered by health insurance. In contrast, the twin Fixed Effect estimation shows that the relationship between education and health insurance is non-causal.

Table 3.3: Summary of Selected Studies on Non-market Externalities of Education

No	Author and year	Data	Country/contries	Estimation Method	Results
1	Daouli *et al.* (2010)	The 1981, 1991, 2001 Greek censuses and the 2004/2005 Greek Household Budget Survey.	Greece	OLS, Probit	There was substantial intergenerational educational mobility during the last three decades in Greece.
2	Sen and Clemente (2010)	The 1986, 1994, and 2001 waves of the Canadian General Social Survey.	Canada	OLS	Parental education has significant intergenerational spillovers.
3	Becker *et.al.* (2009)	The Population Census Prussian county data, 1816 and 1849.	Prussia	OLS and IV	Counties with higher school enrolment rates in 1849 show a steeper fertility decline, both in terms of crude birth rates and marital fertility rates.
4	Silles (2009)	The General Household Survey for England, Scotland and Wales.	UK	OLS, IV	The results of the estimation suggest that one additional year of schooling increases the probability of being in good health by between 4.5 and 5.5 percent.
5	Lundborg (2008)	The first wave (1995) of the Midlife in the United States Survey (MIDUS).	US	OLS, twin FE	The results suggest a causal effect of education on health.
6	Siedler (2007)	Fourteen waves (1980-2004) of the German General Social Survey (ALLBUS).	Germany	Probit, OLS, and IV	Simple probit and OLS estimates suggest a strong and significant positive relationship between years of schooling and a broad range of political outcomes. However, IV estimates utilising exogenous variation in secondary schooling in Germany over the period 1949 to 1969 across Federal states find no evidence that these correlations represent a causal effect of schooling on citizenship.
7	Dee (2004)	The High School and Beyond longitudinal study and the 1972-2000 General Social Surveys (GSS).	US	OLS, 2SLS, Probit	Educational attainment contributes to most measures of civic engagement and attitudes.

Source: Author's compilation.

Using changes in compulsory schooling laws in the United Kingdom as a natural experiment, Silles (2009) evaluates the causal relation between health and education. This study is based on data from the 1980-2003/2004 General Household Survey for England, Scotland and Wales. The main result is that there is a causal effect of schooling on health, and this is established by relying on changes in educational participation caused by the raising of the minimum school leaving age in the United Kingdom. The results suggest that an additional year of schooling increased the probability of being in good health by between 4.5 and 5.5 percent.

Dee (2004) attempts to provide evidence for the presence of education non-market externalities in terms of the effects of schooling on civic participation and attitudes. He identifies the effects of educational attainment using two channels; availability of junior and community college and changes in teen exposure to child labour laws. The effects of college entrance on adult voter and volunteer participation are assessed using data from the High School and Beyond longitudinal study. In addition the effects of years of schooling on adult voter participation, on group memberships and on attitudes towards free speech are estimated using data from the 1972-2000 General Social Surveys (GSS). This study provides evidence that educational attainment contributes to most measures of civic engagement and attitudes. The results confirm that additional schooling has strong and statistically significant effects on voter participation. Furthermore it finds that the additional secondary schooling raises not only the frequency of newspaper readership but also the amount of support for allowing most forms of possibly controversial free speech.

3.6 Conclusion

This chapter provides an outline of the literature relating to returns to education and human capital externalities. It highlights the key issues that are significant in the development of this thesis. The first part of this chapter explores human capital theory. It concludes that this theory is an appropriate basis for analysing the return to education and the human capital externalities of education.

This chapter also provides a brief overview of the theoretical foundation of Mincer’s human capital earnings function. It then discusses the three types of human capital externalities. The chapter argues that investment in education and training not only provides private benefits but also social benefits. Furthermore, it is emphasised that the education externalities consist of market and non-market externalities.

After discussing human capital externalities, this chapter also summarises some of the empirical evidence on the returns to education and human capital externalities. There is a large amount of literature devoted to estimating rates of returns to education and human capital externalities, but there are few empirical studies from Indonesia. Research is needed in order to assess the effectiveness of the current education in terms of the earnings returns in Indonesia. This study attempts to address this issue and fill this research gap.

Most of the previous studies emphasise private returns to education and market externalities of education. Little attention has been given to analysing the non-monetary externalities of education because these are difficult to measure. In contrast to the previous studies on the returns to education and human capital externalities, this study seeks to examine private returns and market externalities from education in Indonesia. The subsequent chapters will address these issues.

Chapter 4

Econometric Methodology

4.1 Introduction

Having reviewed the most relevant literature on the topics of measuring the private return to schooling and measuring the externalities associated with schooling in Chapter 3, attention is now given to the econometric methodology. The objective of this chapter is to describe the methodological issues relating to the estimation of the theoretical models discussed in the previous chapter. The rest of the chapter discusses briefly the methodological steps for Ordinary Least Squares (OLS) and the Instrumental Variable (IV) approach. These were identified in Chapter 3 as two of the main techniques used in the analysis of the payoff to schooling, as well as in the empirical assessment of the externalities of schooling. These techniques can be applied to the data set used in this thesis.[11]

This chapter is organised as follows. Section 4.2 provides a brief overview of the OLS approach. The IV model is discussed in Section 4.3, followed by a conclusion in Section 4.4.

4.2 Ordinary Least Squares (OLS)

Estimation of the human capital earnings function is most often undertaken by OLS. The method of Ordinary Least Squares is attributed to Carl Friedrich Gauss, a German mathematician. Under certain assumptions, the method of least squares has some very attractive statistical properties that have made it one of the most powerful and popular methods of regression analysis (Gujarati, 2004).

The goal of linear regression is to estimate the parameters of the linear conditional mean. Consider the following model:

$$y_i = \beta_1 x_{1i} + \cdots + \beta_k x_{ki} + \mu_i \qquad i = 1, \ldots, n. \qquad (4.1)$$

[11] Other techniques, such as random effects and fixed effects models, which cannot be applied with the data used in this thesis, will not be reviewed.

In matrix notation:

$$y = X\beta + \mu, \tag{4.2}$$

where $y = (y_1, \dots, y_n)'$ denotes a (n x 1) vector of observations on the dependent variable, X is a (n x k) matrix of observations on the explanatory variables (regressors), β is a (k x 1) vector of unknown regression parameters, and $u = (\mu_1, \dots, \mu_n)'$ is a (n x 1) vector of errors (unobserved stochastic disturbances).

The OLS estimator is obtained by choosing the vector β that minimises the sum of squared residuals (SSR),

$$\begin{aligned} SSR\ (\hat{\beta}) &= \textstyle\sum_{i=1}^{n}(y_i - X_i\hat{\beta})^2\ , \\ &= \left(y - X\hat{\beta}\right)'(y - X\hat{\beta}) \\ &= y'y - 2y'X\hat{\beta} + \hat{\beta}'X'X\hat{\beta} \\ &= ||y - X\hat{\beta}||^2. \end{aligned} \tag{4.3}$$

The usual assumptions that are required to obtain a best linear unbiased estimator (BLUE) are as follows (see Wooldridge, 2002; Maddala, 2004):

(i) Zero mean value of disturbance u_i , E(μ_i) = 0 or E($u_i|X_i$) = 0,

(ii) Exogeneity of regressors, E($u_i X_i$) = 0,

(iii) Homoscedasticity or equal variance of u_i, E ($u_i^2|X_i = \sigma^2$),

(iv) Conditionally uncorrelated observations, E($u_i u_j|X_i,X_j$) = 0, $i \neq j$.

Most estimates of the human capital earnings function have been on cross-section data. While violation of assumption (iii) is typically a major issue with the use of such data, the adverse consequences have been minimised through using heteroscedasticity corrected “t” statistics. Autocorrelation (i.e., violation of assumption (iv)) is not typically of concern with cross-section data. Most attention in this type of research has therefore been directed at possible violation of the exogeneity of the regressors (i.e., violation of assumption (ii)). A typical technique used in such cases is IV estimation. This approach has been employed by Ashenfelter and Krueger (1994), Harmon and Walker (1995), Brunello and Miniaci (1999), Callan and Harmon (1999), Uusitalo (1999), Plug (2001), Trostel *et al.* (2002), Lemke and Rischall (2003), Bronars and Oettinger (2006), Miller *et al.* (1995), Liu (2007), Leigh and Ryan (2008), Aslam *et al.* (2010), among others. The main theoretical issues associated with this approach are addressed next.

4.3 Instrumental Variables Approach

The essential assumption for consistency of least-squares estimators is that the model error term is uncorrelated with the regressors, i.e. $E(u_iX_i) = 0$. If this assumption is not fulfilled, the OLS estimator is inconsistent and the OLS estimates can no longer be given a causal interpretation. The instrumental variable (IV) estimator provides a consistent estimator under the very strong assumption that valid instruments exist, where the instruments Z are variables that are correlated with the regressors X that satisfy $E(u_i Z_i) = 0$, and explain part of the variability in the endogenous regressors. Hence, the instruments Z cannot have a direct effect on y. In brief, the IV method can be used whenever the error terms are correlated with one or more of the explanatory variables, regardless of how that correlation may have arisen. The standard IV regression model is obtained by augmenting the standard linear regression model with a model for the endogenous regressors and the instruments. In the remainder of this section the main theoretical issues of the IV approach are addressed.

4.3.1 Sources of Endogeneity

The Instrumental Variable Method was initially proposed by Philips G Wright in 1928 to deal with the problems arising from using endogenous regressors (Souri, 2004). In principle, the problem of endogeneity may arise whenever economists make use of non-experimental data, because in that setting we can never be totally certain what is driving what. In applied econometrics, endogeneity usually arises in one of these following three ways: omitted variables, errors in variables or measurement error, and simultaneity.

1) Omitted Variables

In many cases, economic theory suggests to control for one or more additional variables in the model. Unfortunately the data needed are often not available. Therefore, it is not possible to put the required data in the estimating equation. This phenomenon may produce omitted variables bias. If a proxy variable is available for the unobserved variable, the omitted variables bias can be removed (Wooldridge, 2008). In the estimation of the human capital earnings function, omitted variable bias generally refers to ability bias. This is usually associated with an upward bias in the estimated return.

2) Errors in Variables or Measurement Error

Another way that an endogeneity problem can arise in economic applications is when one or more of the variables in the model contain measurement error. Many economic variables are measured with error for a variety of reasons. When measurement errors exist, the values observed inevitably differ from the true values. Although the measurement error problem and the omitted variable problem have a similar statistical structure, they are conceptually very different. The first conceptual difference between these two problems relates to the nature of the variable. In the measurement error case the variable is observed and has a well-defined, quantitative meaning, but our measures of it may contain error. In the omitted variable case, we do not observe the variable of interest, and we are looking for a variable that is somehow associated with this unobserved variable (i.e. a proxy variable). The second important conceptual difference is that in the measurement error case the mis-measured explanatory variable is the one whose effect is of primary interest. In the proxy variable case, however, we are generally more interested in the effect of the omitted variable (e.g. ability) on some other variable of interest (e.g. schooling) (Wooldridge, 2008).

In the estimation of the human capital earnings function, measurement error bias generally refers to measurement error in the schooling variable. Typically this is associated with a downward bias in the estimate of the return to schooling, which will tend to offset any upward bias associated with omitted ability bias in the study of the private return to schooling. Contrary to the private return case, however, unobserved heterogeneity and measurement error in the study of human capital externalities do not necessarily bias OLS in opposite directions. The direction of bias in the OLS estimates or the effect of endogeneity is influenced by the relative importance of unobserved heterogeneity in the demand and supply for labour. The OLS estimate will be upward biased if average education variation across regions is pushed by unobserved *demand* shocks. On the other hand, if variation in average education across regions is driven by unobserved *supply* shocks, the OLS estimate is biased down (Moretti, 1998).

3) Simultaneity

Simultaneity occurs when the regressor and the error term are related to each other through a system of simultaneous equations. This phenomenon is known as endogeneity bias, simultaneous equations bias or, simply simultaneity bias. (Wooldridge, 2008). This is not of immediate concern in the current study, and will not be pursued further.

Sometimes the distinctions among omitted variable, measurement error, and simultaneity as the three possible sources of endogeneity are unclear. In fact, an equation may have more than one source of endogeneity.

4.3.2 Instrumental Variable Estimation: 2SLS

Two Stage Least Squares (2SLS) was invented by Theil (1953) and Basmann (1957). The 2SLS estimator has its name from the fact that it can be obtained by two consecutive OLS regressions.

Consider the equation (4.2)

$$y = X\beta + \mu, \tag{4.2}$$

where some of the variables in X are potentially endogenous.

Then proceed with the following steps.

1. Regress X on Z, i.e. estimate the following model:

$$X = Z\Pi + \epsilon, \tag{4.3}$$

where X and β are defined above. Z is a n x p matrix containing the instrumental variables, and ϵ is a n x k matrix containing the error terms. The matrix Π represents the effect of the instruments on the endogenous regressors. The exogenous variables in X should appear in Z as well. The variables x which appear in X but not in Z are called endogenous regressors, and the ones that are included in Z are called exogenous regressors. Additional variables in Z which are not included in X are called the instruments (Wooldridge, 2002).

The OLS estimator for Π is

$$\hat{\Pi} = (Z'Z)^{-1}\, Z'X. \tag{4.4}$$

Equation (4.4) is known as a reduced form equation.

2. Estimate the following model $y = (Z\hat{\Pi})\beta + v$.

In the second step y is regressed on $Z\hat{\Pi}$, which is the projection of X on Z. The OLS estimator for β from the second step is called a 2SLS estimator, which is an IV estimator.

In the context of 2SLS, the equivalent condition of correlation between instruments and regressor is:

$$p\lim\left(\frac{Z'X}{n}\right) = Q_{zx},$$

where Q_{zx} is a p x k matrix that has rank k. This condition is known as the rank condition.

Under the following assumptions:

(i) Linearity:

$y_i = X_i\beta + u_i,$ and $E(u_i) = 0.$

(ii) Independence:

(y_i, X_i, Z_i) are identically and independently distributed (iid) with y scalar and X_i 1 x k, Z_i 1 x p, p ≥ k. This assumption means that regressors, instruments and dependent variables are independent across observations.

(iii) $E\left(\frac{XX}{n}\right) = Q_{XX}$, which is positive definite.

(iv) $E\left(\frac{1}{n}ZX\right) = Q_{ZX}$, which is of rank k.

Condition (iv) means that the instruments should be sufficiently correlated with the regressors. This is called the rank condition.

(v) $E\left(\frac{1}{n}Z \in\right) = 0.$

Condition (v) means that the instruments should be exogenous.

(vi) $E\left(\frac{\epsilon\epsilon}{Z}\right) = \sigma^2 I_n.$

then

$$p\lim\hat{\beta}_{2sls} = \beta,$$

and $n^{1/2}\left(\hat{\beta}_{2sls} - \beta\right) \xrightarrow{d} N\left(0, \sigma^2(Q_{xz}Q_{zz}^{-1}Q_{zx})^{-1}\right),$

and $\left(\frac{s^{-2}X'Z}{n}(Z'Z/n)^{-1}\left(\frac{Z'X}{n}\right)\right)^{\frac{1}{2}} n^{1/2}(b_{iv} - \beta) \xrightarrow{d} N(0, I_k),$

where $s^2 = \frac{e'e}{n} - k$. When p > k, or there are more instruments than endogenous variables, the model is called overidentified. On the other hand, when p = k, or the number of instruments is equal to the number of endogenous regressors, the model is called exactly identified. The 2SLS estimator simplifies in the exact identification case, i.e. when p = k to:

$$\hat{\beta}_{2SLS} = (Z'X)^{-1}Z'y \text{ or } \hat{\beta}_{IV} = (Z'X)^{-1}Z'y. \qquad (4.5)$$

The IV estimator can always be reformulated as

$$\hat{\beta}_{IV} = (\hat{X}' \hat{X})^{-1} \hat{X}' y. \qquad (4.6)$$

4.3.3 Instrument Validity and Relevance

Cameron and Trivedi (2010) state that instrument validity relies more on persuasive argument, economic theory, and norms established in prior related empirical studies. However, it is generally accepted that a valid instrumental variable must satisfy two conditions, known as instrument relevance and instrument exogeneity (see Stock and Watson, 2007):

1. Instrument relevance: corr (Z_i, X_i) $\neq 0$.
2. Instrument exogeneity: corr (Z_i, μ_i) = 0.

The relevance of the instruments means that the instrument is not a weak instrument. There is no single definition of a weak instrument. Cameron and Trivedi (2008) provide the following signals of a weak instrument:

(i) Scalar regressor *X* and scalar instrument *Z*: A weak instrument is one for which $r^2_{x,z}$ is small.

(ii) Scalar regressor *X* and vector of instruments *Z*: The instruments are weak if the R^2 from a regression of *X* on *Z*, denoted $R^2_{x,z}$, is small or if the *F*-statistic for test of overall fit in this regression is small.

(iii) Multiple regressors *X* with only one endogenous: A weak instrument is one for which the partial R^2 is low or the partial *F*-statistic is small.

If an instrument is relevant, then variation in the instrument is related to variation in X_i. If in addition the instrument is exogenous, then that part of the variation of X_i captured by the instrumental variable is exogenous. Thus, an instrument that is relevant and exogenous can capture movements in X_i that are exogenous. This exogenous variation can in turn be used to estimate the population coefficient β_i.

Important practical issues in adopting an IV approach include determining whether IV methods are necessary and determining whether the instruments are valid. Unfortunately, the tests of validity are limited. They require the assumption that in a just-identified model the instruments are valid and test only overidentifying restrictions. Although IV estimators are consistent given valid instruments, they can be much less efficient than the OLS estimator and can have a finite-sample distribution that, for usual finite-sample sizes, differs greatly from the asymptotic distribution. These problems are greatly magnified if instruments are only weakly correlated with the variables being instrumented. One way that weak instruments can arise is if there are many more instruments than needed. This is simply dealt with by dropping some of the instruments (see Donald and Newey, 2001). A more fundamental problem arises when even with the minimal number of instruments one or more of the instruments are weak.

4.3.4 Testing for Endogeneity of the Regressors

The discussion in the previous section shows that the IV approach can be used when the OLS estimator fails because there is correlation between an explanatory variable and the error term. A test for checking the presence of a correlation between an explanatory variable and the error term is needed. The procedure to test for endogeneity can be dated back to a pioneering paper by Durbin (1954), and it was subsequently extended by Wu (1973) and Hausman (1978). This test is called the Durbin-Wu-Hausman test, or DWH test. The test is performed by comparing $\hat{\beta}_{OLS}$ and $\hat{\beta}_{IV}$:

$$H = (\hat{\beta}_{IV} - \hat{\beta}_{OLS})'[\widehat{Avar}(\hat{\beta}_{IV}) - \widehat{Avar}(\hat{\beta}_{OLS})]^{-1}(\hat{\beta}_{IV} - \hat{\beta}_{OLS}) \overset{A}{\sim} X_J^2,$$

The null hypothesis is that there are no endogenous variables or that endogeneity does not affect the OLS estimator. The null and alternative hypotheses for the DWH test can be expressed as:

$$H_0: y = X\beta + \in, \qquad \in \sim IID(0, \sigma^2 I), \quad E(X' \in) = 0, \qquad and$$

$$H_A: y = X\beta + \in, \qquad \in \sim IID(0, \sigma^2 I), \quad E(X' \in) \neq 0.$$

Under the null hypothesis, both the OLS and the IV estimators are consistent. Thus, the difference between them converges to zero. If the null hypothesis is true, the OLS estimator $\hat{\beta}_{OLS}$ should be used because it is more efficient. Under the alternative hypothesis, the IV estimator $\hat{\beta}_{IV}$ is consistent, but the OLS estimator $\hat{\beta}_{OLS}$ is not consistent. If the null hypothesis is not true, the IV estimator $\hat{\beta}_{IV}$ should be used because it is consistent.

The idea of the DWH test is to check whether the difference $\hat{\beta}_{IV}$ - $\hat{\beta}_{OLS}$ is significantly different from zero in the available sample. Briefly, the implementation of the DWH test can be described as the following procedure. For notational simplicity let $X_i^* = (X_{i,k1+1}, \ldots X_{ik})'$. First, X^* is regressed on Z and the fitted values from this regression are $Z(Z'Z)^{-1}Z'X^*$. Then y is regressed on X and on $Z(Z'Z)^{-1}Z'X^*$. Let $\hat{\delta}$ be the OLS coefficient on $Z(Z'Z)^{-1}Z'X^*$. Then an F-test can be performed for the null that $\delta = 0$ versus the alternative $\delta \neq 0$. Under the null, (k - k_1) F is asymptotically distributed as $x_{k-k_1}^2$, while under the alternative it diverges to positive infinity. If we reject (do not reject) the null of $\delta = 0$, then we reject (do not reject) the null that $E(X'\epsilon) = 0$.

4.3.5 The Instrumental Variables Method in Practice

Estimating the private return to schooling and the value of human capital externalities by OLS may not always be appropriate. This is because of the strong possibility of correlation between the disturbance *u* and the schooling variable. As discussed above, this correlation may produce a biased estimator. Because of such bias, it therefore becomes advisable to apply IV methods. When adopting the IV approach, it is important to determine the right instrument for the model. Finding a suitable instrument is not easy. However, social and natural experiments can be useful and many such instruments have been used (see Harmon and Walker, 1995; Duflo, 2001; Plug, 2001; Liu, 2007; Leigh and Ryan, 2008). Alternatively, parental background variables are often chosen (see Brunello and Miniaci, 1999; Callan and Harmon, 1999; Uusitalo, 1999; Trostel *et al*., 2002; Lemke and Rischall, 2003). But to be useful these instruments must satisfy the IV criteria of being correlated with the schooling variable and correctly excluded from the earnings equation. The following are examples of the variables used as instruments in empirical study: family background (Brunello and Miniaci, 1999; Callan and Harmon, 1999; Uusitalo, 1999; Trostel *et al*., 2002; Lemke and Rischall, 2003), sibling's report of the other sibling's education (Ashenfelter and Krueger, 1994; Bronars and Oettinger, 2006; Miller *et al*., 1995 and 2006), the month of birth (Plug, 2001; Leigh and Ryan, 2008), government policy in education (Duflo, 2001), and changes in the minimum school leaving ages (compulsory education law) (Harmon and Walker, 1995; Liu, 2007; Leigh and Ryan, 2008).

Tables 4.1 and 4.2 provide a summary of selected studies on, respectively, the return to education and human capital externalities utilising IV as the methodological approach.

Given the importance of the IV approach to research in this area, additional comment on seven studies (the first four studies are on the private return to schooling and the final three studies cover the human capital externalities) are presented below. The first and the second of these studies, Angrist and Krueger (1991), and Harmon and Walker (1995), utilise institutional features of the education system as instruments in the model. Following this we cover studies that adopt family background information as instrument variables, namely Ashenfelter and Zimmerman (1997), and Lemke and Rischall (2003). The three studies involving the use of the IV method when quantifying human capital externalities are by Acemoglu and Angrist (2000), Moretti (2004), and Liu (2006).

Angrist and Krueger (1991) use an individual’s quarter of birth interacted with year of birth or state of birth as an instrument for their schooling variable. In general, the IV estimates of the return to schooling from this study are slightly higher than the corresponding OLS estimates. However, the differences between the OLS and the IV estimates are typically statistically insignificant. This study, therefore, can be argued to show that there is little endogeneity bias in the conventional OLS estimate of the return to schooling.

Harmon and Walker (1995) use a pair of dummy variables that capture changes in the minimum school leaving age in Britain - from 14 to 15 in 1947 and from 15 to 16 in 1973 - as instruments for their schooling variable. The IV estimate (15.25 percent) was reasonably precisely estimated, and was considerably higher than the OLS estimate (6.13 percent). Hence, in contrast to Angrist and Krueger (1991), this study suggests that the possible endogeneity of the schooling variable should be taken seriously.

Table 4.1: Summary of Selected Empirical Studies on the Return to Education Using IV as the Methodological Approach

No.	Author (s)	Instrument (s)	Control (s)	Note (s)
1	Angrist and Krueger (1991)	Quarter of birth interacted with year of birth.	Quadratic in age, race, marital status, and urban residence.	To correct bias in the return to schooling due to omitted ability variable, the authors create a natural experiment where quarter of birth is used as an instrument for education.
2	Harmon and Walker (1995)	Indicator for changes in the minimum school leaving age in 1974 and 1973.	Quadratic in age, year, and region.	To address the endogeneity of schooling, this study exploits the experimental nature of two changes in the minimum school leaving age to provide instruments for education.
3	Miller *et al.* (1995)	The co-twin's report on educational attainment.	Gender, marital status, interaction between gender and marital status, race, and quadratic in age.	To deal with an ability bias problem, this study use one twin's responses on the difference in schooling for the pair in a within-twin earnings function. The key idea behind this strategy is that some of the unobserved differences that bias a cross-sectional comparison of education and earnings are reduced or eliminated within families. To address measurement error problems, the co-twin's report on other twin's responses is used as instrument.
4	Ashenfelter and Zimmerman (1997)	- Brothers' education. - Father's education.	Age.	The omitted variable and measurement error problems were tackled using one brother's (father or son) schooling as an instrumental variable for his sibling's (son or father) schooling.
5	Lemke and Rischall (2003)	- Quarter of birth. - College proximity. - Parental education (father's and mother's education).	Parental income, Armed Forces Qualification Test[12] , parental education, age, race, living in the South in 1995, and living in Metropolitan Statistical Area in 1995.	Three types of instruments, namely parental education, quarter of birth, and college proximity, were utilised to cope with endogeneity of schooling problem.
6	Aslam *et al.* (2010)	- The distance in metres to nearest primary school when the individual was of school-going age. - Square of the distance in metres to nearest primary school when the individual was of school-going age. - Father's completed education in years. - Mother's completed education in years. - The score on the Raven test.[13]	Gender and dummy variable for short-literacy test.	This study addresses the endogeneity of schooling and cognitive skills using two approaches: IV and household fixed-effects. The vector of instruments used to control for the endogeneity of schooling attainment and of cognitive skills includes: parental education (father's and mother's completed years of schooling), distance to primary school in metres (when individual was of primary school-going age) and its square, and the individual's Raven test score.

Source: Author's compilation.

[12] The AFQT is a measure of skill for people under 18.
[13] The Raven Progressive Matrices test assesses innate ability via literacy, numeracy and health knowledge tests.

Another important set of variables to identify the causal effect of schooling in the IV approach comes from family background information, such as father's education and mother's education. This information can be included in the estimating equation as a direct control for unobserved ability, or used as an instrument for completed education. Ashenfelter and Zimmerman (1997), Lemke and Rischall (2003), and Aslam *et al.* (2010) are examples of researchers who employ family background as an instrumental variable.

Ashenfelter and Zimmerman (1997) employ father's schooling as an instrument in one set of models, and brother's schooling in another. The use of brother's schooling as an instrument leads to IV estimates that are 1.5-7.4 percent above the corresponding OLS estimates. When father's schooling is used as an instrument the IV estimates are 5.2-6.2 percent higher than the OLS estimates. This study therefore shows the importance of considering endogeneity bias via the IV method, and draws attention to family background factors being useful instruments.

Lemke and Rischall (2003) exploit both institutional features of the education system (quarter of birth and college proximity) and family background information (parental education as instruments). When using parental education to instrument the schooling variable and neither parental income nor the Armed Forces Qualification Test (AFQT) are included in the wage equation, the return to education is 13.4 percent, which exceeds the comparable OLS estimate of 9.4 percent. When the AFQT and parental income are introduced into the wage equation, instrumenting with parental education actually leads to lower IV estimates than those obtained using OLS. Nevertheless, the authors argue that parental education is a valid and useful instrument. Different from previous results, when adopting quarter of birth as an instrument for schooling, the Basmann test rejects the validity of all of the quarter of birth instruments. When utilising college proximity as an instrument for the schooling variable, the Basmann test fails to reject the validity of the college proximity instruments, and therefore the IV estimates of the return to schooling were imprecise. The estimated effects of parental income and the AFQT on wages were also statistically insignificant. In sum, when adopting the institutional features of the education system as instruments, the weak correlation between the instruments and years of schooling generates imprecise estimates of the return to schooling. Hence, these findings suggest a preference for parental education over institutional factors as instruments for the schooling variable in the wage equation.

Thus, studies that use an IV approach in the analysis of the private return to schooling generally report an advantage to the method. Moreover, the family background information often used as instruments appears to have offered a statistically sound basis for this type of estimation. The following passages will review variables used to instrument the aggregate human capital that is essential to the empirical assessment of human capital externalities.

Acemoglu and Angrist (2000) measure the aggregate human capital by the average level of schooling in the state. To allow for the possibility that education levels may be endogenous they instrument for the average level of schooling in each state using dummies for compulsory schooling laws in the US and the differences in child labour laws across states. In comparison, when the private rate of return was considered, the instruments for the individual's level of schooling were quarter of birth dummy variables. Acemoglu and Angrist (2000) show that inconsistent estimates of the private return to education will lead to inconsistent estimates of the externality, because individual and aggregate schooling are correlated. Under the IV approach, the estimates revealed that a year increase in the average level of schooling led to only a 1-3 percent increase in wages, and this was not significantly different from zero. In contrast, the OLS estimates suggested that externalities were much more important, with the impact of an extra year of average schooling being around 7 percent. This finding can be explained in part by the fact that these two instruments - compulsory attendance laws and child labour laws - mainly affect the left-hand side of the educational distribution, mostly in middle school or high school, and could be weakly correlated with the regional fraction of college graduates (Morreti, 2006; Canton, 2009). This study therefore shows that it is necessary to find the instruments that affect the entire education distribution.

Table 4.2: Summary of Selected Empirical Studies on Human Capital Externalities Using IV as the Methodological Approach

No.	Author (s)	Instrument (s)	Control (s)	Note (s)
1	Acemoglu and Angrist (2000)	- Quarter of birth dummy variables. - Percentage of child labour. - Percentage of compulsory attendance.	Age, individual education, state average education, state of residence.	- Quarters of birth dummy variables are used to instrument the individual's schooling. - To solve the problem of omitted variables bias from correlation between average schooling and other state year effects embodied in the error component the authors construct instruments using compulsory schooling laws effective in individuals' states of birth at the time they were 14. - Dummies of compulsory attendance laws and child labour laws are used to instrument individual as well average schooling variables.
2	Moretti (2004)	- The city demographic structure (age structure). - The presence of a land-grant college in a city.	Sex, race, individual education and experience as well as college share at the level of 2001 Metropolitan Statistical Area.	Age structure used as instrument for first differences model and the presence of a land grant college used as an instrument for cross-sectional estimations.
3	Liu (2007)	- Compulsory Education Law. - The share of college graduates in the city population in 1990.	Gender, city average education in years, city-sector average education in years, the fraction of college-educated workers, the fraction of workers employed in the business sector, the fraction of workers employed in the government sector, the fraction of workers employed in the industry sector, the fraction of workers employed in the commerce sector, the fraction of workers employed in the state sector, the fraction of workers employed in the collective sector, including the town and village enterprises, the fraction of workers employed in the foreign-investment sector, including joint ventures and wholly foreign-owned enterprises.	The problem of omitted variable bias is tackled in the following ways: (i) the author introduces proxy variables for unobserved factors into the earnings regression, (ii) the lagged city average education or lagged dependent variable is employed to account for unobserved city-specific factors, (iii) assuming no structural change in the earnings equation between 1988 and 1995, the author ran city-fixed-effects regressions to purge city-specific and time-invariant unobservable, (iv) this study estimates the external returns to education by implementing city-fixed-effects regressions using cross-sectional data from 1995 to restrict externalities to operate at the city-sector level.
4	Muravyev (2008)	- City college share in 1994. - City college share in 1989. - Number of higher education establishments in a city at the end of the Soviet time.	Index of the cost of living, dummy for the cities whose economies are centred on the oil extraction industry, dummy variable for cities which are administrative centres of the regions, city size (inhabitants), and regional dummies, a dummy variable for the presence of wage arrears in either of the two jobs, work experience, work experience squared, and gender.	- To solve identification problems arising from the endogeneity of average education, the study exploits a natural experiment. - For robustness checks the authors use four important characteristics of cities: location, status (an administrative centre of a region or not), prevalence of the oil extraction industry in the city economy and city size.
5	García-Fontes and Hidalgo (2009)	Demographic variables.	Schooling level, gender, works in agriculture dummy, marital status, share of workers by schooling level, fraction of workers with secondary or college education, total workers, physical capital stock and ICT capital stock, and population proportions for each age group.	- The authors instrument the change in regional schooling levels over the 1981-1991 period by 1981 demographic structure and the change in regional schooling levels over the 1991-2001 period by 1991 demographic structure. - For robustness analysis, this study employs total regional physical capital and ICT capital.

Source: Author's compilation.

Moretti (2004) examines the spillover effects from a college education among different education groups. This externality was measured by comparing wages for otherwise similar individuals who work in cities with different shares of college graduates in the labour force. The existence of unobservable characteristics of individuals and cities that may raise wages and be correlated with college share was a major issue in this comparison. The unobservable city-specific demand shocks were handled by using two instrumental variables, namely: the (lagged) city demographic structure and the presence of a land-grant college. In this study, human capital externalities are identified using variation in the number of college graduates. Different from Acemoglu and Angrist (2000), Moretti (2004) does find significant human capital externalities for US cities. This shows that adopting instruments that affect the upper part of the education distribution is important for identifying external returns to schooling.

Liu (2006) estimates the external returns to education in Chinese cities. Two instruments are used in the IV section of this analysis: the first instrument relates to a compulsory education law (CEL), whereas the second one is a measure of city-specific human capital from a past period. The OLS estimates indicate that a one-year increase in city average education could raise individual earnings from 4.9 percent to 6.7 percent. The 2SLS estimates of the external returns range from 11 percent to 13 percent. This study provides two important conclusions: firstly, the human capital's contribution through externalities is comparable to its direct contribution. Secondly, private returns as well as external returns to education respond to institutional changes. Hence, this study illustrates the necessity of considering endogeneity bias using an IV-2SLS approach, and the importance of adopting CEL and a measure of city specific human capital as instruments.

4.5 Conclusion

This chapter has outlined the research methodology that will be utilised in the analysis that follows. Two methods of regression analysis have been discussed: OLS and the IV model. The IV results from the studies discussed suggest that it is particularly important to consider family background in any instrumental variables analysis of the return to education. In the next chapter, attention is given to the empirical study of the economic returns to schooling in the context of Indonesia.

Chapter 5

Estimates of Mincerian Returns to Schooling in Indonesia

5.1 Introduction

The focus of this chapter is the presentation of empirical evidence on the private returns to education in Indonesia. Although the returns to education has been a topic of considerable interest in the empirical labour and education economics literatures for around 50 years, the analysis of returns to education remains a relevant issue for both the developed and the developing economies. Numerous studies, for many different countries and time periods, have confirmed that better-educated individuals receive higher wages and have occupations of higher status than less-educated individuals. For most developed countries, there is general agreement over the size and the patterns of the return to education across sub-groups of the population. In terms of the empirical findings from developing countries, however, there has been an ongoing debate concerning even the magnitude of the returns to schooling. Some studies, for example, provide evidence of a relatively low private return to schooling in developing countries, whereas there are numerous other empirical studies that find that the return to schooling is quite high.

Despite the voluminous empirical literatures on the returns to schooling in less developed countries, to date there have been only a limited number of studies based on Indonesian data. The current set of analyses for Indonesia therefore has the potential to fill a major gap in the literature.

The plan of the chapter is as follows. In the next section we draw upon the previous chapters to briefly describe the empirical model and estimation methods. Section 3 discusses the data sources and documents the decisions made when extracting the data set used in the estimations. Results and interpretation are explored in Section 4. This presentation of results commences with estimates from the standard Mincerian model that employs years of schooling in the earnings function. Then the return to schooling based on more detailed information on educational attainment is examined. Following this the discussion turns to estimates of the return to schooling obtained after additional control variables are included in the earnings functions. In order to check the possibility of selectivity bias in the analysis, this section also presents estimates of Heckman's two-step model. Separate estimations for males and females are undertaken for all specifications. Finally, Section 5 concludes the chapter.

5.2 Empirical Models and Estimation Methods

In this Chapter, the economic and econometric methods described in the previous chapters are applied to Indonesian data. In particular, the analyses presented below adopt the standard Mincerian and the augmented Mincerian models that were discussed in Chapters 3 and 4. Thus, this analysis begins by estimating the return to schooling using a standard Mincer equation. Following this a number of control variables, such as tenure, marital status, and area of residence, are included in the estimating equation. The estimates presented in this chapter are mostly obtained by the Ordinary Least Squares (OLS) method. The possibility of selectivity bias is explored by using Heckman's two-step approach.

5.2.1 The Standard Mincerian Model

The specification of the earnings equation used below is based on the human capital model developed by Mincer (1974). This model assumes that (i) the only costs of schooling are the foregone earnings, and (ii) each individual starts working immediately after completion of school. The model shows that the natural logarithm of earnings can be expressed as a function of years of schooling, post schooling labour market experience and its quadratic term. Furthermore, this relationship provides a direct measure of the returns to schooling through the coefficient of the years of schooling variable in the earnings regression. While Mincer and subsequent researchers have added a variety of control variables to this basic model, and corrected for ability bias, our analysis begins with this basic earnings equation, which may be written as follows:

$$\ln(earnings_i) = \beta_0 + \beta_1 yrschyr_i + \beta_2 expr_i + \beta_3 expr_i^2 + \mu_i \qquad (5.1\text{-a})$$

where $earnings_i$ is monthly earnings for individual i, $yrschyr_i$ is years of schooling for individual i, $expr_i$ is a measure of work experience for individual i, $expr_i^2$ is experience squared for individual i, and μ_i is a disturbance term representing other factors which cannot be explicitly measured, and which are assumed to be independent of *yrschyr*$_i$ and *expr*$_i$. According to human capital theory β_1 = r, and so the estimated regression coefficient β_1 is interpreted as the average private rate of return to one additional year of schooling.

As will be discussed further below, the experience variable in the majority of the empirical studies in this field of research is a measure of potential labour market experience rather than a measure of actual labour market experience. Potential labour market experience is typically constructed by subtracting a person's school leaving age from their chronological age. This has been a matter of some controversy. Blinder (1976), for example, argues that using potential work experience in the earnings function for females is hazardous. This is because potential work experience is a suitable proxy only for individuals who have continuous work histories, without interruptions such as childbearing, spells of unemployment, and the like. In the presence of a discontinuous work history, using age instead of potential work experience is probably more appropriate.

Thus equation 5.1-a can be rewritten by replacing potential work experience with age.

$$\ln(earnings_i) = \beta_0 + \beta_1 yrschyr_i + \beta_2 age_i + \beta_3 age_i^2 + \mu_i \qquad (5.1\text{-b})$$

Since female workers are included in this study, both potential work experience and age will be utilised to check the robustness of the estimates. Hence, each equation will be estimated twice. The first specification uses experience and experience squared, while the second specification employs age and age squared as regressors.

There is a further limitation of the potential labour market experience variable that needs to be noted. For some individuals their actual number of years spent to accomplish a certain education level may differ from the statutory number of years for finishing that level of education. The actual years of schooling for completion of any given education level could be less or more than the statutory number. This occurs because of the possibility of joining acceleration classes, grade repetition, and temporary school dropout. Unfortunately, this study cannot accommodate this experience, and the statutory number of years is utilised in this study.

5.2.2. The Standard Mincerian Model with Level of Education

The standard model described in Equations 5.1-a and 5.1-b can be modified into a more flexible specification by substituting years of schooling with a series of dummy variables for different educational levels, such as primary, secondary, university, etc. This more flexible approach offers advantages where the rate of return varies across education levels. In this chapter, seven levels of education are considered: primary school, junior secondary school, general senior secondary school, vocational senior secondary school, college, undergraduate and master degree. This modified Mincerian earnings equation can be written as follows:

$$\ln(earnings_i) = \beta_0 + \sum_k \beta_k S.Dum_{ik} + \beta_2 expr_i + \beta_3 expr_i^2 + \mu_i \qquad (5.2\text{-a})$$

$$\ln(earnings_i) = \beta_0 + \sum_k \beta_k S.Dum_{ik} + \beta_2 age_i + \beta_3 age_i^2 + \mu_i \qquad (5.2\text{-b})$$

where *S.Dum* consists of the dummies for the level of education. To calculate the rate of return to an additional year of schooling under this flexible approach, this study follows Sakellariou (2003), El-Hamidi (2005), and Kimenyi *et al.* (2006) by dividing the difference between the coefficients of adjacent schooling levels by the difference in the years of schooling associated with the schooling levels. Hence, in this specification, the private rate of return to education at the kth level of education is estimated by the following formula:

$$r_k = \frac{(\beta_k - \beta_{k-1})}{\Delta n_k} \qquad (5.3)$$

where β_k is the coefficient of a specific level of education, β_{k-1} is the coefficient of the previous level of education, and Δn is the difference in years of schooling between k and k-1.

The number of years required to complete primary school is six. Three more years are needed to complete junior secondary school, and another three years are required to complete either vocational senior secondary school or general senior secondary school. A further three years are needed to complete college. An average of four years is needed to complete a bachelor's (undergraduate) degree at the university level, and an additional two years are needed to complete a master degree at the university level.

5.2.3 Control Variables

To provide more detailed evidence on the returns to education in Indonesia, each equation (5.1-a, 5.1-b, 5.2-a, and 5.2-b) is augmented with other variables that may influence earnings. The first such variable is tenure. This variable represents the work experience in the present job. Current job tenure is usually viewed as a measure of firm-specific training and knowledge. The second variable is gender. Typically a variable that distinguishes females from males is entered into the estimating equation to capture gender discrimination, the effects of intermittent labour force attachment, and the earnings consequences of unobserved work-home duties-leisure outcomes that are correlated with gender. The third variable is marital status. Marital status is typically associated with household specialisation. The specialisation hypothesis argues that a married couple can engage in specialisation of their household tasks. Then male workers are able to focus their time and effort on labour market activities (Gray, 1997), and females, having relatively low market wages, allocate proportionally more time to home duties. Therefore, being married most likely affects the wages of males positively while having the opposite effect on the wages of females due to child bearing and their other domestic tasks. The last variable is a residential dummy (rural versus urban), which is intended to control for the earnings differential between urban and rural areas. Hence, the equations with these control variables become:

$$\ln(earnings_i) = \beta_0 + \beta_1 yrschyr_i + \beta_2 expr_i + \beta_3 expr_i^2 + \beta_4 tenure_i + \beta_5 tenure_i^2 + \beta_6 female_i + \beta_7 married_i + \beta_8 urban_i + \mu_i \quad (5.4\text{-a})$$

$$\ln(earnings_i) = \beta_0 + \beta_1 yrschyr_i + \beta_2 age_i + \beta_3 age_i^2 + \beta_4 tenure_i + \beta_5 tenure_i^2 + \beta_6 female_i + \beta_7 married_i + \beta_8 urban_i + \mu_i \quad (5.4\text{-b})$$

$$\ln(earnings_i) = \beta_0 + \textstyle\sum_k \beta_k S.Dum_{ik} + \beta_2 expr_i + \beta_3 expr_i^2 + \beta_4 tenure_i + {}_5 tenure_i^2 + \beta_6 female_i + \beta_7 married_i + \beta_8 urban_i + \mu_i \quad (5.5\text{-a})$$

$$\ln(earnings_i) = \beta_0 + \textstyle\sum_k \beta_k S.Dum_{ik} + \beta_2 age_i + \beta_3 age_i^2 + \beta_4 tenure_i + \beta_5 tenure_i^2 + \beta_6 female_i + \beta_7 married_i + \beta_8 urban_i + \mu_i \quad (5.5\text{-b})$$

where $tenure_i$ represents the job tenure for individual i, $tenure_i^2$ is tenure squared for individual i, *female*$_i$ denotes the dummy variable for the gender of individual i, *married*$_i$ denotes the dummy for marital status for individual i, and *urban*$_i$ is a residential dummy (urban versus rural) for individual i. All other variables are the same as before.

5.3 Data Sources and Extracting of the Dataset

5.3.1 Data Sources

The data set used in the empirical analysis is the Indonesian Family Life Survey 4 (IFLS4). IFLS4 is a nationally representative sample comprising 13,536 households and 50,580 individuals, spread across provinces on the islands of Java, Sumatra, Bali, West Nusa Tenggara, Kalimantan, and Sulawesi. Together these provinces encompass approximately 83 percent of the Indonesian population and much of its heterogeneity. The coverage area of the survey can be seen in Figure 5.1. The survey collects data on individual respondents, their families, and their households. Extensive data on the communities in which respondents live, as well as data on the health and education facilities they use, are obtained from the household survey. IFLS4 was fielded in late 2007 and early 2008. It was a collaborative effort by RAND, the Center for Population and Policy Studies (CPPS) of the University of Gadjah Mada, and Survey Meter.

For the analysis of the private returns to schooling, the sample is restricted to individuals 15 to 65 years old, who were not full-time students, reported non-missing labour income, provided information on schooling, and supplied information on family background. Persons in the military during the survey week are omitted, as it is generally argued that the wages of those in the armed forces do not necessary reflect market forces. A total of 4596 observations satisfy these criteria and are utilised in the analysis.

Figure 5.1: IFLS Survey Coverage

Source: IFLS, http://www.rand.org/labor/FLS/IFLS.html.

5.3.2 Data Extracting Procedure and Variable Definition

For the purposes of the empirical analysis for this chapter, an extract of data was created from the IFLS4 data base. To create the extract, data from the individual-level files and household-level files had to be merged. As noted above, persons in the individual file who were aged less than 15 and more than 65 were excluded from the sample. In addition, only individuals who provided full information about their education, employment, and family background were included in the sample. Besides that, persons in school or the military during the survey week were omitted.

The extract contains both IFLS4 variables and derived variables for each person. The variables contained in each person's record are as follows: unique identifiers for individuals and their household, years of schooling, highest level of education obtained, age, potential work experience, gender, marital status, area (rural-urban), and amount of earnings by month. The construction of the main variables is discussed below and the definitions are given in Table 5.1.

Table 5.1: Definitions of Variables

Symbols	Variables	Definition
Ln (earnings)	Monthly earnings (log)	Monthly earnings in log form.
yrschyr	Years of schooling	Number of years of schooling of the respondent.
expr	Experience	Potential work experience.
$expr^2$	$Experience^2$	The square of potential work experience.
age	Age	Age of individual.
age^2	Age^2	The square of age.
tenure	Tenure	Work experience in the present job.
$tenure^2$	$Tenure^2$	The squared of work experience in the present job.
female	Dummy for gender	1 if individual is female; 0 otherwise.
married	Dummy for marital status	1 if individual is married; 0 otherwise.
urban	Dummy for area	1 if individual lives in urban area; 0 otherwise.

The dependent variable in this analysis is the natural logarithm of monthly earnings. These monthly earnings include the value of all benefits secured by an individual in their job. The unit of measurement is rupiah (Rp) (US$1 was approximately equal to Rp9,000 at the time of the 2007/2008 survey). Monthly earnings are used instead of an hourly earnings indicator, because this is the figure respondents were explicitly asked to supply. While an hourly wage measure could be constructed, calculation of hourly wages would require using another variable, hours worked in the reference month, which is in turn subject to measurement error. Hence the monthly wage data are argued to be less prone to measurement error. There is also a preference for the use of monthly earnings based on the fact that in Indonesia employer/employee agreements are generally based on monthly wages.

The IFLS4 has information on the highest education level and the highest grade completed. In constructing the years of schooling variable we combine information on the highest education level and the highest grade completed to obtain the individual's actual years of schooling. For the set of dummies for education level, we employ seven dichotomous variables for the different schooling categories, namely, primary school, junior secondary school, general senior secondary school, vocational senior secondary school, college or diploma, undergraduate, and master degree.

There is one independent variable that needs to be constructed from other information in the data set, namely potential work experience. Measures of actual labour force experience, an important variable in the study of earnings determination, are absent from the IFLS4 data sets. However a potential labour force experience variable can be calculated from the information available. Most empirical studies usually use the following basic formula to derive a measure of potential work experience: age minus years of schooling minus official age to start primary school (6 or 7). However, for the purposes of calculating potential work experience in this study the following formula will be used: age minus years of schooling minus age first attended primary school. The aim of using this formula is to obtain more precise data on potential work experience since the age individuals first attended primary school varies appreciably. It ranges from 5 to 14 years in the data set.

5.3.3 Distribution of the Sample

The summary statistics for the main variables used in this chapter are reported in Table 5.2. The mean total monthly earnings are Rp1,339,521 across the workers. The mean years of schooling are relatively low, specifically 10.68 years, or just one year higher than the 9 years of compulsory study. The workers in the sample have mean work experience and age of approximately 17.79 years and 35.19 years, respectively. The mean length of job tenure is 7.85 years. The Table 5.2 data reveal that male and female workers have broadly similar levels of schooling, potential labour market experience, age and job tenure. They differ appreciably in terms of earnings, where the mean for males (Rp1,476,118) is 38.46 percent above the mean for females (Rp1,066,059). We return to this issue below.

Table 5.2: Summary Statistics of Main Variables

Variables	All		Males		Females	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Dependent Variable						
Monthly earnings (IDR)	1,339,521	1,961,290	1,476,118	2,137,155	1,066,059	1,514,442
Monthly earnings (log)	5.913	0.4378	5.973	0.408	5.792	0.468
Independent Variables						
Years of schooling	10.683	3.744	10.608	3.616	10.833	3.986
Experience	17.788	10.600	18.042	10.259	17.279	11.238
Experience squared	428.734	479.227	430.709	472.415	424.780	492.716
Age	35.192	9.741	35.417	9.561	34.741	10.078
Age squared	1333.327	751.375	1345.776	746.820	1308.406	760.046
Control Variables						
Tenure	7.852	8.116	7.890	8.036	7.779	8.275
Tenure squared	127.499	247.153	126.885	246.885	128.943	247.763
Female (dummy for gender)	0.333	0.471				
Marital status dummy	0.866	0.340	0.899	0.302	0.801	0.399
Dummy for urban area	0.676	0.468	0.649	0.477	0.730	0.444

Source: Author's calculation based IFLS4 data set.

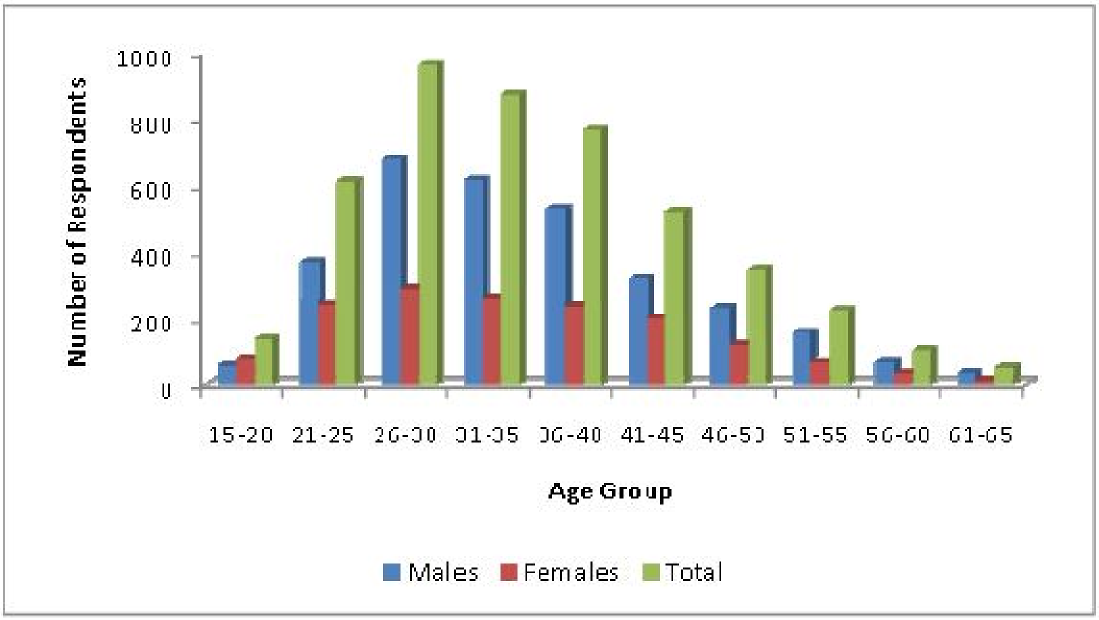
The distribution of the sample by gender, area, and marital status is examined in Table 5.3. Approximately 67 percent (3,108 individuals) of the sample are male and about 90 percent of these male respondents are married. The married comprise about 80 percent of the female respondents in the sample. Based on the rural-urban area of the residence of respondents, 3,108 individuals, or about 68 percent of respondents, in the sample come from urban areas and 1,488, or about 32 percent, are from rural areas.

Table 5.3: The Distribution of Sample by Gender, Marital Status, and Area

	Females			Males			Total
	Married	Other	Total	Married	Other	Total	
Urban	867	251	1,118	1,743	247	1,990	3,108
Rural	360	53	413	1,012	63	1,075	1,488
Total	1,227	304	1,531	2,755	310	3,065	**4,596**

Source: Author's calculation based on IFLS4 data set.

Figure 5.2: The Distribution of Sample by Gender and Age



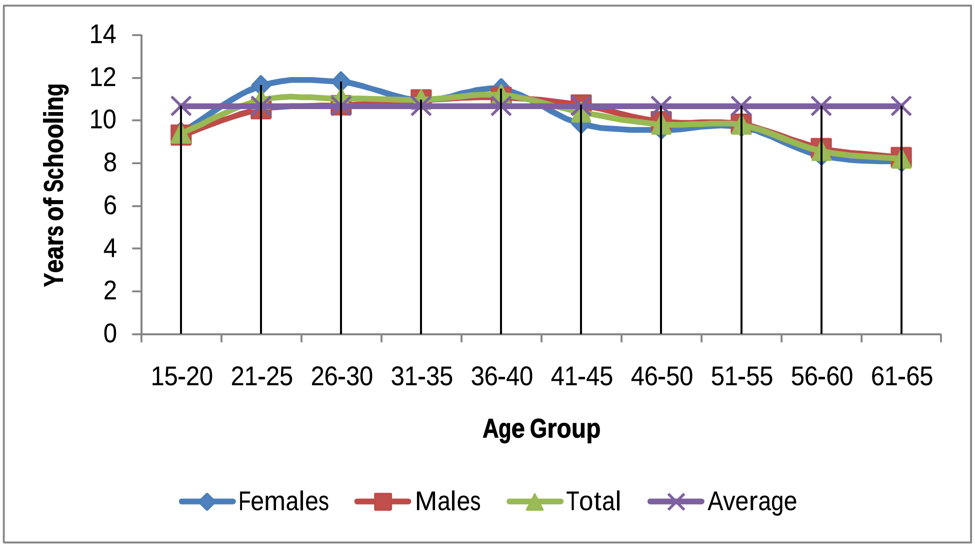
Source: Author's calculation based on IFLS4 data set.

Elaborating further on the characteristics of the sample, Figure 5.2 presents the distribution of the sample according to gender and age group. The age of the individuals in the sample varies, by construction, from 15 to 65 years old. The number of the respondents in the sample initially increases with age and then decreases. The greatest number of individuals in the sample belongs to the age group of 26-30 years old, with around 21 percent of the male and female workers. The youngest group, which is 15-20 years old, has approximately 3 percent of the sample. The oldest age group, which is 61-65 years old, consists of about 1 percent of the sample.

5.3.4 Schooling, Earnings, Experience, and Age: The Basic Facts

The years of schooling of the respondents in the sample range from 1 year to 18 years. The mean of the years of schooling is 10.68 years. Examination of schooling levels across age groups shows that the trend of the years of schooling is downward sloping. In other words the older the group the lower the average years of schooling. Thus, the highest average years of schooling is 11.2, which occurs in the 36-40 years age group. The oldest group, of age 61-65 years, has the lowest average years of schooling (8.17). The average years of schooling completed is 10.60 for men and 10.85 years for women. However, across the 15-20 to 36-40 years age group, female workers have a higher average years of schooling than male workers. For the older cohorts the average years of schooling for females and males are almost the same. These cohort differences, and the difference by gender across age groups, are also typical of most western countries. The detailed information about the average years of schooling by age group is presented in Figure 5.3.

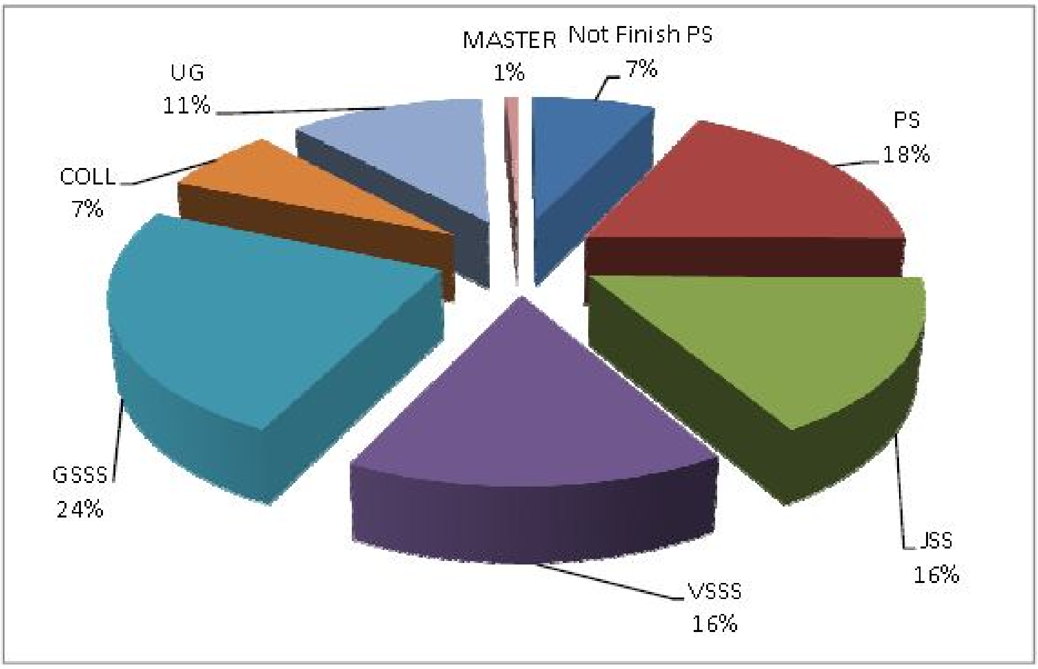
Figure 5.3: Average Years of Schooling by Age Group



Source: Author's calculation based on IFLS4 data set.

Figure 5.4 describes the distribution of the sample based on educational attainment. Respondents who do not finish their primary school are approximately 7 percent of the total sample. Around 18 percent of the sample graduated from primary school. Respondents who hold the junior secondary school level comprise approximately 16 percent of the total sample. The percentage of the respondents in the sample who are qualified in general senior secondary school, vocational senior secondary school, college, undergraduate, and master degree are 24, 16, 7, 11, and 1 percent, respectively.

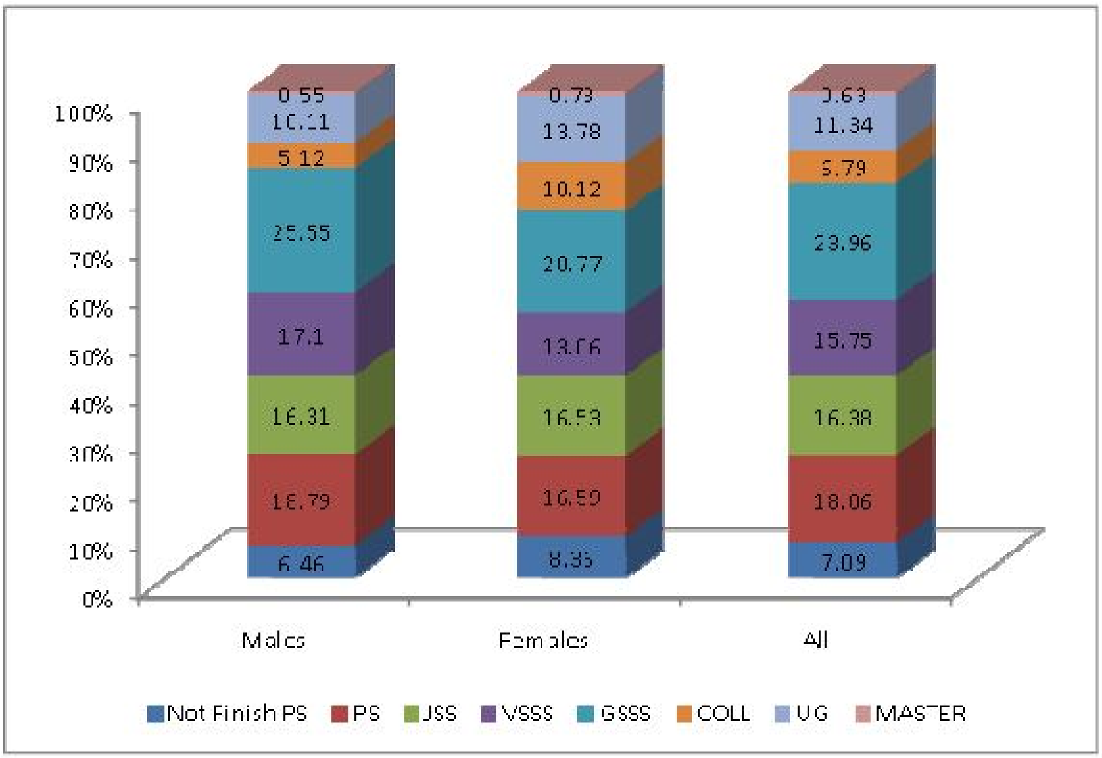
Figure 5.4: Distribution of Sample by Education Attainment



Notes: Not finish PS: not finished Primary School; PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; COLL: College; UG: Undergraduate; MASTER: Master degree.
Source: Author's calculation based on IFLS4 data set.

Turning to the information on educational attainment by gender (see Figure 5.5), it is observed that there is a slightly different pattern in educational attainment composition for female and male respondents. For female respondents, the smallest percentage is for those holding a master degree, with 0.78 percent of the female sample. The second lowest percentage is for the 'did not finish primary school' category, followed by the college, vocational senior secondary school, undergraduate, junior secondary school, and primary school categories, with 8.36 percent, 10.12 percent, 13.06 percent, 13.78 percent, 16.55 percent, and 16.59 percent respectively, and the highest percentage is for individuals with general senior secondary school qualification, which is 20.77 percent of the female sample. For male respondents, the order from the lowest to the highest percentage is as follows: master degree (0.55 percent), college (5.12 percent), did not finish primary school (6.48 percent), undergraduate (10.11 percent), junior secondary school (16.31 percent), vocational senior secondary school (17.1 percent), primary school (18.79 percent), and general senior secondary school (25.55 percent).

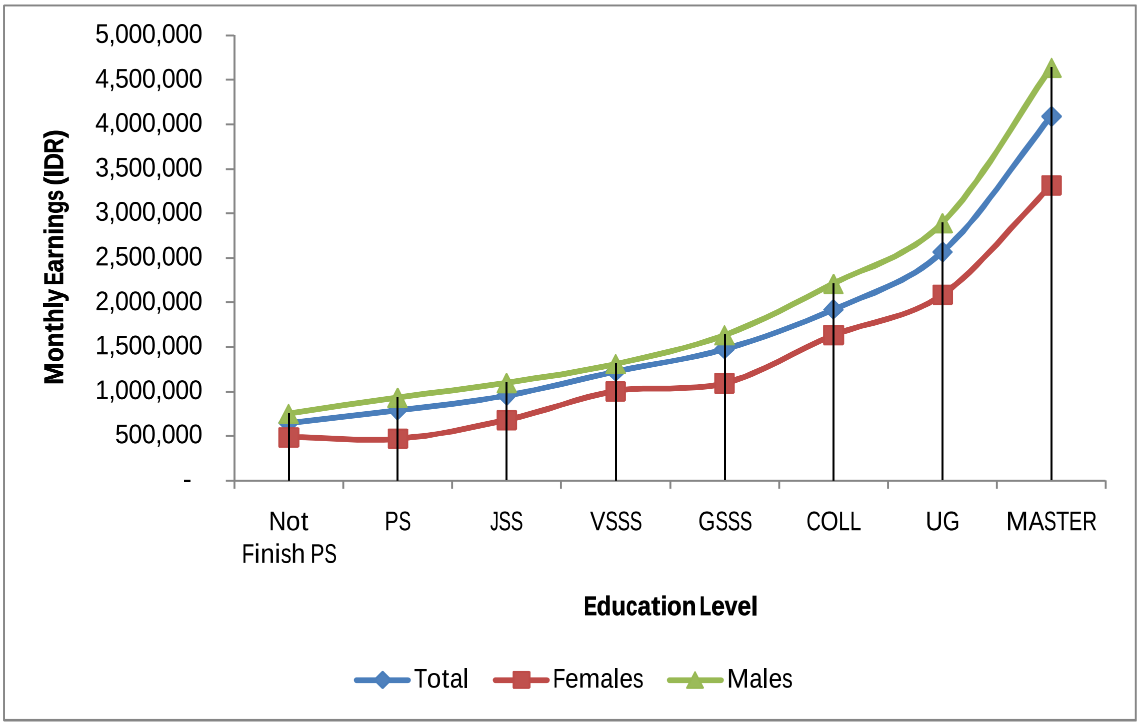
Figure 5.5: Mean Educational Attainment by Gender



Notes: Not finish PS: not finished Primary School; PS: Primary School; JSS: Junior Secondary School; GSSS: General Senior Secondary School; VSSS: Vocational Senior Secondary School; COLL: College; UG: Undergraduate; MASTER: Master degree.
Source: Author's calculation based on IFLS4 data set.

The breakdown of the earnings profiles by educational levels separately for men and women is presented in Figure 5.6. The patterns in the figure coincide with the main prediction of human capital theory, which states that more educated individuals earn more as a result of improved productivity. The average monthly earnings range from about Rp650,000 for individuals who do not finish their primary school to about Rp4,000,000 for individuals with a master degree. Female workers have lower average monthly earnings for all education levels than their male counterparts. At the lowest education level, female workers who do not finish their primary education receive average monthly earnings about Rp300,000 lower than those of male workers with the same education level. On the other hand, differences of average monthly earnings between female workers and male workers with a master degree are approximately Rp800,000. In percent terms, however, the gender earnings gap tends to decline as the level of education rises. Thus the differences are 50.04, 38.20, 33.29, 23.40, 26.24, 27.93, and 28.49 percent for primary school, junior secondary school, general senior secondary school, vocational senior secondary school, college, undergraduate, and master degree, respectively.

Figure 5.6: Mean Monthly Earnings by Educational Attainment

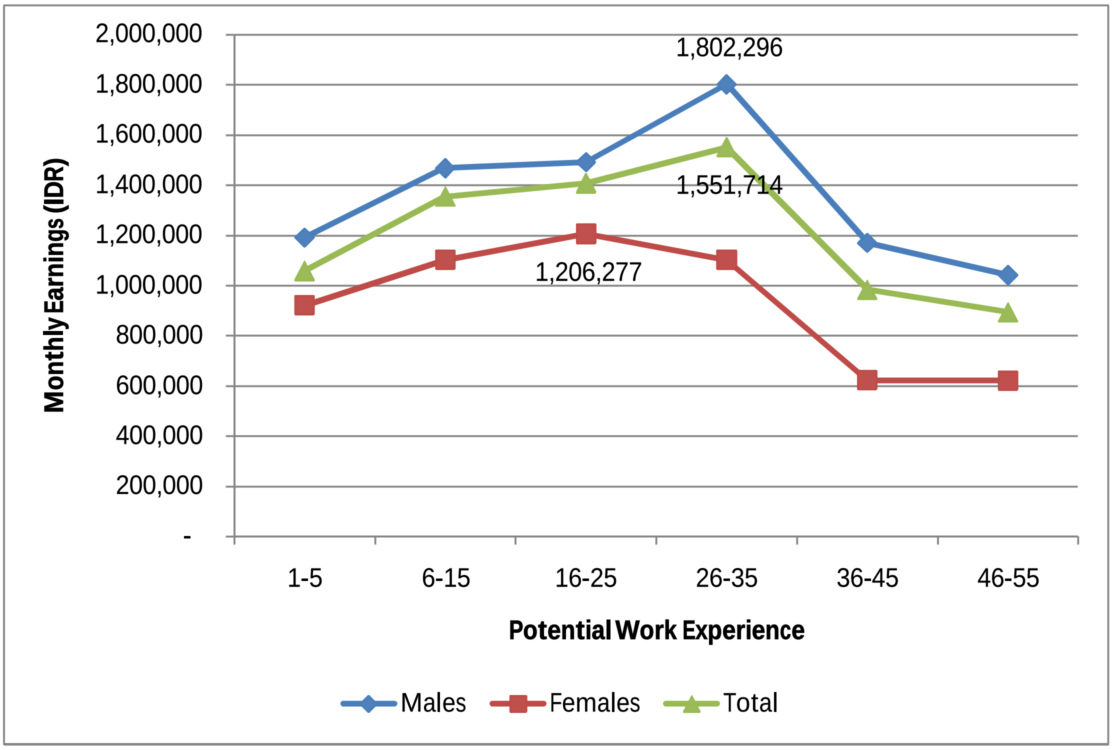


Notes: Not finish PS: not finished Primary School; PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; COLL: College; UG: Undergraduate; MASTER: Master degree.
Source: Author's calculation based on IFLS4 data set.

Figure 5.7 displays the relationship between average monthly earnings and potential work experience based on the IFLS4 data set.[14] Initially, earnings rise with experience, after around 26-35 years of labour market activity earnings decline with additional years of experience. The average earnings for females reach their peak when the workers have 16-25 years of experience. In comparison, male workers reach their highest average earnings at 26-35 years of work experience. At the peak position female workers have average earnings of approximately Rp1200,000, and male workers receive about Rp1800,000. This is a female earnings disadvantage of 33 percent of the male earnings.

[14] The detailed information on the construction of the potential work experience variable is presented in sub-section 5.3.2 Data Extracting Procedure and Variable Definition.

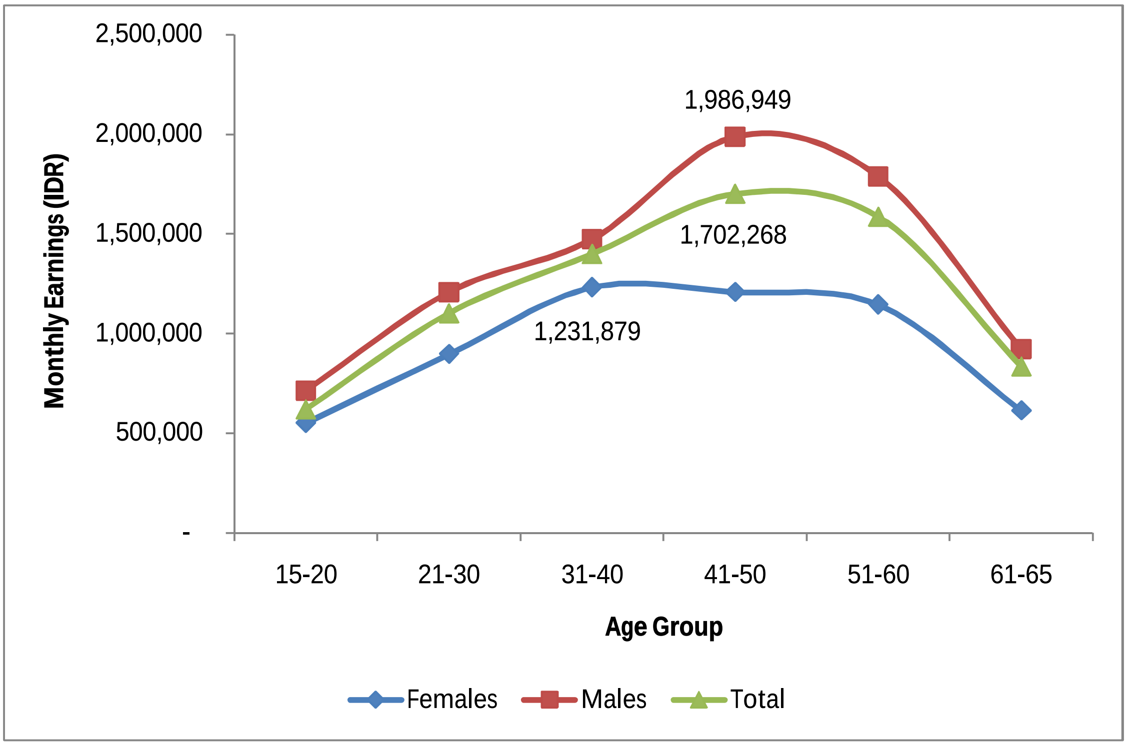
Figure 5.7: Potential Work Experience - Monthly Earnings Profile



Source: Author's calculation based on IFLS4 data set.

Figure 5.8 presents the relationship between average monthly earnings and age. As expected given the method of constructing the potential labour market experience variable, the shapes of the three curves that show the relationship between average monthly earnings and age are similar to the curves that show the relationship between average monthly earnings and potential work experience. Initially, earnings rise with age, peak around ages 41-50, and then decline in the pre-retirement years. These results follow the typical of '*life cycle hypothesis*' of Modigliani. Moreover, it is observed that the age-earnings profiles of females reach their turning point earlier than those of males. Thus the earnings-age profile of females peaks in the 31-40 years age group, whereas the earnings-age profile of males peaks in the 41-50 age groups. These experience-earnings and age-earnings profiles patterns are typically found in less developed countries. The tendency for the experience-earnings and age-earnings profiles for females to peak before those of males could indicate the existence of discrimination in promotion rates in the labour market for females.

Figure 5.8: Age - Monthly Earnings Profile



Source: Author's calculation based on IFLS4 data set.

5.4 Results and Interpretation

The analysis commences with results from the standard Mincer equation with no control variables. This is followed by empirical findings of the returns to schooling from the augmented Mincerian model that includes control variables. Comparisons of the results from all specifications are then discussed in detail.

5.4.1 The Standard Mincerian Model

In this section, OLS estimates of the earnings function parameters are reported, assuming education to be exogenous. Following the common approach used in the literature, the econometric analysis of the private returns to schooling starts by estimating the basic Mincerian function, where, as described in the empirical model and estimation method section, the natural logarithm of earnings is regressed on years of schooling, potential work experience and its squared term. The results are reported in Table 5.4.[15]

[15] The reported coefficients were estimated using STATA 11.1.

Table 5.4: OLS Estimates of Standard Mincerian Earnings Function

	(a)	(b)	(c)	(d)	(e)	(f)
				age proxying experience		
	Model 5.1-a-all	**Model 5.1-a-male**	**Model 5.1-a-female**	**Model 5.1-b-all**	**Model 5.1-b-male**	**Model 5.1-b-female**
Constant	5.12447 (0.02718)***	5.25857 (0.03354)***	4.92210 (0.04398)***	4.84851 (0.07113)***	5.04175 (0.08816)***	4.65561 (0.11789)***
Years of Schooling	0.05663 (0.00172)***	0.05278 (0.00206)***	0.06459 (0.00290)***	0.05070 (0.00160)***	0.04704 (0.00190)***	0.05882 (0.00265)***
Experience	0.01603 (0.00195)***	0.01224 (0.00240)***	0.01540 (0.00327)***			
Experience^2	-0.00023 (0.00005)***	-0.00015 (0.00006)***	-0.00023 (0.00008)***			
Age				0.02393 (0.00401)***	0.01894 (0.00489)***	0.02303 (0.00691)***
Age^2				-0.00024 (0.00005)***	-0.00018 (0.00007)***	-0.00023 (0.00010)**
R^2	0.2051	0.1899	0.2585	0.2031	0.1890	0.2566
Observations	4596	3065	1531	4596	3065	1531
Chow test (*F*-test)			63.53			64.55
p-value			0.0000			0.0000

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 5.4 presents the OLS coefficients estimated for the total sample and for males and females, separately. The Chow tests reject the null hypothesis of equality of the regression coefficients for males and females. The six standard models explain from about 19 to about 26 percent of the variation in actual earnings, figures which are comparable to other studies in the literature. All the coefficients reported in the table have the expected signs and are statistically significant at the level of $\alpha = 0.01$, except for the age squared variable in model 5.1-b-female, which is statistically significant only at the level of $\alpha = 0.05$.

According to the Table 5.4 results, an additional year of education is associated with an annual 5.66 percent increase in earnings in model 5.1-a-all, and with a 5.07 percent increase in earnings in model 5.1-b-all. These estimates of the return to schooling in Indonesia are substantially smaller than the Psacharopoulos (1981) average estimate of 14 percent for Less Developed Countries, and the Psacharopoulos (1994) average estimate of 9.6 percent for Asian countries. However these results are in agreement with some empirical studies, for example: Jamison and Gaag (1987) in China, Flanagan (1998) in the Czech Republic, Wei *et al.* (1999) in China, Maurer-Fazio and Dinh (2004) in China, Aromolaran (2006) in Nigeria, and Aslam *et al.* (2010) in Pakistan. A relatively low rate of return to schooling is generally faced by countries experiencing economic transition, such as China and the former Russian countries.

Typically, the return to schooling in such countries is low in the early stage of the economic transition process, and then gradually increases after market oriented economic reform is implemented. The Indonesian economy shifted from a controlled economy to a market driven economy in 1966 (Ananta and Arifin, 2008). Referring to the general pattern of the return to schooling in economic transition countries, the low return to schooling in Indonesia in the late 2000s invites a question. At this period, where the economic reform process had already reached the market driven economy stage, the return to schooling is expected to be higher than the estimates described above. Moreover, Duflo (2001), using data from a 1995 intercensal survey of Indonesia, found estimates of economic returns to schooling ranging from 6.8 to 10.6 percent. This suggests that the relatively low return to schooling in the current study of data for 2007-2008 is triggered by some other source. A likely candidate in this regard is a decline in the quality of school and a significant increase in the supply of educated workers in the labour market, due to a combination of events such as the massive school construction program in 1973 and 1974 and the compulsory education program in 1984. Both explanations, though particularly the latter, featured in accounts of the decline in the return to schooling in the US in the 1970s.

The estimates of the return to schooling for females (6.46 percent and 5.88 percent) are higher than those for males (5.28 percent and 4.70 percent). The t-test confirms that these differences are statistically different, indicating that schooling is more financially rewarding in the labour market for females than for males. This result is consistent with the findings of many empirical studies, such as Deolalikar (1993), and Behrman and Deolalikar (1993) in Indonesia, Miller *et al.* (1997) in Australia, Flanagan (1998) in the Czech Republic, Brunello *et al.* (2000) in Italy, Lopez-Avecedo (2001) in Mexico, and Asadullah (2006) in Bangladesh.

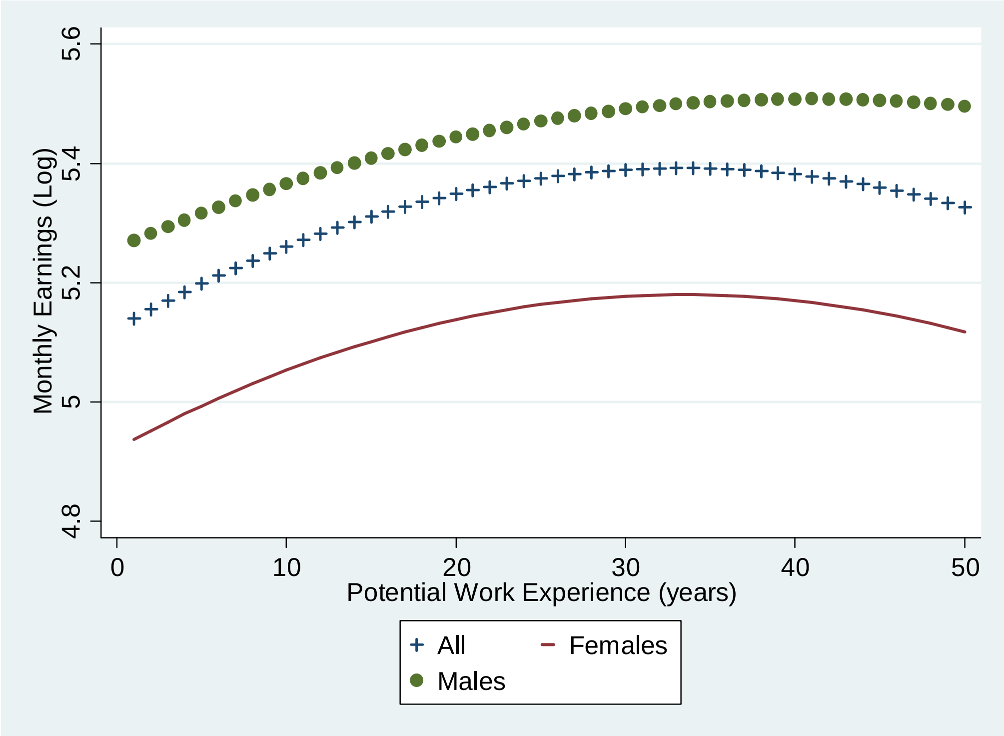
The coefficients on the potential labour market experience variable and its squared term have the expected signs, and portray the usual concavity of the experience-earnings profile. The increase in earnings associated with an extra year of potential labour market experience is given as:

$$\frac{\partial \ln earnings}{\partial expr} = \hat{\beta}_2 + 2\hat{\beta}_3 expr,$$

where $\hat{\beta}_2$ is the estimated coefficient on the experience variable, and $\hat{\beta}_3$ is the estimated coefficient on the experience squared variable. Thus this payoff varies with the level of potential work experience. Among labour market entrants (experience = 0) the return estimated for the total sample is 1.6 percent. At 10 years of potential labour market experience the return is 1.14 percent, and at 20 years of potential labour market experience the return is 0.68 percent. The increase in earnings associated with additional labour market experience for females exceeds that for males up to around 20 years of experience. For example, among labour market entrants it is 1.54 percent for females and 1.22 percent for males. At experience = 10 it is 1.08 percent for females and 0.92 percent for males. Beyond 20 years of experience, however, the increase in earnings per year of labour market experience for males exceeds that for females, and for a number of years (e.g. at experience = 25 and experience = 35) it is positive whereas that for females is negative. This gender difference in the payoff to experience across levels of experience could be due to the following reasons. First, it could reflect a cohort effect, where the younger female workers in the sample have joined the labour force under different - perhaps more favourable - circumstances than the older female workers in the sample. Second, it could relate to selectivity in labour force participation. In the young cohort, females in the labour force may be heavily selected toward more able and talented individuals. Third, the younger cohorts in the sample tend to have better education than the older cohorts in the sample, and there may be complementarities between labour market experience and the level of education.

Also of interest is the level of experience at which the predicted experience-earnings profile peaks. This is where $\hat{\beta}_2 + 2\hat{\beta}_3 expr = 0$. This occurs when potential work experience reaches 34.85, 40.80, and 33.48 years for all, male, and female samples respectively (see Figure 5.9).

Figure 5.9: Experience - Earnings Profiles

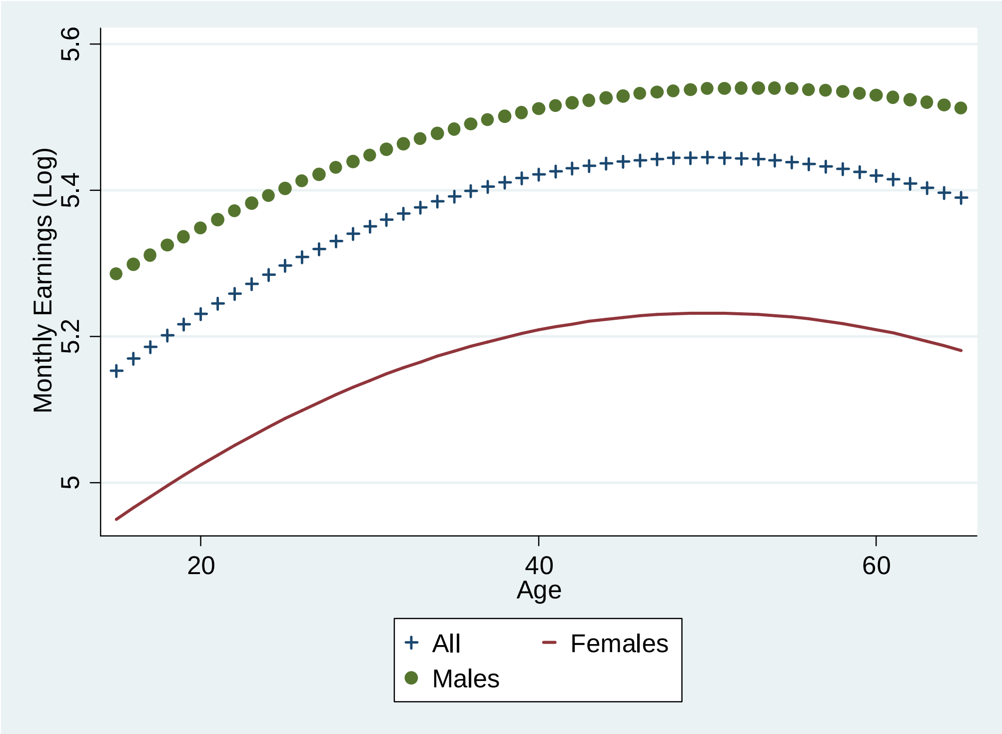


Source: Author's calculation based on Table 5.4.

Figure 5.9 uses the estimates from Table 5.4 to predict experience-earnings profiles. The figure presents some patterns worth noting. As discussed above, the experience-earnings profiles have concave, first rising and then falling after reaching a given number of years. Based on the previous calculation of the experience-earnings profile we know that the earnings of male workers increase with experience until their peak at 40.80 years. Thus for a male leaving education at age 16, this peak would be at age 57. Female workers reach the peak of their experience-earnings profile earlier than their male counterparts, at 33.48 years. Thus for females leaving school at age 16 this peak would occur at 50 years. This would be well after women with career interruptions due to child bearing and rearing have returned to the labour market.

Estimation of the standard Mincerian model with age in place of potential experience leads to estimated coefficients that differ somewhat from the corresponding results reported in columns (a), (b), and (c) of Table 5.4. However, the sign of every coefficient, and the general pattern of the results, are similar. The rates of return to schooling reported in Table 5.4 columns (d), (e), and (f) are slightly lower, by 0.59, 0.57, and 0.58 percentage points, in comparison with those reported in Table 5.4 columns (a), (b), and (c), respectively. Thus, an additional year of schooling increases earnings by 5.07, 4.70, and 5.88 percent for males and females combined, males, and females, respectively. In other words, using age instead of potential work experience results in the same pattern of females having a higher return to schooling. This result is comparable with Blinder's (1976) finding. The differences between males and females in the return to schooling is, however, wider for the specification using potential work experience.

Figure 5.10: Age - Earnings Profiles



Source: Author's calculation based on Table 5.4.

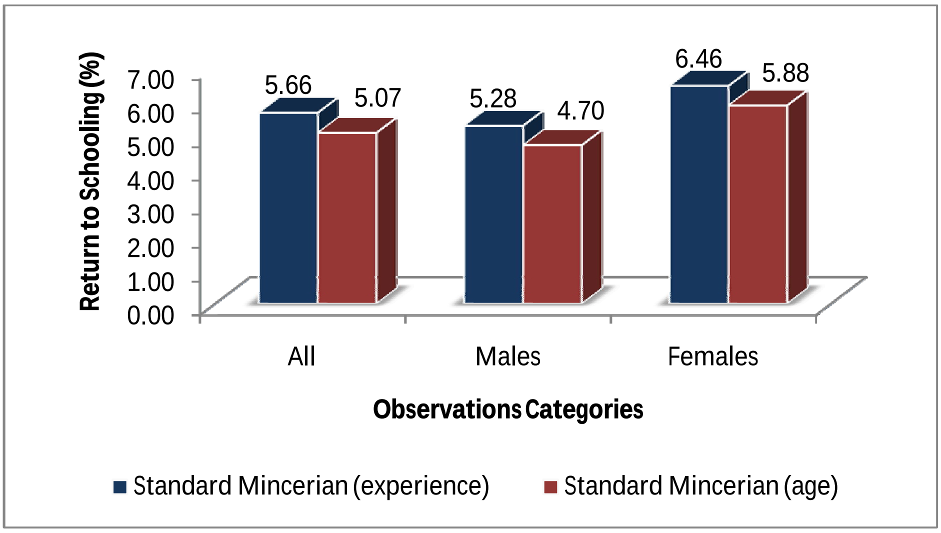
Predicted age-earnings profiles obtained from the estimates are presented in Figure 5.10. These predictions demonstrate the usual concavity of the age-earnings profile. The increase in earnings associated with an extra year of age is given as:

$$\frac{\partial \ln earnings}{\partial age} = \hat{\beta}_2 + 2\hat{\beta}_3 age,$$

where $\hat{\beta}_2$ is the estimated coefficient on the age variable, and $\hat{\beta}_3$ is the estimated coefficient on the age squared variable. Thus this payoff varies with the age of the worker. The age-earnings profiles display rapid initial earnings growth; they peak where $\hat{\beta}_2 + 2\hat{\beta}_3 age = 0$, which is around 49.9 (combined sample), 52.6 (male sample), and 50.1 (female sample) years of age, and decline slightly toward the end of the career (see Figure 5.10).

Similar to the effects of potential work experience on earnings for males and females, the changes in earnings associated with additional age for males are lower than those for females. Among labour market entrants (age of 15), the increase in earnings associated with age is 1.35 percent for males and 1.61 percent for females. However, from the age of 50 the change in earnings associated with age is negative for females. For males the negative change starts 3 years later, that is at the age of 53.

Figure 5.11: The Standard Mincerian Return to Schooling



Source: Author’s calculation based on Table 5.4.

Comparison of the return to schooling among the six specifications from Table 5.4 is provided in Figure 5.11. Using either potential work experience or age in the earnings function to estimate the returns to schooling yields a range of 4.70 to 6.46 percent increase in earnings associated with each additional year of schooling. We turn now to examine whether these estimates are sensitive to the way the information on educational attainment is incorporated into the model.

5.4.2 The Standard Mincerian Model with Different Levels of Education

So far the continuous years of schooling variable has been utilised as the measure of educational attainment. The estimates obtained using this measure will now be complemented with a more detailed investigation by examining returns to specific school levels and types.

In order to estimate the rates of return to each separate level of education, this study utilises a model with dummy variables that take the value of 1 when a level is completed and 0 otherwise. When the schooling variable is broken down into the seven different types of education - primary school, junior secondary school, vocational senior secondary school, general senior secondary school, college, undergraduate, and master - more insight is gained into the incentives that the labour market provides for investing in education by individuals and households in Indonesia. As noted earlier, this flexible specification allows any non-linearity in the returns to schooling to be captured. The OLS estimates of the standard Mincerian earnings function based on the level of education are reported in Table 5.5.

Table 5.5: OLS Estimates of Standard Mincerian Earnings Function with Level of Education Dummy Variables

	(a)	(b)	(c)	(d)	(e)	(f)
				age proxying experience		
	All	Males	Females	All	Males	Females
	Model 5.2-a-all	Model 5.2-a-male	Model 5.2-a-female	Model 5.2-b-all	Model 5.2-b-male	Model 5.2-b-female
Constant	5.40310	5.51588	5.28616	5.11737	5.30074	5.00943
	(0.03171)***	(0.03907)***	(0.05190)***	(0.07629)***	(0.09519)***	(0.12519)***
Primary School	0.08844	0.10768	-0.00642	0.09780	0.10770	0.01007
	(0.02839)***	(0.03326)***	(0.04812)	(0.02793)***	(0.03311)***	(0.04629)
Junior Secondary School	0.21890	0.20810	0.20702	0.21759	0.19627	0.21626
	(0.02939)***	(0.03458)***	(0.05037)***	(0.02803)***	(0.03364)***	(0.04631)***
Vocational Senior Secondary School	0.39778	0.35739	0.41390	0.37622	0.32860	0.40314
	(0.02907)***	(0.03414)***	(0.05142)***	(0.02729)***	(0.03253)***	(0.04681)***
General Senior Secondary School	0.40897	0.38555	0.39177	0.38551	0.35501	0.37900
	(0.02908)***	(0.03384)***	(0.05251)***	(0.02715)***	(0.03213)***	(0.04735)***
College	0.57240	0.56612	0.61261	0.52662	0.51723	0.57804
	(0.03330)***	(0.04230)***	(0.05256)***	(0.03180)***	(0.04067)***	(0.04854)***
Undergraduate	0.67959	0.64903	0.72768	0.63311	0.59839	0.69267
	(0.03053)***	(0.03679)***	(0.05121)***	(0.02874)***	(0.03524)***	(0.04615)***
Master	0.97564	0.96502	0.99615	0.92272	0.90536	0.96250
	(0.05044)***	(0.06274)***	(0.07343)***	(0.04836)***	(0.06031)***	(0.07056)***
Experience	0.01622	0.01200	0.01693			
	(0.00197)***	(0.00241)***	(0.00329)***			
Experience^2	-0.00026	-0.00017	-0.00029			
	(0.00005)***	(0.00006)***	(0.00008)***			
Age				0.02193	0.01667	0.02128
				(0.00404)***	(0.00492)***	(0.00696)***
Age^2				-0.00022	-0.00016	-0.00022
				(0.00005)***	(0.00007)**	(0.00010)**
R^2	0.2045	0.1888	0.2728	0.2020	0.1883	0.2683
Observations	4596	3065	1531	4596	3065	1531
Chow test (*F*-test)			28.84			29.04
p-value			0.0000			0.0000

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively. "Did not finish Primary School" is the benchmark group for the educational attainment categories.

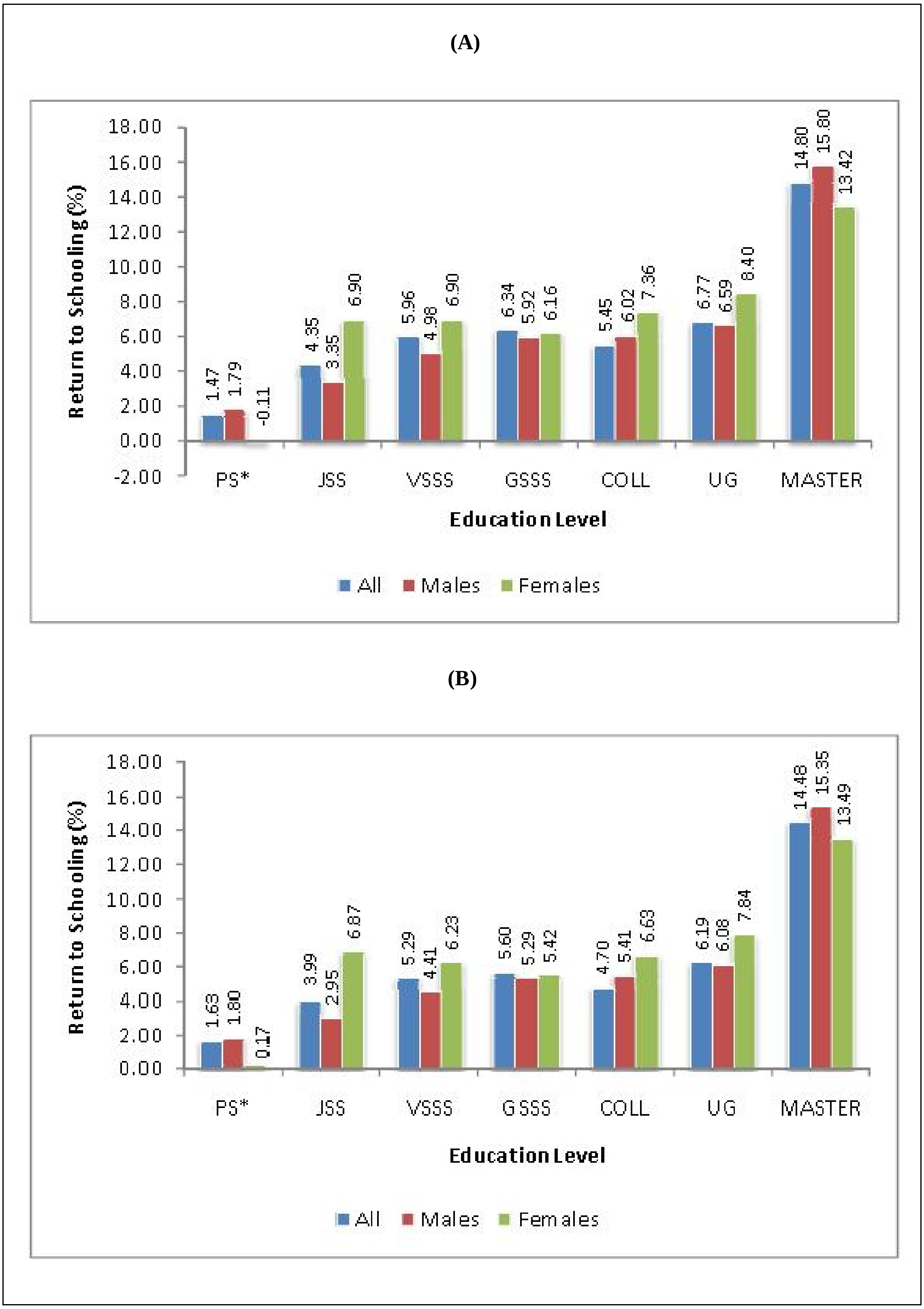
The omitted education category is for the lowest group of "Did not finish Primary School", and the education levels included in the model form a hierarchy, from lowest to highest. Hence, it is expected that the estimated coefficients will all be positive, and increase in magnitude as one reads down the table. Following this change to the way that the information on educational attainment is included in the estimating equation, there is little change to the estimated coefficients of either the experience or age variables. Estimating the return to schooling using potential work experience or age yields highly statistically significant coefficients for almost all the variables. The sole exception is the coefficient for primary school for females. Replacing the potential work experience variables by the age variables is associated with a decrease in most of the coefficients of the education dummy variables for all samples. The result from the *F*-test confirms that the coefficients of the level of education variables for males and females are statistically different. The fact that the value of the constant term is higher for males than for females indicates that males, without schooling and work experience, earn more than comparable females. This can possibly be interpreted as an indication of the existence of wage discrimination against females in the labour market.

Based on the results presented in Table 5.5, the returns to schooling for each type of education level can be calculated using Equation 5.3. Figure 5.12 presents the marginal return to completing each additional level of education, e.g., junior secondary school compared to primary school and general senior secondary school compared to junior secondary school. The comparison between general senior secondary schools and vocational senior secondary schools also can be accommodated. School types are ranked by increasing number of years of schooling required to finish that level of education. Figure 5.12 panel (A) shows the return to education derived from models 5.2-a-all, 5.2-a-male, and 5.2-a-female, while panel (B) presents the return to schooling derived from models 5.2-b-all, 5.2-b-male, and 5.2-b-female.

Among the wage earners, the return to schooling at the primary school level is 1.47 percent in the model based on potential labour market experience (1.63 in the model based on age) for the full sample, 1.79 (1.80) percent for males, and -0.11 (0.17) percent for females. The return to schooling for junior secondary school is estimated to be 4.35 (3.99) percent for the full sample, 3.35 (2.95) percent for males, and 6.90 (6.87) percent for females. At the level of general senior secondary school the return to schooling is 6.34 (5.60) percent for the full sample, 5.92 (5.29) percent for males, and 6.16 (5.42) percent for females. The workers with vocational senior secondary school have a return to schooling as much as 5.96 (5.29) percent for the full sample, 4.98 (4.41) percent for males, and 6.90 (6.23) percent for females. These figures confirm that male workers with vocational senior secondary school have a lower return to each year of schooling than general senior secondary school graduate males. On the contrary, females with vocational senior secondary school have a higher return to schooling than general senior secondary school graduate females. Workers with college education receive a 5.45 (4.70) percent return to schooling for the full sample, a 6.02 (5.41) percent return for males, and a 7.36 (6.63) percent return for females. Individuals with an undergraduate level of education have a return to schooling of 6.77 (6.19) percent for the full sample, 6.59 (6.08) percent for males, and 8.40 (7.84) percent for females. The return to schooling for a master degree is 14.80 (14.48) percent for the full sample, 15.80 (15.35) percent for males, and 13.42 (13.49) percent for females. All these figures are substantially lower than the average returns to schooling in Asian countries. Psacharopoulos (1981, 1985, and 1994) finds that the returns to schooling for Asian countries are 31 to 39 percent, 15 to 18.9 percent, and 18 to 19.9 percent for primary, secondary, and tertiary education, respectively.

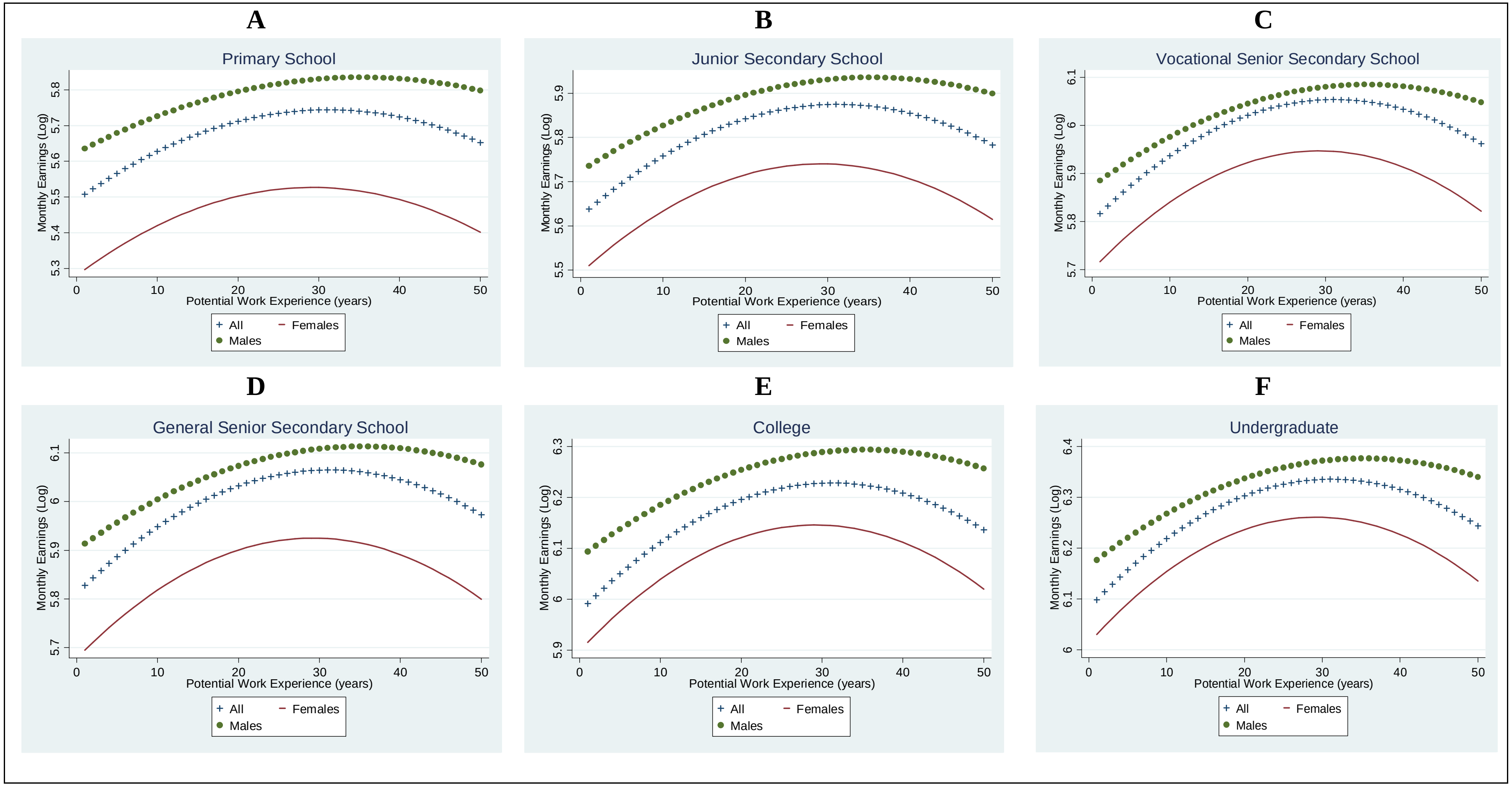
It can be seen in panel (A) that males have lower returns to schooling than females at the secondary (junior and senior secondary schools) and tertiary levels (college and undergraduate only). Panel (B) confirms that the returns to schooling for males exceed those for females for primary school and master degree. These patterns are similar to those obtained by Deolalikar (1993). The differences in returns between males and females are not very large, however. They range from 0.13 to 1.96 percentage points.

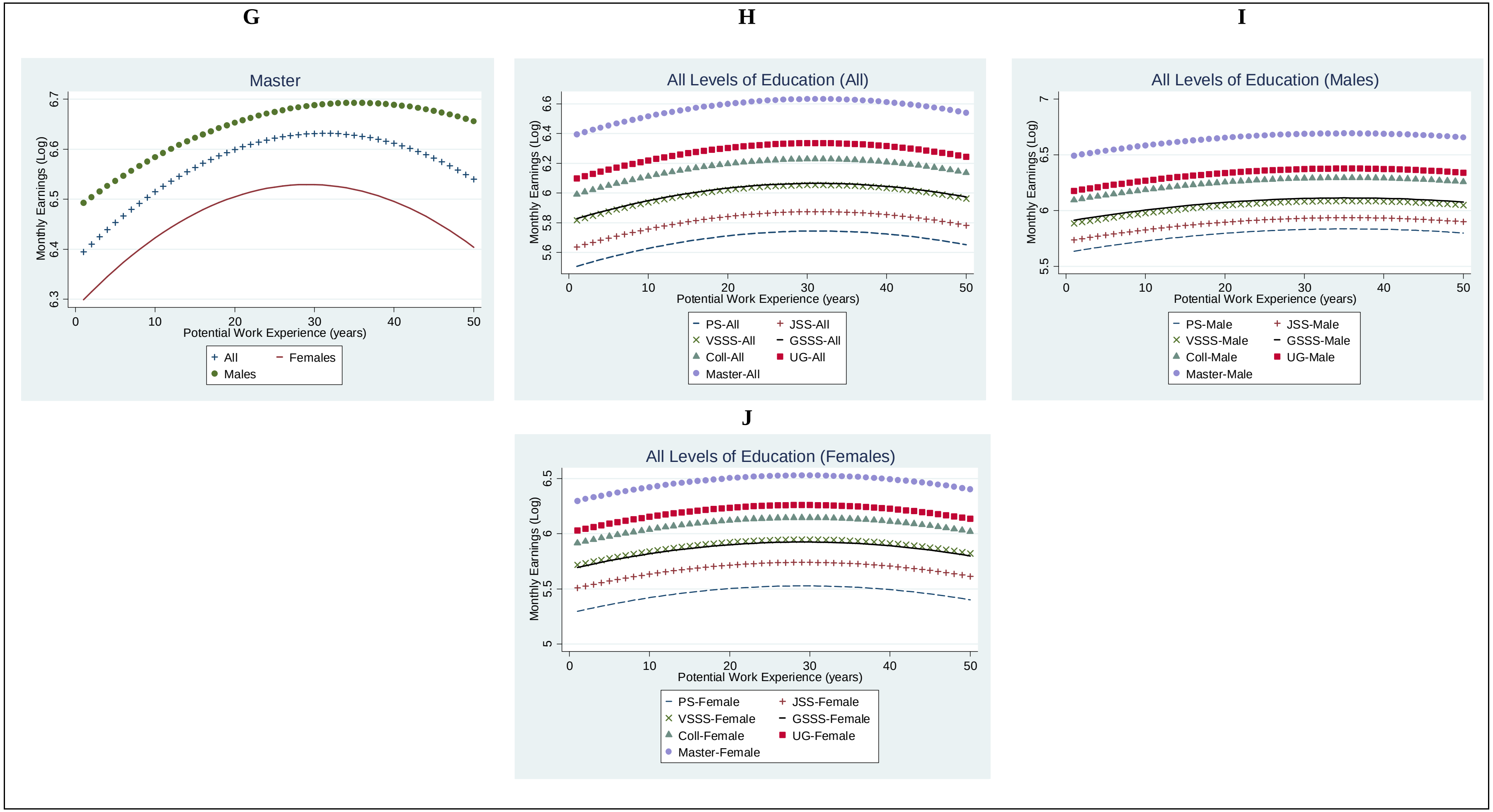
Figure 5.12: Standard Mincerian Return to Schooling Based on Model with Level of Education Dummy Variables



Notes: PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; COLL: College; UG: Undergraduate; MASTER: Master degree.
*: Primary School coefficient for female sample is statistically insignificant.
Source: Author's calculation based on Table 5.5.

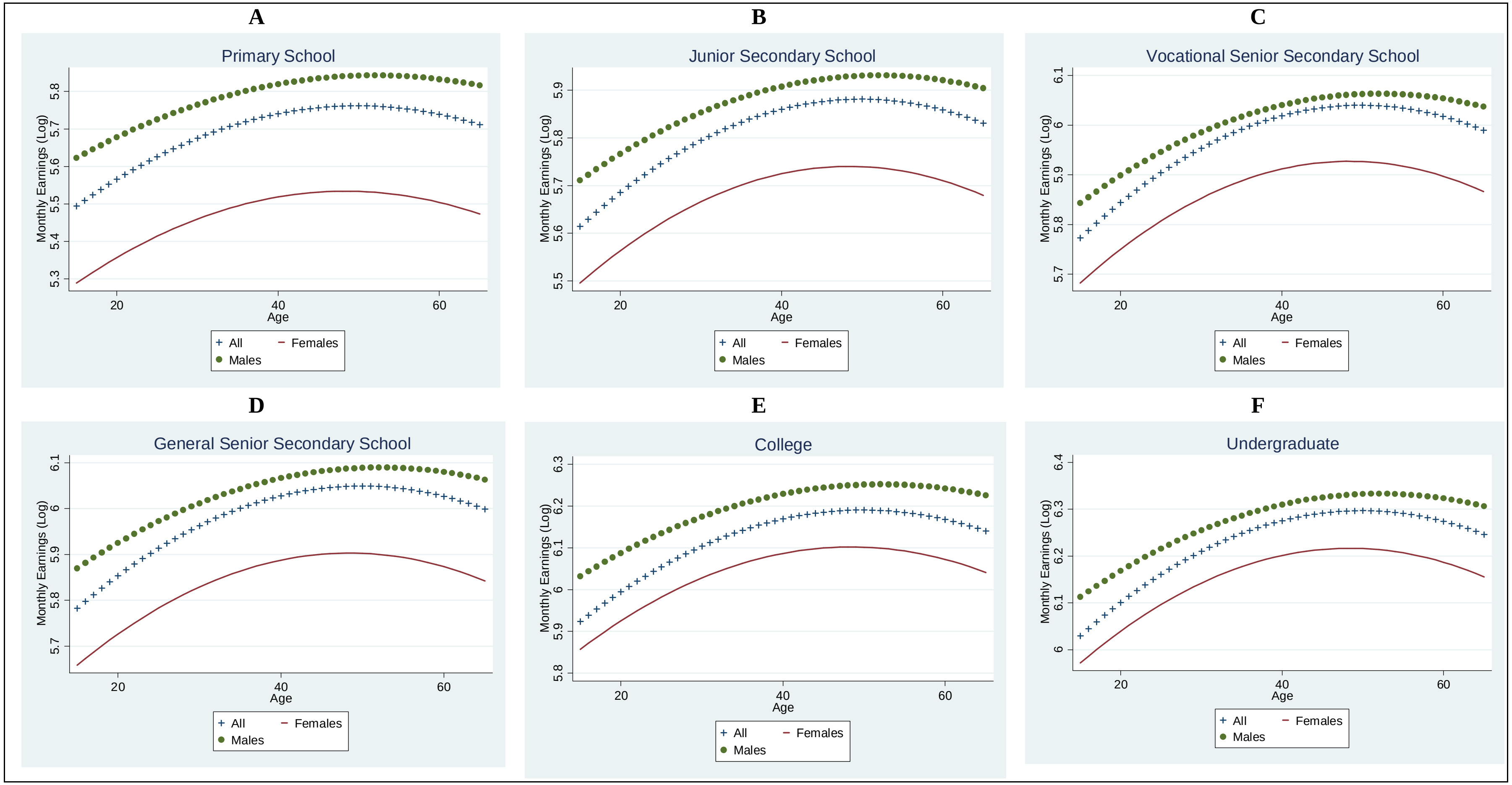
Figure 5.13: Experience - Earnings Profiles by Gender and Educational Attainment

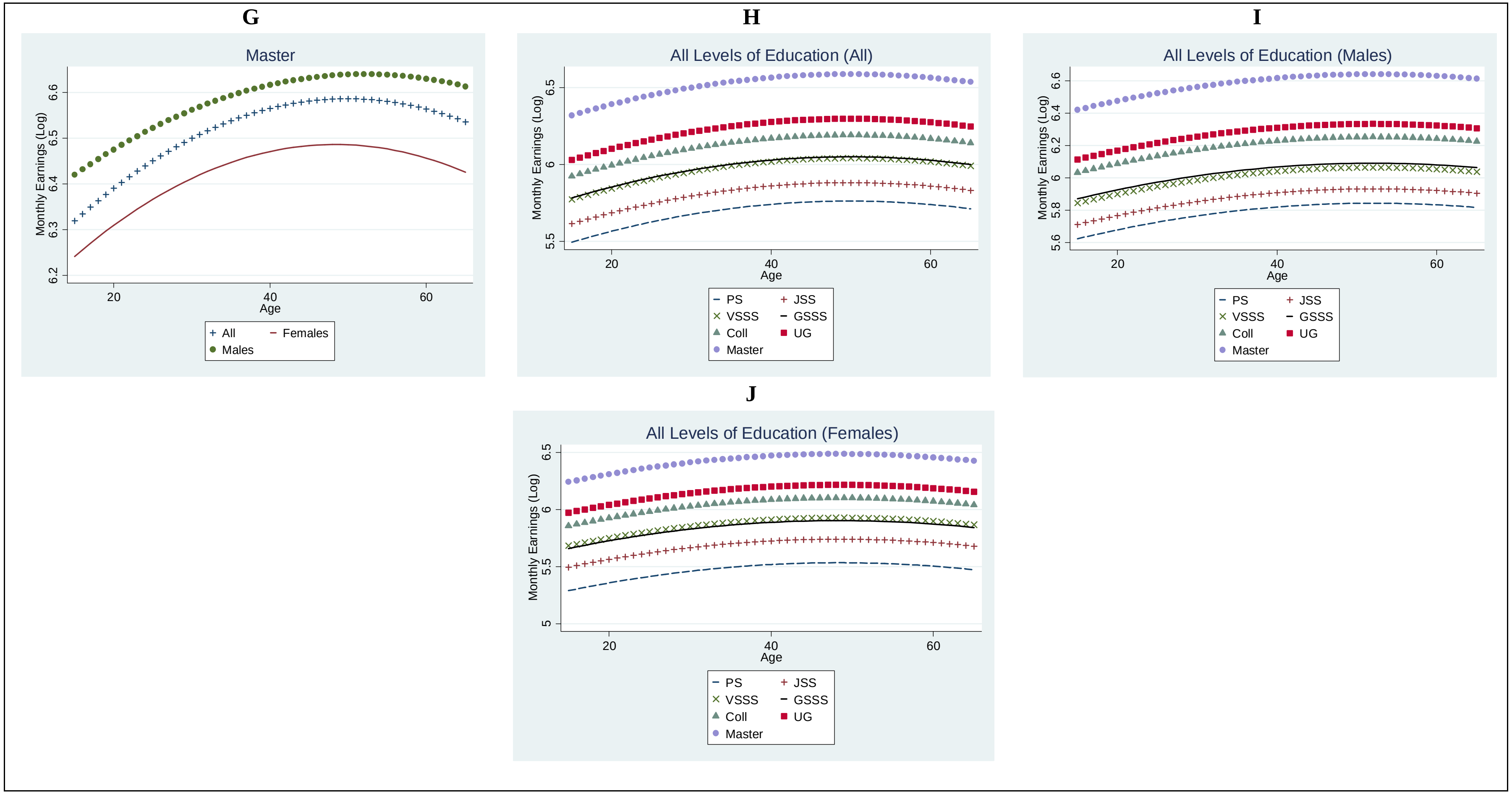




Notes: PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; Coll: College; UG: Undergraduate; Master: Master degree.
Source: Author’s calculation based on Table 5.5.

Figure 5.14: Age - Earnings Profile by Gender and Educational Attainment





Notes: PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; Coll: College; UG: Undergraduate; Master: Master degree.
Source: Author’s calculation based on Table 5.5.

Figures 5.13 and 5.14 display the predicted experience-earnings and age-earnings profiles (for the combined sample as well as those for the separate samples of males and females) by education level along with the profiles by level of education within each of the three samples analysed. Given the additive nature of the earnings equation, each profile displays the same bell shape where earnings rise with work experience (age) then decline after reaching the turning point. These experience-earnings and age-earnings profiles again show a clear tendency for females to reach the earnings turning point earlier than males. Thus female workers reach the turning point of their experience-earnings (age-earnings) profile at 29.19 (48.36) years of potential work experience (age), while males get to the turning point of their experience-earnings (age-earnings) profile at 35.29 (52.09) years of potential work experience (age). Compared to the estimates obtained using the continuous years of schooling variable, these estimated turning points generally occur several years earlier. Further, as demonstrated in Figure 5.13 the experience-earnings profiles of males and females differ noticeably, with those of males being flatter than those of females. The gender comparison within each level of education (see Panels A to G) show that females have lower earnings compared to males with the same level of potential labour market experience or age. Moreover, the greater female earnings disadvantage among the less-educated than among the better education that was commented on earlier is clearly evident in this set of predictions.

Finally, the predicted profiles by level of education (Panels H to J) reinforce the story from Figure 5.12, to the effect that the acquisition of higher levels of education in Indonesia is financially rewarding, and the greatest rewards are obtained at the highest level of educational attainment.

5.4.3 Mincerian Earnings Function with Control Variables.

The specification used above could be viewed as rather naïve, in the sense that it assumes away all factors other than for schooling and experience that may influence earnings. Accordingly, in this sub-section the analysis proceeds by augmenting the basic Mincerian model with additional explanatory variables. These additional explanatory variables are tenure, tenure squared, gender, marital status, and the control for area of residence. Table 5.6 presents the private rate of return to education from this augmented specification for the full sample and for males and females separately, using Equations 5.4 and 5.5. The estimated coefficients are jointly significant, as indicated by the *F*-test. Moreover, as the controls for the additional factors influencing earnings are introduced, the explanatory power of the augmented model rises for all specifications compared to the previous specifications (standard model). Most of the coefficients are estimated with statistical precision (low standard error), and have the expected signs. Tenure, gender (female), and the urban variables are statistically significant at the 1 percent level of significance for all specifications. The marital status variable, however, is significant only for females. In line with the previous estimates, the t-test rejects the null hypothesis of equality of the regression coefficients of schooling for males and females.

Table 5.6: OLS Estimates of Augmented Mincerian Earnings Functions

	(a)	(b)	(c)	(d)	(e)	(f)
					age proxying experience	
	Model 5.4-a-all	Model 5.4-a-males	Model 5.4-a-females	Model 5.4-b-all	Model 5.4-b-males	Model 5.4-b-females
Constant	5.21403	5.24319	4.95118	5.04476	5.08215	4.77053
	(0.02801)***	(0.03406)***	(0.04849)***	(0.07681)***	(0.09599)***	(0.13128)***
Years of Schooling	0.04930	0.04586	0.05429	0.04721	0.04357	0.05259
	(0.00182)***	(0.00221)***	(0.00321)***	(0.00161)***	(0.00202)***	(0.00271)***
Experience	0.00768	0.00734	0.00795			
	(0.00227)**	(0.00284)***	(0.00392)**			
Experience^2	-0.00013	-0.00012	-0.00015			
	(0.00005)***	(0.00007)**	(0.00009)*			
Age				0.01358	0.01299	0.01428
				(0.00468)***	(0.09600)**	(0.00811)*
Age^2				-0.00016	-0.00015	-0.00017
				(0.00007)**	(0.00008)*	(0.00011)
Tenure	0.01584	0.01139	0.02432	0.01599	0.01149	0.02455
	(0.00212) ***	(0.00260)***	(0.00388)***	(0.00213)***	(0.00259)***	(0.00392)***
Tenure^2	-0.00028	-0.00017	-0.00052	-0.00028	-0.00016	-0.00052
	(0.00007)***	(0.00009)*	(0.00009)***	(0.00007)***	(0.00009)*	(0.00013)***
Female	-0.19334			-0.19500		
	(0.01223)***			(0.01219)***		
Married	-0.00461	0.03276	-0.05018	-0.00429	0.03251	-0.04932
	(0.01633)	(0.02132)	(0.02499)**	(0.01653)	(0.02167)	(0.02527)*
Urban	0.10824	0.09994	0.13455	0.10833	0.10008	0.13459
	(0.01330)***	(0.01556)***	(0.02541)***	(0.01330)***	(0.01556)***	(0.02546)***
R^2	0.2735	0.2152	0.3032	0.2732	0.2150	0.3019
Observations	4596	3065	1531	4596	3065	1531
Chow test (*F*-test)			37.43			37.93
p-value			0.0000			0.0000

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The coefficient of the dummy variable for gender (female) in the pooled sample, whether using experience or age in the earnings function, is negative and highly statistically significant. These results indicate that, holding other variables constant, females face an earnings disadvantage in the Indonesian labour market of around 20 percent. These results are consistent with some previous estimates of the Mincer equation in other developing country samples, for example, Kazianga (2004) in Burkina Faso and Qian and Smyth (2008) in China.

The first new variable (other than the gender variable) to consider is job tenure. This measure is included in the model along with work experience (age). By doing so, it is possible to obtain an indication on the relative importance of general and firm specific human capital for earnings determination. The increase in earnings associated with an extra year of tenure is given as:

$$\frac{\partial \ln earnings}{\partial tenure} = \hat{\beta}_4 + 2\hat{\beta}_5 tenure,$$

where $\hat{\beta}_4$ is the estimated coefficient on the tenure variable, and $\hat{\beta}_5$ is the estimated coefficient on the tenure squared variable. Thus this payoff varies with the level of tenure. All the specifications show that tenure has a larger partial effect than experience and age over much of the early parts of the experience-earnings and age-earnings profiles. For example, in model 5.4-a-male (5.4-a-female), the coefficient for potential work experience is 0.00734 (0.00795), and the coefficient for tenure is 0.01139 (0.02432). This suggests that seniority in terms of job tenure is relatively more important than potential work experience among those in their first year in the labour force or in their current job. This pattern holds over much of the early career. For example, after 10 years of seniority an additional year in the job increases earnings by 0.799 (1.392) percent for males (females), while after 10 years of work experience an additional year of experience increases earnings by approximately 0.494 (0.495) percent for males (females). When experience is replaced by age the results suggest the same pattern, where, for 25 years old workers an additional year increases their earnings by 0.549 percent for male workers and by 0.578 for female workers, while following 10 years of job tenure an additional year on the job raises earnings by 0.829 percent for male workers, and by 1.415 percent for female workers.[16]

The estimates also suggest that, on average, residents of urban areas receive significantly higher earnings than individuals living in rural areas. The coefficient of the urban dummy variable ranges from 0.09994 to 0.13459 in the 6 specifications

[16] These calculations are comparable for workers who join the labour market at 15 years of age.

presented in Table 5.6. These estimates imply that the workers from urban areas earn 9.99 to 13.46 percent more than workers from rural areas, with the difference being significant at the 1 percent significance level.[17] Comparing the male and female samples, the coefficient of the urban dummy variable is higher for females than it is for males. This gender differential in the estimates of the partial effects of urban area residence in the earnings equation, where the effect is larger for females, is consistent with the evidence in relation to schooling and job tenure.

As mentioned earlier in this sub-section, the marital status variable is significant only for females. Being married has a positive, though statistically insignificant, effect on earnings for males but leads to around 5 percent lower earnings for female workers, presumably because of the extra home duties they undertake and child bearing/rearing activities. In other words, being married is most likely to have little effect on the wages of male workers while it has a negative effect on the wages of female workers.

Figure 5.15 compares the experience-earnings and the tenure-earnings profiles. Similar to the experience-earnings and age-earnings profiles, the tenure-earnings profiles display rapid initial earnings growth, and then decline after reaching a maximum point. For all three samples (Panels A, B, and C), the tenure-earnings profiles lie above the experience-earnings profiles and have a steeper shape. This pattern reinforces the comment above, to the effect that tenure is a more important determinant for earnings than potential labour market experience among both males and females. That is, employers value seniority in terms of job tenure more than potential work experience. The profiles in Panel C, for females, have a different pattern from those in Panel A (all) and Panel B (males). In Panels A and B the tenure-earnings profiles are above the experience-earnings profiles at all relevant years of work experience, while for female workers (Panel C) the changes in earnings with experience over the first few years in the labour market and the few years near to the retirement age exceed the changes in earnings with tenure.

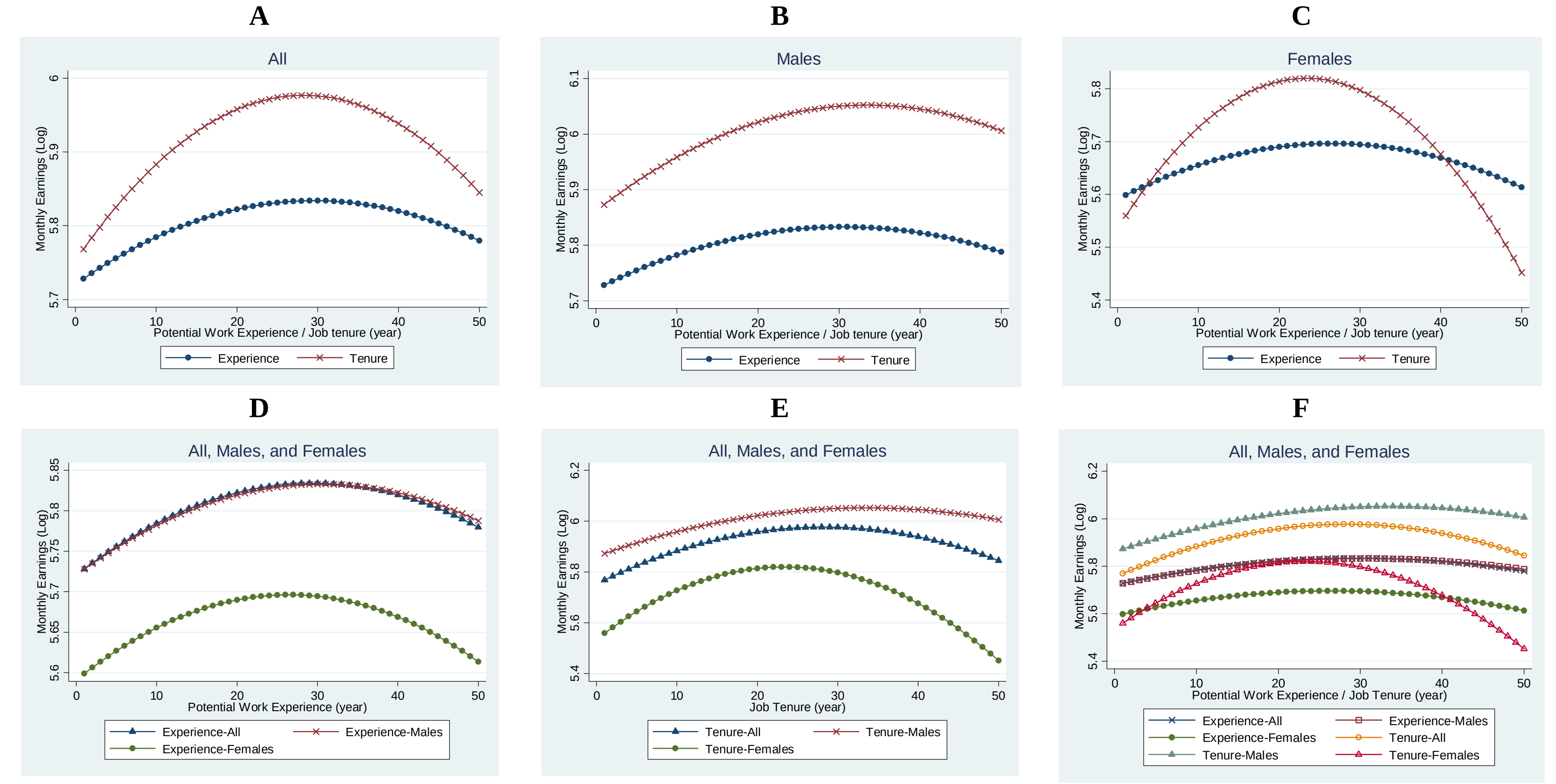
[17] The detailed explanation of how to calculate relative effects from dummy variable coefficients can be found in Halvorsen and Palmquist (1980). To avoid confusion between numbers discussed in the text for relative effects computed using Halvorsen and Palmquist's (1980) algorithm and the coefficients in the Table, the approximations provided by the estimated coefficients are used in the discussion. For example, the coefficient of the urban dummy variable ranges from 0.09994 to 0.13459 across the 6 specifications in Table 5.6. Using Halvorsen and Palmquist's (1980) algorithm, the relative effect on earnings is 0.105 (exp (0.09994) -1 = 1.105105 - 1) to 0.144 (exp (0.13459) - 1 = 1.144068 - 1), and these imply that the workers from urban areas earn 10.5 to 14.4 percent more than workers from rural areas, with the difference being significant at the 1 percent significance level. It is apparent that the coefficients discussed in the text are close approximations to these effects.

Comparison of the experience-earnings profiles by gender (Panel D) reveals patterns similar to those discussed in relation to the basic Mincerian model. Male workers reach their experience-earnings peak at 30.58 years of experience, while female workers reach their experience-earnings peak earlier than their male counterparts, which is at 26.50 years of experience.

Comparing the tenure-earnings profiles for females and males (see Panel E), there are two main points of interest. First, the gap between females' tenure-earnings profile and that of males initially narrows with years in the job. However, after females' tenure-earnings reach its peak, the gender gap gets wider. Second, the peak of the tenure-earnings profile, where $\hat{\beta}_4 + 2\hat{\beta}_5 tenure = 0$, for females (23.38 years) occurs before that for males (33.50 years). This also means that male workers get to their experience-earnings peak earlier than their tenure-earnings peak. In the case of female workers, however, the tenure-earnings peak comes earlier than the experience-earnings peak.

Panel F compares the experience-earnings and tenure-earnings profiles for all, male, and female samples. Both the experience-earnings and tenure-earnings profiles of female workers lie below those of male workers and have a steeper shape. Females reach the turning point earlier than males in the case of both the experience-earnings and tenure-earnings profiles.

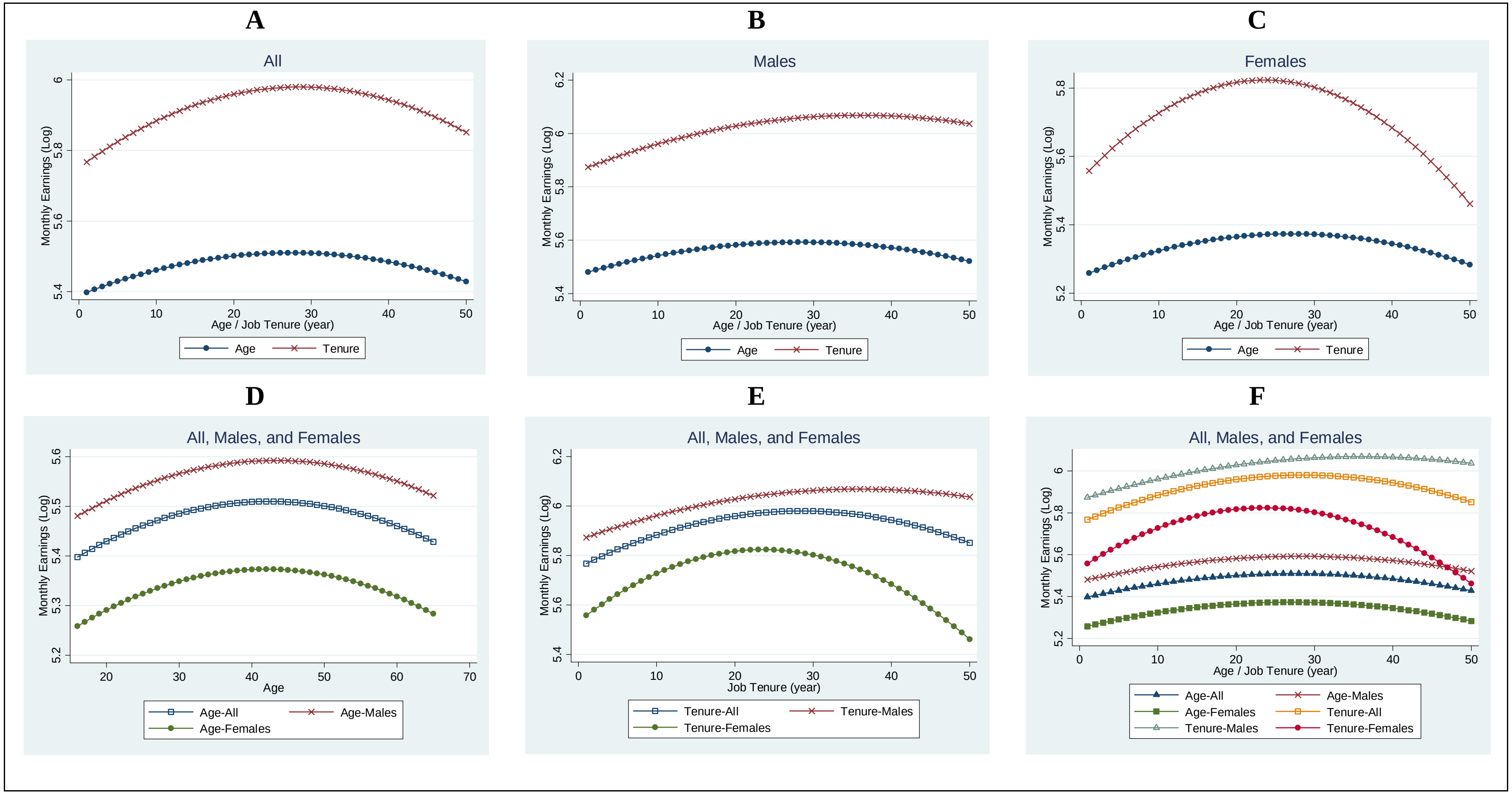
Figure 5.15: Experience - Earnings and Tenure - Earnings Profiles (Augmented Mincerian Model)[18]



Source: Author's calculation based on Table 5.6.

[18] In order to avoid a presentational problem due to comparing various groups, to construct these 6 diagrams, the formula of "the mean log earnings - ($\hat{\beta}_{expr}$ or $\hat{\beta}_{tenure}$ X $\overline{expr}$ or $\overline{tenure}$ + $\hat{\beta}_{expr^2}$ or $\hat{\beta}_{tenure^2}$ X $\overline{expr^2}$ or $\overline{tenure^2}$)" is used instead of the intercept.

Figure 5.16: Age - Earnings and Tenure - Earnings Profiles (Augmented Mincerian Model)[19]



Notes: In order to have reasonable comparison, the age-earnings profile that starts from 15 years of age is compared to the tenure-earnings profile that start from 0 year of job tenure.
Source: Author's calculation based on Table 5.6.

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[19] In order to avoid presentational problem due to comparing various groups to construct these 6 diagrams, the formula of "the mean log earnings - ($\hat{\beta}_{age}$ or $\hat{\beta}_{tenure}$ X $\overline{age}$ or $\overline{tenure}$ + $\hat{\beta}_{age^2}$ or $\hat{\beta}_{tenure^2}$ X $\overline{age^2}$ or $\overline{tenure^2}$)" is used instead of the intercept.

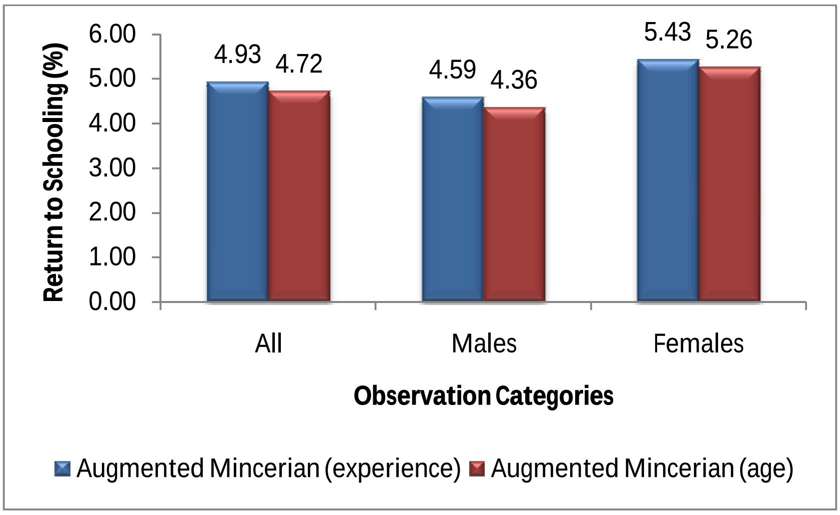
Figure 5.16 shows comparison of the age-earnings and the tenure-earnings profiles. Here, age-earnings profiles that start from the age of 15 are compared to tenure-earnings profiles that start from 0 year of job tenure. In other words, a worker with 5 years of job experience is compared with a 20 years old worker. Similar to the comparison between the experience-earnings and tenure-earnings profiles, the tenure-earnings profile also lies above the age-earnings profile for all samples (all, males, and females) and has a steeper shape than the age-earnings profile (see the experience-tenure comparisons for each sample in Panels A, B, and C). Male workers reach their age-earnings peak at the age of 43.30 years, while female workers get to their age-earnings peak about one year earlier, which is 42 years. In order to achieve the tenure-earnings peak, male workers need to work at the same job continuously for 35.91 years, while female workers reach their tenure-earnings peak at 23.61 years of job tenure.

The gender comparisons of the age-earnings profiles in Panel D have patterns similar to those discussed for the experience-earnings profiles in Figure 15.5. Female workers reach their age-earnings turning point (42 years) slightly earlier than male workers (43.30 years).

Panel E, which contains the gender comparisons of the tenure-earnings profiles, shows the same pattern as the tenure-earnings profiles in Figure 15.5 Panel E, where the gap between females' tenure-earnings profile and that of males initially narrows with increases in job tenure, and then increases after the peak of the tenure-earnings profile is reached for females. The maximum point of the tenure-earnings profile for males (35.91 years) occurs well after that for females (23.61years).

Panel F compares the age-earnings and tenure-earnings profiles for all, males, and females. Females reach the maximum point of their age-earnings and tenure-earnings profiles earlier than males, and their age-earnings and tenure-earnings profiles lie below those of males.

Figure 5.17: Augmented Mincerian Return to Schooling



Source: Author's calculation based on Table 5.6.

Using the results from Table 5.6, the estimates of the return to additional years of schooling are presented in Figure 5.17. The estimates from the augmented Mincerian model (where the extra control variables are for gender (for full sample only), marital status, tenure and its square, and urban) yield a return to schooling that varies from 4.36 to 5.43 percent. The estimate of the return to schooling using age in the earnings function is lower than that obtained using potential work experience. This return to schooling for females, however, is again slightly higher than that for males. This finding supports the results from previous estimations.

5.4.4 Augmented Mincerian Earnings Function with Levels of Education

Table 5.7 presents the private rate of return to education from this augmented specification with the dummy variables for different educational attainments for the full sample, and for males and females separately, using equations 5.5. The estimated coefficients are jointly significant, as indicated by the *F*-test. Moreover, as the controls for additional factors influencing earnings are introduced, the explanatory power of the augmented model rises for all specifications compared to the previous specifications (standard model). Most of the variables are estimated with statistical precision (low standard error), and have the expected signs. Similar to the finding obtained using the standard Mincerian model, the results from the augmented Mincerian model show that the private earnings return to additional years of schooling increases as the level of education increases. Consistent with the previous estimates, the *F*-test rejects the null hypothesis of equality of the regression coefficients for the level of education variables for males and females. This confirms that the structure of the returns to schooling for females and returns to schooling for males are statistically different.

Consistent with earlier results from the specifications using years of schooling, tenure has a greater impact on earnings than potential work experience and age for all samples (all, males, and females). Comparing the effects of potential work experience and job tenure in models 5.5-a-all, 5.5-a-male, and 5.5-a-female, it can be summarised that among labour market entrants (experience and tenure = 0), the increase in earnings associated with potential work experience is 0.79, 0.69, and 0.98 percent for the pooled, male, and female samples, respectively. On the other hand, the return to job tenure is 1.54, 1.14, and 2.29 percent for the pooled, male, and female samples, respectively. When the workers have 10 years of potential work experience and job tenure, the increase in earnings associated with additional potential work experience is 0.29, 0.41, and 0.52 percent for the pooled, male, and female samples, respectively, and the increase in earnings associated with additional job tenure is 1.04, 0.84, and 1.39 percent for the pooled, male, and female samples, respectively. A similar pattern is revealed from the comparison between the age and job tenure effects on earnings. Among workers with 0 tenure (age of 15), the increase in earnings associated with an additional year of age is 0.65, 0.65, and 0.73 percent for the pooled, male, and female samples, respectively, and the increase in earnings associated with an additional year of job tenure is 1.62, 1.19, and 2.43 percent for the pooled, male, and female samples, respectively. At 10 years of job tenure or age of 25, the increase in earnings associated with an additional year of age is 0.39, 0.43, and 0.41 percent for the pooled, male, and female samples, respectively, and the return to an additional year of tenure is 1.06, 0.83, and 1.43 percent for the pooled, male, and female samples, respectively.

The marital status variable is significant only when the male and female samples are examined separately, and it is not significant for the specification estimated using the full sample. This latter result is presumably due to the pooling of two samples that are characterised by opposite impacts of the married variable. Being married has a positive effect on earnings for males. However, for females the effect is the opposite to that for males. This probably is evidence that is consistent with the specialisation hypothesis. By being married male workers can devote more of their time and effort to labour market activities. As a result married male workers gain an increase in earnings. On the other hand, female workers experience a contrasting story. Being married leads to lower earnings for female workers, presumably because of the extra home duties they undertake and child bearing/rearing activities.

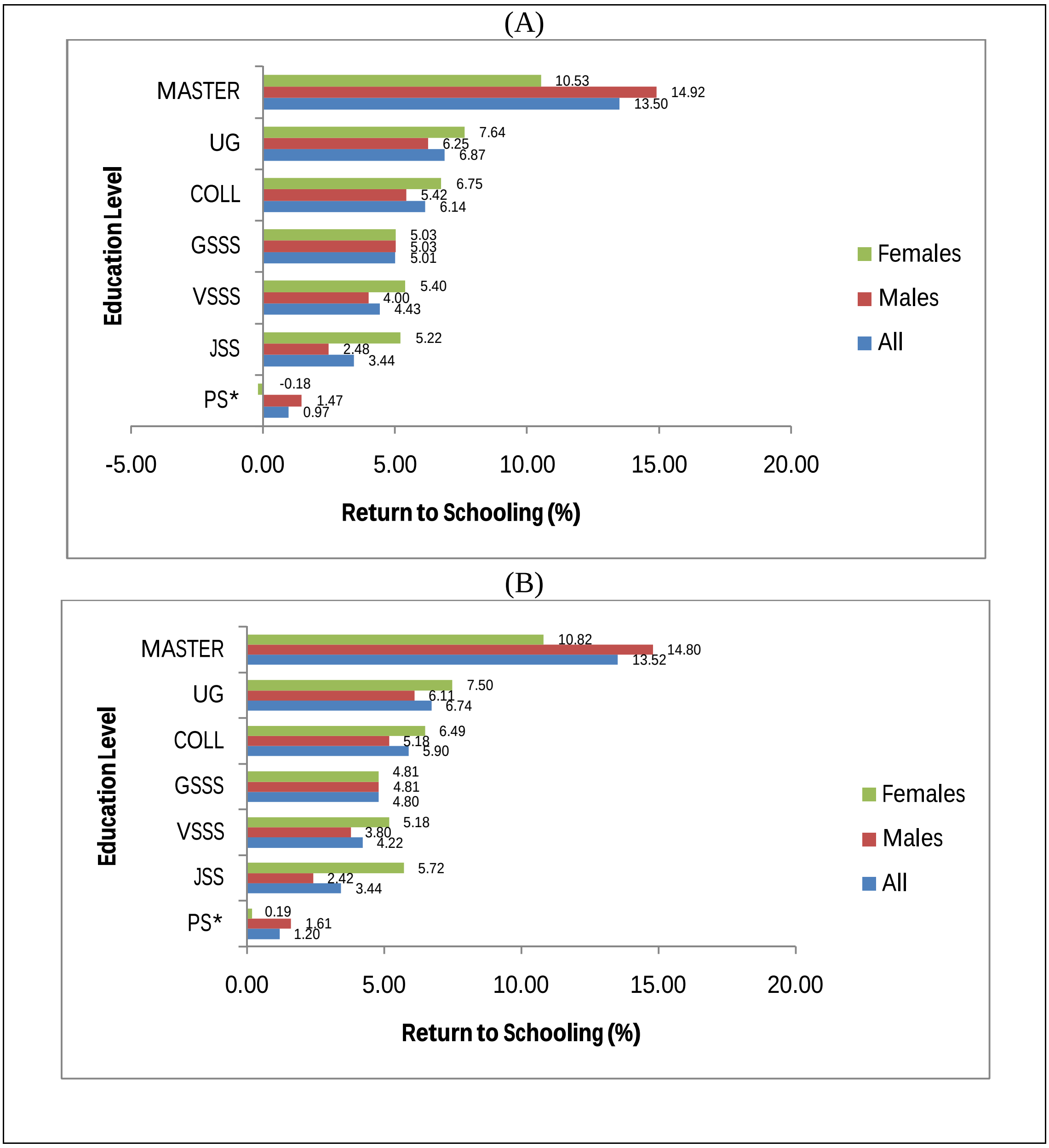
Table 5.7: OLS Estimates of Augmented Mincerian Earnings Functions with Level of Education Dummy Variables

	(a)	(b)	(c)	(d)	(e)	(f)
				age proxying experience		
	All Model	**Males** Model	**Females** Model	**All** Model	**Males** Model	**Females** Model
Constant	5.48788	5.47758	5.28159	5.34357	5.34218	5.10884
	(0.03259)***	(0.03955)***	(0.05577)***	(0.08179)***	(0.10334)***	(0.13560)***
Primary School	0.05838	0.08796	-0.01075	0.07194	0.09685	0.01153
	(0.02755)**	(0.03370)***	(0.04751)	(0.02699)***	(0.03335)***	(0.04599)
Junior Secondary School	0.16145	0.16233	0.15651	0.17514	0.16950	0.18321
	(0.02880)***	(0.03512)***	(0.05068)***	(0.02739)***	(0.03408)***	(0.14599)***
Vocational Senior Secondary School	0.29428	0.28233	0.31844	0.30183	0.28339	0.33873
	(0.02925)***	(0.03550)***	(0.05229)***	(0.02713)***	(0.03360)***	(0.04687)***
General Senior Secondary School	0.31181	0.31320	0.30747	0.31915	0.31395	0.32740
	(0.02921)***	(0.03513)***	(0.05317)***	(0.02693)***	(0.03304)***	(0.04748)***
College	0.49607	0.47589	0.51007	0.49619	0.46943	0.52214
	(0.03334)***	(0.04265)***	(0.05495)***	(0.03105)***	(0.04049)***	(0.04922)***
Undergraduate	0.58669	0.56321	0.61310	0.58874	0.55826	0.62728
	(0.03096)***	(0.03821)***	(0.05316)***	(0.02843)***	(0.03602)***	(0.04670)***
Master	0.85669	0.86161	0.82363	0.85908	0.85421	0.84360
	(0.05104)***	(0.06791)***	(0.07638)***	(0.04886)***	(0.06569)***	(0.07130)***
Experience	0.00794	0.00690	0.00977			
	(0.00228)***	(0.00287)**	(0.00390)**			
Experience^2	-0.00025	-0.00014	-0.00023			
	(0.00017)***	(0.00009)**	0.00009)**			
Age				0.01044	0.00984	0.01213
				(0.00471)**	(0.00589)*	(0.00807)
Age^2				-0.00013	-0.00011	-0.00016
				(0.00006)**	(0.00008)	(0.00011)
Tenure	0.01541	0.01143	0.02290	0. 01623	0.01194	0.02433
	(0.00212) ***	(0.00015***	(0.00388)***	(0.00212)***	(0.00257)***	(0.00391)***
Tenure^2	-0.00025	-0.00015	-0.00045	-0.00028	-0.00018	-0.00050
	(0.00007)***	(0.00009)*	(0.00013)***	(0.00007)***	(0.00009)**	(0.00013)***
Female	-0.20404			-0.20523		
	(0.03259)***			(0.01231)***		
Married	-0.00563	0.03528	-0.05584	-0.00011	0.03765	-0.04575
	(0.01613)	(0.02109)*	(0.02473)**	(0.01642)	(0.02154)*	(0.02508)*
Urban	0.11515	0.10970	0.12851	0.11491	0.10931	0.12917
	(0.01347)***	(0.01582)***	(0.02571)***	(0.01349)***	(0.01583)***	(0.02580)***
R^2	0.2785	0.2176	0.3150	0.2772	0.2169	0.3124
Observations	4596	3065	1531	4596	3065	1531
Chow test (*F*-test)			23.85			24.03
p-value			0.0000			0.0000

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The estimates for the dummy variable for urban area of residence suggest that, on average, residents of urban areas receive significantly higher earnings than individuals living in the rural areas. The coefficients of the urban dummy variable for males are 0.10970 (specification using experience) and 0.10931 (specification using age), while for females they are 0.12851 and 0.12917. These results thus show that male workers from urban areas earn 10.97 (10.93) percent more than male workers from rural areas. They similarly show that female workers from urban areas earn 12.85 (12.92) percent more than their counterparts from rural areas.

Figure 5.18: Augmented Mincerian Return to Schooling Based on Model with Level of Education Dummy Variables



Notes: PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; COLL: College; UG: Undergraduate; MASTER: Master degree.
*: Primary School coefficient for female sample is statistically insignificant.
Source: Author's calculation based on Table 5.7.

The estimated returns to schooling at each educational qualification are presented in Figure 5.18. Panel A compares the return to schooling by gender and educational attainment derived from the specification using the potential work experience variables. Panel B compares the return to schooling by gender and educational attainment derived from the specification based on the age variables. Males have a higher return to schooling than females at the levels of primary school and master degree. However the coefficients of the primary school variable for females are insignificant. Comparing between general senior secondary school and vocational senior secondary school, females who hold vocational senior secondary school education earn a higher return to schooling than females with general senior secondary school education. Among males the opposite relativity is observed. As noted previously, in these specifications, the ***F***-test rejects the null hypothesis of equality for males and females of the regression coefficients of the level of education variables.

5.4.5 Selectivity Bias

It is frequently argued that the returns to education for females derived from either the standard or augmented Mincerian models may be biased because the females who participate in the labour force are not representative of all females. This is known as sample selection bias, and it is generally regarded as a potentially important, though difficult to address, econometric issue in this type of applied research.

In order to correct for such a potential selectivity bias, a two-step Heckman (1979) selection correction approach can be adopted.[20] This two-step approach re-casts the sample selection problem as an omitted variable problem, and so provides, in principle at least, a tractable means of addressing the issue. A probit model of the labour force participation probability of a female is estimated in the first step. Then, in the second step, the derived inverse Mills ratio (λ) is included in the earnings function as an additional explanatory variable. In addition to years of schooling or the dummies for education level, potential experience or age, experience squared or age squared, marital status and urban area of residence, household size, a dummy variable for the existence of a child younger than five years old in the household, a dummy variable for religion, and a dummy variable for the existence of either a father or mother in the household are included in the probit model. These four variables are included in the model of the decision of whether females participate in labour market because it is presumed that they are some of the factors that directly influence whether females join the labour market and which do not affect market earnings. It is

[20] The Heckman two-step method is outlined in Appendix A5.1.

argued that household size, the presence of children younger than five years old, and the presence of the father or mother in the household influence females' decision to join the labour market since these three variables have an impact on females in terms of the amount of domestic duties and time that has to be devoted to their family. The religion of the respondent (Islam) is included in the probit model since religious/Islamic values are of critical importance in many parts of Indonesia. Many believe that female Muslims are not supposed to join the labour market. Given this model of labour force participation, and the earnings equations used previously, it is seen that the dummy variable for the existence of a child younger than five years old in the household, the dummy variable for religion, the dummy variable for the existence of father or mother in the household and the variable for household size are used, along with the non-linearity of the sample selectivity (λ) term, for identification purposes.[21]

The Heckman model estimates are reported in Tables 5.8 and 5.9. All the variables in the probit labour force participation model have the expected signs and are statistically significant in all eight sets of estimates. All the identifying variables have strong, negative impacts on the participation probability. Each of these effects is highly statistically significant, which suggest that there should not be any major multicollinearity problems following the inclusion of the λ term in the earnings equation. However, when the inverse Mills ratio, λ, is included in the earnings function for the augmented Mincerian model based on the years of schooling variable (see Table 5.6) it turns out to be statistically not significant. Therefore, it can be argued that the corresponding estimates for this model reported in Table 5.6 do not suffer from selectivity bias. However, in the Heckman equations for the standard Mincerian model based on the years of schooling variable, the standard Mincerian model with the educational attainment dummy variables, and the augmented Mincerian model with the educational attainment dummy variables, the selectivity (λ) term is significant at either the 10 or 5 percent levels of significance. Note, moreover, that the estimated coefficient on the selectivity term is negative. One interpretation of this is that there is negative selection into the paid labour force. That is, there are unmeasured factors that lead to lower earnings among labour force participants.

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[21] Summary statistics for the sample used in the first-step of the Heckman correction are presented in Appendix A5.2.

Table 5.8: Estimates of the Selectivity Bias Corrected Earnings Equations (Standard Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
			age proxying experience				age proxying experience	
	Probit	Mincerian	Probit	Mincerian	Probit	Mincerian	Probit	Mincerian
Constant	0.01614	5.01873	-1.40818	4.79431	-1.03794	5.47520	-1.76206	5.22700
	(0.10157)	(0.07413)***	(0.19618)***	(0.13785)***	(0.09953)***	(0.11028)***	(0.21108)***	(0.16633)***
Years of Schooling	-0.00181	0.06451	-0.01112	0.05823				
	(0.00567)	(0.00299)***	(0.00507)	(0.00268)***				
Primary School					0.35796	-0.03727	0.32754	-0.01603
					(0.06357)***	(0.04757)	(0.06236)***	(0.04575)
Junior Secondary School					0.57157	0.16189	0.51736	0.17824
					(0.06710)***	(0.05310)***	(0.06611)***	(0.04905)***
Vocational Senior Secondary School					0.88651	0.34510	0.80133	0.34443
					(0.07521)***	(0.06129)***	(0.07288)***	(0.05524)***
General Senior Secondary School					0.89153	0.32294	0.79601	0.32097
					(0.06894)***	(0.05907)***	(0.06606)***	(0.05229)***
College					1.55581	0.50373	1.44096	0.48338
					(0.09393)***	(0.07705)***	(0.09094)***	(0.06829)***
Undergraduate					1.86879	0.60505	1.73529	0.58625
					(0.09298)***	(0.08078)***	(0.08946)***	(0.07054)***
Master					2.57776	0.85178	2.43835	0.83464
					(0.41313)***	(0.14468)***	(0.40346)***	(0.13838)***
Experience	0.02150	0.01444			0.03530	0.01494		
	(0.00503)***	(0.00319)***			(0.00532)***	(0.00332)***		
Experience^2	-0.00073	-0.00019			-0.00068	-0.00026		
	(0.00011)**	(0.00007)***			(0.00111)***	(0.00007)***		
Age			0.08687	0.01810			0.06753	0.01769
			(0.01014)***	(0.00009)*			(0.01063)***	(0.00685)*
Age^2			-0.00126	-0.00016			-0.00095	-0.00017
			(0..00013)***	(0.00009)*			(0.00014)***	(0.00009)*
Household size	-0.03083		-0.03344		-0.03029		-0.01702	
	(0.00649)***		(0.00644)***		(0.00678)***		(0.00671)**	
Child under 5	-0.42703		-0.43155		-0.42234		-0.51033	
	(0.03751)***		(0.03741)***		(0.03928)***		(0.03943)***	
Muslim	-0.44424		0.44954		-0.33787		-0.35471	
	(0.05412)***		(0.05414)***		(0.05662)***		(0.05686)***	
Father/mother lives in the same house	-1.79403		-1.78893		-1.83621		-1.92391	
	(0.13816)***		(0.15020)***		(0.14549)***		(0.14519)***	
λ		-0.07352		-0.08837	-0.09162	-0.09128		-0.08733
		(0.04274)*		(0.04303)**	(0.09953)*	(0.04731)*		(0.04393)**
Adj R^2		0.0459		0.1016	0.2147	0.2353		0.1871
Observations	7911	7911	7911	7911	7911	7911	7911	7911
Censored observations	6380	6380	6380	6380	6380	6380	6380	6380
Uncensored observations	1531	1531	1531	1531	1531	1531	1531	1531

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 5.9: Estimates of the Selectivity Bias Corrected Earnings Equations (Augmented Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
			age proxying experience				age proxying experience	
	Probit	Mincerian	Probit	Mincerian	Probit	Mincerian	Probit	Mincerian
Constant	0.35173	5.02265	-1.58430	4.95700	-0.64129	5.44357	-1.93534	5.34256
	(0.11293)***	(0.06938)***	(0.20587)***	(0.16880)***	(0.10928)***	(0.10208)***	(0.21823)***	(0.17905)***
Years of Schooling	-0.01695	0.05499	-0.00003	0.05253				
	(0.00584)***	(0.00317)***	(0.00522)	(0.00268)***				
Primary School					0.34977	-0.04076	0.34801	-0.01582
					(0.06409)***	(0.04681)	(0.06332)***	(0.04507)
Junior Secondary School					0.53183	0.11361	0.50777	0.14482
					(0.06858)***	(0.05217)**	(0.06800)***	(0.04836)***
Vocational Senior Secondary School					0.80916	0.25549	0.73662	0.28487
					(0.07788)***	(0.06002)***	(0.07585)***	(0.05381)***
General Senior Secondary School					0.82537	0.24315	0.74205	0.27290
					(0.07121)***	(0.05807)***	(0.06860)***	(0.05119)***
College					1.49863	0.40615	1.38927	0.43277
					(0.09654)***	(0.07647)***	(0.09372)***	(0.06702)***
Undergraduate					1.80802	0.49470	1.66900	0.52611
					(0.09592)***	(0.08063)***	(0.09227)***	(0.06968)***
Master					2.50108	0.68456	2.34880	0.72202
					(0.41508)***	(0.14263)***	(0.40288)***	(0.13548)***
Experience	0.03595	0.00601			0.05112	0.00654		
	(0.00539)***	(0.00378)			(0.00571)***	(0.00396)*		
Experience^2	-0.00112	-0.00009			-0.00108	-0.00017		
	(0.00012)***	(0.00009)			(0.00012)***	(0.00009)*		
Age			0.12494	0.00756			0.10946	0.00545
			(0.01114)***	(0.00843)			(0.01154)***	(0.00815)
Age^2			-0.00180	-0.00008			-0.00152	-0.00007
			(0.00014)***	(0.00011)			(0.00015)***	(0.00011)
Tenure		0.02422		0.02439		0.02270		0.02407
		(0.00369)***		(0.00370)***		(0.00366)***		(0.00367)***
Tenure^2		-0.00052		-0.00051		-0.00045		-0.00049
		(0.00012)***		(0.00012)***		(0.00012)***		(0.00012)***
Married	-0.63521	-0.01260	-0.70964	-0.00634	-0.67668	-0.00698	-0.74590	0.00465
	(0.05638)***	(0.03679)	(0.05748)***	(0.03820)	(0.05798)***	(0.03755)	(0.05989)***	(0.03804)
Urban	0.43750	0.11234	0.43036	0.11150	0.17998	0.11688	0.20378	0.11651
	(0.03760)***	(0.02765)***	(0.03780)***	(0.02751)***	(0.04026)***	(0.02445)***	(0.04032)***	(0.17905)***
Household size	-0.03515		-0.03194		-0.03478		-0.02059	
	(0.00662)***		(0.00665)***		(0.00688)***		(0.00683)***	
Child under 5	-0.34892		-0.36606		-0.33924		-0.42678	
	(0.03867)***		(0.03882)***		(0.04023)***		(0.04033)***	
Muslim	-0.43157		-0.43788		-0.33553		-0.35516	
	(0.05521)***		(0.05562)***		(0.05745)***		(0.05784)***	
Father/mother lives in the same house	-2.00666		-2.04009		-2.04244		-2.17925	
	(0.11293)***		(0.14533)***		(0.14893)***		(0.15016)***	
λ		-0.06906		-0.07288		-0.09291		-0.08754

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
			age proxying experience				age proxying experience	
	Probit	Mincerian	Probit	Mincerian	Probit	Mincerian	Probit	Mincerian
		(0.04528)		(0.04501)		(0.04919)*		(0.04591)*
Adj R^2		0.1198		0.1688		0.2666		0.3106
Observations	7911	7911	7911	7911	7911	7911	7911	7911
Censored observations	6380	6380	6380	6380	6380	6380	6380	6380
Uncensored observations	1531	1531	1531	1531	1531	1531	1531	1531

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The signs and significance of the schooling coefficients are broadly similar across the uncorrected and the corrected earnings functions. The magnitudes of most coefficients appear to be slightly smaller in the selectivity-corrected specifications. In sum, it seems that sample selection bias is not a serious problem in this study, since the estimated returns to schooling do not change much after they are corrected using Heckman's two-step approach.

5.4.5 Standard Mincerian, Augmented Mincerian, and Heckman Selectivity Bias Corrected: A Comparison of Returns to Schooling

The estimated return to schooling using both the standard Mincerian and the augmented Mincerian earnings functions, obtained using OLS and the Heckman selectivity correction model, have been discussed in the previous sub-sections. Comparing across the results from these alternative models for when a continuous years of schooling is used (see Table 5.10), some differences and some similarities are found. Employing the augmented Mincerian earnings function with the variables for tenure, tenure squared, gender, marital status, and urban area of residence lifts the explanatory power in all specifications. Moreover, estimating the return to schooling using the Mincerian earnings function with these five extra control variables results in a slightly lower return to schooling for most specifications compared to the results obtained from the standard Mincerian model. Furthermore, estimating the return to schooling using the Heckman selectivity correction model for both the standard and the augmented Mincerian earnings function leads to a lower return to schooling for all samples compared with the results obtained from the Mincerian model without correction for selectivity bias. This confirms that the results from the standard model, which show that the return to schooling in Indonesia is much lower than the average return to schooling in Asian countries, are robust to these specification and the methods of estimation issues.

Table 5.10: A Comparison of the Returns to Schooling

	Standard Mincerian (experience)	Standard Mincerian (age)	Augmented Mincerian (experience)	Augmented Mincerian (age)	Standard Mincerian-Heckman Selectivity Corrected (experience)	Standard Mincerian-Heckman Selectivity Corrected (age)
All	5.66	5.07	4.93	4.72		
Males	5.28	4.70	4.59	4.36		
Females	6.46	5.88	5.43	5.26	6.45	5.80

Source: Author's calculation based on Tables 5.4, 5.6, and 5.8.

The differences in the return to schooling between any two adjacent schooling levels are generally moderate or even quite small. This can be seen in Table 5.11, which presents the comparison of the returns to schooling across the standard Mincerian, augmented Mincerian and Heckman selectivity corrected models based on the dummy variables for educational attainment. On average, workers with junior secondary school earn a return to their investment in schooling 3 times more than those with primary school. Individuals with vocational senior secondary school and general senior secondary school have a return to schooling 1.3 and 1.42 times higher than those with junior secondary school, respectively. Workers with college and undergraduate levels of education receive a return to schooling 1.01 and 1.22 times more than those with general senior secondary school, respectively. Individuals with a master degree get a return to schooling 2.12 times higher than those with a undergraduate degree. These patterns are not sensitive to the specification of the earnings equation or the method of estimation.

Comparing the returns to additional years of schooling for males and females, on average females have a 1.24 times higher return to schooling than males. The patterns in the return to schooling across the education levels for the standard Mincerian and augmented Mincerian estimates are comparable, with the return to schooling increasing with the level of education. In terms of vocational and general education, the results, both in the earnings function without and with additional control variables, are consistent. Males with general senior secondary school earn a higher return to schooling than those with vocational senior secondary school. On the other hand, females with vocational senior secondary school receive a higher return to schooling than those with general senior secondary school. The possible explanation for this case is that for males vocational senior secondary school is not considered as a terminal degree but as a route to college or university, whereas it is a terminal degree for females.

Table 5.11: A Comparison of the Return to Schooling from the Model Using Dummy Variables for Educational Attainment

	Standard Mincerian (experience)			Standard Mincerian (age)			Augmented Mincerian (experience)			Augmented Mincerian (age)			Standard Mincerian-Heckman Selectivity Corrected (experience)	Standard Mincerian-Heckman Selectivity Corrected (age)	Augmented Mincerian-Heckman Selectivity Corrected (experience)	Augmented Mincerian-Heckman Selectivity Corrected (age)
Education Level	All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females	Females	Females	Females	Females
PS	1.47	1.79	-0.11	1.63	1.80	0.17	0.97	1.47	-0.18	1.20	1.61	0.19	-0.62	-0.27	-0.68	-0.26
JSS	4.35	3.35	6.90	3.99	2.95	6.87	3.44	2.48	5.22	3.44	2.42	5.72	5.40	5.94	3.79	4.83
VSSS	5.96	4.98	6.90	5.29	4.41	6.23	4.43	4.00	5.40	4.22	3.80	5.18	6.11	5.54	4.73	4.67
GSSS	6.34	5.92	6.16	5.60	5.29	5.42	5.01	5.03	5.03	4.80	4.82	4.81	5.37	4.76	4.32	4.27
COLL	5.45	6.02	7.36	4.70	5.41	6.63	6.14	5.42	6.75	5.90	5.18	6.49	6.03	5.41	5.43	5.33
UG	6.77	6.59	8.40	6.19	6.08	7.84	6.87	6.25	7.64	6.74	6.11	7.50	7.05	6.63	6.29	6.33
MASTER	14.80	15.80	13.42	14.48	15.35	13.49	13.50	14.92	13.52	13.50	14.80	10.82	12.34	12.42	9.49	9.80

Notes: PS: Primary School; JSS: Junior Secondary School; VSSS: Vocational Senior Secondary School; GSSS: General Senior Secondary School; COLL: College; UG: Undergraduate; MASTER: Master degree.

Source: Author’s calculation based on Tables 5.5, 5.7, 5.8, and 5.9.

5.5 Conclusion

This chapter reports evidence on the returns to schooling in Indonesia and highlights some important points. Separate estimates are obtained for males and females. OLS is employed as the primary methodological approach to measure the return to schooling. In order to correct for the possibility of selectivity bias, Heckman's two-step model is adopted. The results suggest that there is no selectivity bias for the augmented Mincerian model based on the years of schooling variable. On the other hand, in the Heckman equations for the standard Mincerian model based on the years of schooling variable, the standard Mincerian model with dummy variables for educational attainment, and the augmented Mincerian model with dummy variables for educational attainment, the selectivity correction (λ) term is significant at the 10 and 5 percent levels of significance. However, after comparing the estimated return to schooling from the uncorrected and corrected models, it can be concluded that sample selection bias is not a serious problem in this study, since the estimated returns to schooling do not change much after they are corrected using Heckman's two-step approach.

The estimation of the standard and augmented Mincerian earnings functions revealed that the return for an extra year of schooling is positive and significant. The standard Mincerian approach yields 5.28 (using experience) and 4.70 (using age) percent returns to schooling for males, and 6.46 and 5.88 percent returns to schooling for females. Taking selectivity bias into account, the return to schooling for females decreases slightly to 6.45 and 5.81 percent, respectively, for the specifications based on potential labour market experience and age. When employing the augmented Mincerian model that includes the control variables for tenure and its square, marital status, and urban area of residence, the return to schooling tends to decrease, where males' returns to schooling are 4.59 and 4.36 percent, and females' returns to schooling are 5.43 and 5.26 percent, respectively, for the specifications based on potential labour market experience and age. These results confirm that the returns to schooling in Indonesia are low in comparison with the return to schooling in many other countries, particularly Asian and developing countries. Furthermore, it is clearly shown that the returns to schooling are higher for females than for males, which is in agreement with the findings of other studies, e.g. Deolalikar (1993) and Behrman and Deolalikar (1993) in Indonesia, Miller *et al.* (1997) in Australia, Flanagan (1998) in the Czech Republic, Brunello *et al.* (2000) in Italy, Lopez-Avecedo (2001) in Mexico, and Asadullah (2006) in Bangladesh. In terms of the model based on the dummy variables for educational attainment, the return to schooling in Indonesia tends to increase as the level of education increases, reflecting an increasing return to schooling. Additionally, males and females have different patterns at the senior secondary education level. Males have a higher return to schooling if they graduated from general senior secondary school rather than from vocational senior secondary school. Females have the opposite pattern, where females with vocational senior secondary school have a higher return to schooling than females with general senior secondary school.

Although the conventional economic view, based on the principle of diminishing returns, suggests that the earnings return to schooling should decline as individuals extend their level of education (Psacharopoulos, 1981, 1985, and 1989; Schultz, 2003 and 2004), this study finds to the contrary that the private earnings return to schooling increases as the level of education increases. This result is supported by previous empirical studies by Ryoo *et al.* (1993), Strauss and Thomas (1994), Liu *et al*. (2000), Tsakloglou and Cholezas (2000), and Aromolaran (2010).

The results show that statistical control for tenure and its squared term is more important than taking account of either potential work experience or age. Marital status has a positive impact on earnings for males but it has a negative impact on earnings for females. These results support the household specialisation hypothesis. The estimates also suggest that, on average, residents of urban areas receive significantly higher earnings than individuals living in the rural areas.

The estimates of the return to schooling based on additional years of schooling and the different levels of education using the OLS method presented in this chapter provide some valuable information on the Indonesian education sector. However, these empirical analyses may have limitations. In particular, in this chapter the endogeneity of schooling was not taken into account. Devoting a separate study to it may shed more light on the return to schooling in Indonesia. Accordingly, the following chapter investigates the return to schooling taking into account the potential of endogeneity of schooling.

Chapter 6

Returns to Schooling in Indonesia: Instrumental Variable Approach

6.1 Introduction

Empirical study of the private return to schooling in Indonesia using Ordinary Least Squares (OLS) is documented in Chapter 5. In that chapter, the analysis did not take account of ability bias. Given the evidence on the apparent role of ability bias for other countries, documented in Chapter 3, it is of practical importance to see whether ability bias impacts the estimate of the return to schooling in Indonesia. This issue is considered here by adopting the Instrumental Variable (IV) approach.

The major novelty of this study is that it canvasses a wide range of potential instruments for use in the estimation of the private return to schooling in Indonesia. In particular, in addition to the usual instruments of the parents' levels of education, it uses two variables that have not been employed to date in Indonesia, and which have received limited attention in the literature in general, namely, pre-school attendance and delayed primary school enrolment. It also considers the use of compulsory school attendance laws and a school development program as instruments. Furthermore, in contrast to previous studies that only examine the benefit of education, this study adopts an alternative perspective - proposed by Oreopoulos (2003) - by taking into account foregone earnings to quantify the opportunity cost of dropping out from school. These estimates are argued to provide a more useful guide for private, and even public, investment in education.

The remainder of this chapter consists of a general discussion on empirical models and estimation methods in Section 6.2, followed by a description of the data in Section 6.3. Section 6.4 reports and discusses the empirical results. The analysis in this section commences by exploring the four sets of instruments that will be considered in the IV approach to the estimation of the return to schooling using various samples and specifications. The quality, validity, and relevance of each set of instruments are evaluated to find the most reliable set. Then all the estimated results are compared and discussed. To enrich the analysis, the discussion in Section 6.4 is closed by relating the benefit of schooling to the foregone earnings. The final section summarises and concludes.

6.2. Empirical Models and Estimation Methods

It was argued in Chapter 4 that the OLS estimations of the economic returns to schooling from Equations 5.1-a and 5.1-b (see Chapter 5) may not be precise, since they are affected by three potentially damaging major biases. Measurement error bias may arise in the case of the schooling variable because the schooling information is provided in levels rather than in years (Chen and Hamori, 2009). To reduce the potential impact of this source of measurement error, similar to the analysis in Chapter 5, this analysis combines the information on the highest education level and the highest grade completed to obtain the individual's actual years of schooling. The second problem that may lead to an endogeneity problem is simultaneity. However, simultaneity is not of immediate concern in the current study, and will not be pursued further. Omitted ability variable bias is the third of the three problems that may adversely impact the estimate of the return to schooling. The schooling endogeneity problem caused by an omitted ability variable can be remedied by either employing a natural experiment approach or an IV estimation technique. The essence of this 'natural experiment' approach is to find a setting where the explanatory variable of interest (here, schooling) is highly likely to be exogenous. For example, Angrist and Krueger (1991) adopted quarter of birth interacted with year of birth as instruments, Plug (2001), and Lemke and Rischall (2003) employed quarter of birth as instruments, and Leigh and Ryan (2005 and 2006) used month of birth, month of birth interacted with year of birth, and change of compulsory education law as instruments. The basic idea of the IV estimator is to proceed in two stages. First, estimate the effect of the instrumental variable on schooling; then estimate the effect of the instrumental variable on earnings. Since, by assumption, the instrument is correlated with earnings only because it influences schooling, the ratio of the effect of the instrument on earnings to its effect on schooling provides an estimate of the causal effect of schooling on earnings (Ashenfelter *et al.*, 1999).

In order to address potential endogeneity bias, this study adopts an IV approach and uses several instruments. The following two-equation model describing the natural logarithm of monthly earnings ($\ln(earnings_i)$) and years of schooling ($\ln(yrschyr_i)$) is commonly applied to handle the endogeneity of schooling:

$$\ln(earnings_i) = \delta X_i + \beta yrschyr_i + \mu_i \quad (6.1)$$

$$\ln(yrschyr_i) = \varphi Z_i + \varepsilon_i \quad (6.2)$$

where X and Z are vectors of observed variables, $E(X_i \mu_i) = E(Z_i \varepsilon_i) = 0$, and β is interpreted as the return to schooling (Card, 1993). The explanatory variables employed in equation (6.1) in this chapter are the same as those utilised in Chapter 5. Hence, X for the standard Mincerian model represents experience and its square (age and its square). In the case of the augmented Mincerian model the X vector consists of experience and its square (age and its square), tenure and its square, marital status, urban area of residence, and gender status (for the pooled sample only).

The IFLS4 data base contains a number of potential instruments for the years of schooling variable. For the purposes of this chapter, two broad categories of instruments are considered. The first category is variables that vary across individuals in a given age category. These include father's years of schooling, mother's years of schooling, a dummy variable for pre-school attendance, and a variable that records delayed enrolment in primary school (age of primary school enrolment). The second category is variables that are the same for all individuals in a given age category. There are three of these variables, namely, a dummy variable for the first compulsory school attendance law (CSAL-1), a dummy variable for the second compulsory school attendance law (CSAL-2), and a dummy variable for the INPRES program. These compulsory school attendance laws and the INPRES program were discussed in Chapter 2.

6.3 Data

The data used in this chapter are the same as the data used in Chapter 5, other than for the additional variables that are used as instruments, namely, father's and mother's years of schooling, dummy variables for compulsory school attendance, the INPRES program, and pre-school attendance, and the age of primary school enrolment. The descriptive statistics of the sample are given in Table 6.1. To assist readers, this table also contains the descriptive statistics for the variables previously reviewed in Chapter 5.

Table 6.1: Summary Statistics

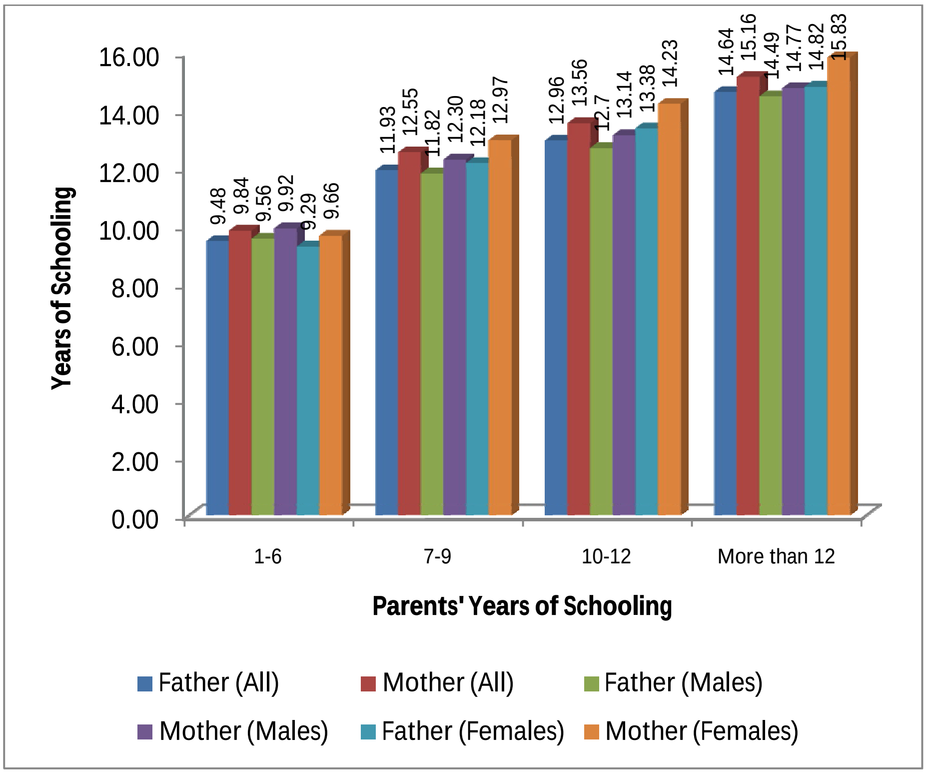
Variables	All		Males		Females	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Dependent Variable						
Monthly earnings (IDR)	1,339,521	1,961,290	1,476,118	2,137,155	1,066,059	1,514,442
Monthly earnings (log)	5.913	0.4378	5.973	0.408	5.792	0.468
Independent Variables						
Years of schooling	10.683	3.744	10.608	3.616	10.833	3.986
Experience	17.788	10.600	18.042	10.259	17.279	11.238
Experience squared	428.734	479.227	430.709	472.415	424.780	492.716
Age	35.192	9.741	35.417	9.561	34.741	10.078
Age squared	1333.327	751.375	1345.776	746.820	1308.406	760.046
Control Variables						
Tenure	7.852	8.116	7.890	8.036	7.779	8.275
Tenure squared	127.499	247.153	126.885	246.885	128.943	247.763
Female (dummy for gender)	0.333	0.471				
Marital status dummy	0.866	0.340	0.899	0.302	0.801	0.399
Dummy for urban area	0.676	0.468	0.649	0.477	0.730	0.444
Instruments						
Father’s years of schooling	7.469	3.400	7.321	3.317	7.767	3.542
Mother’s years of schooling	6.490	2.963	6.370	2.934	6.731	3.009
CSAL-1	0.569	0.495	0.570	0.495	0.568	0.495
CSAL-2	0.293	0.455	0.276	0.447	0.328	0.470
INPRES Program	0.732	0.443	0.737	0.440	0.722	0.470
Pre-School attendance	0.249	0.433	0.221	0.415	0.306	0.461
Age of Primary School Enrolment	6.721	0.780	6.767	0.796	6.628	0.737

Source: Author’s calculation based on IFLS4 data set.

Since the data used here are identical with the data employed in the previous chapter, the discussion that follows will focus only on the instruments. The first set of instruments relates to parents’ years of schooling (father’s and mother’s years of schooling).

Figure 6.1 shows the relationship between parents’ years of schooling and the years of schooling of the respondents in the sample. There are some interesting facts captured in this figure. Firstly, this figure exposes that the years of schooling increase with the parents’ years of schooling for all sample categories. This pattern provides evidence for the intergeneration human capital spillover from parents to their sons and daughters. Secondly, the average years of schooling for each group is higher than their parents’ average years of schooling. For example, parents with 1 to 6 years of schooling have a son or a daughter with around 9 years of schooling, while parents with 7 to 9 years of schooling have a son or a daughter with more than 10 years of schooling. This implies that the younger generation tends to have a better education. Thirdly, the years of schooling of the daughters exceed those of the sons across all sample sets and years of schooling categories, whereas, from Table 6.1, the average years of schooling of the father (7.469) exceed those of the mother (6.490). This reveals that the relative schooling levels of males and females in Indonesia are similar to those observed in many Western countries, where older males tend to have more schooling than older females, but younger males tend to have less schooling than younger females.

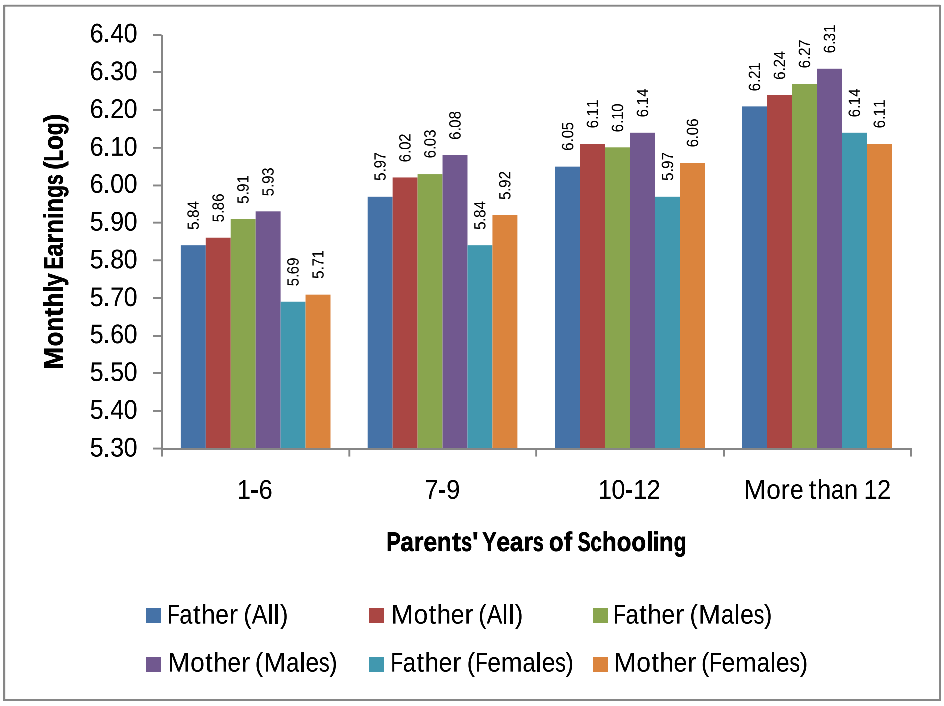
Figure 6.1: Years of Schooling and Parents' Years of Schooling



Source: Author's calculation based on IFLS4 data set.

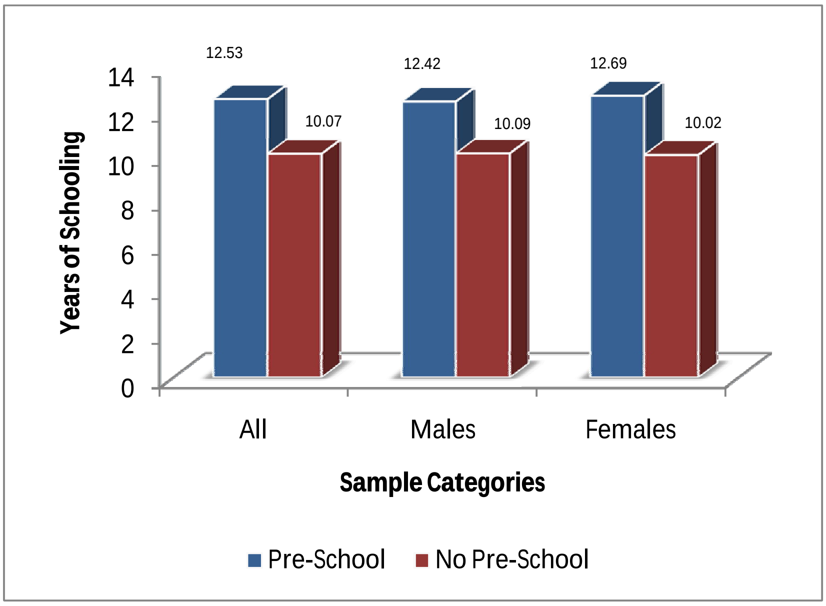
The relationship between monthly earnings and parents' years of schooling is described in Figure 6.2. Monthly earnings are positively correlated with parents' years of schooling for all sample categories. The IV approach needs to maintain, however, that the reason for this relationship is that the parents' levels of education lead to a higher level of schooling for their offspring, and it is this superior schooling attainment that gives rise to the pattern in Figure 6.2.

Figure 6.2: Monthly Earnings and Parents' Years of Schooling



Source: Author's calculation based on IFLS4 data set.

Figure 6.3: Pre-School Attendance and Years of Schooling

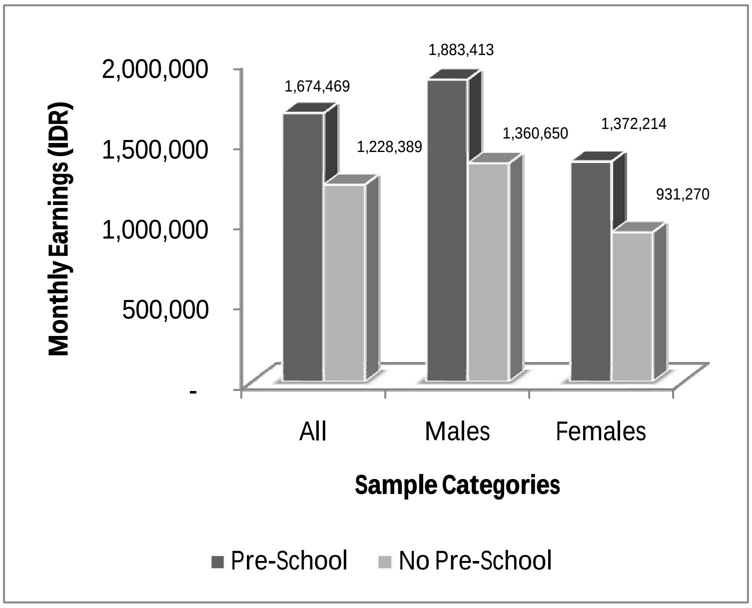


Source: Author's calculation based on IFLS4 data set.

Figure 6.3 describes the correlation between pre-school attendance and years of schooling. Individuals who attended pre-school tend to have a greater number of years of schooling. Males without pre-school have an average length of schooling of 10.09 years, while their male counterparts who attended pre-school have 23.09

percent more years of schooling, which is 12.42 years. Females who did not attend pre-school have an average years of schooling of 10.02 years, whereas for females with pre-school the average years of schooling is 12.69 years, and this is 26.65 percent greater than that of females without pre-school. In other words, there is a strong positive relationship between pre-school attendance and the duration of schooling.

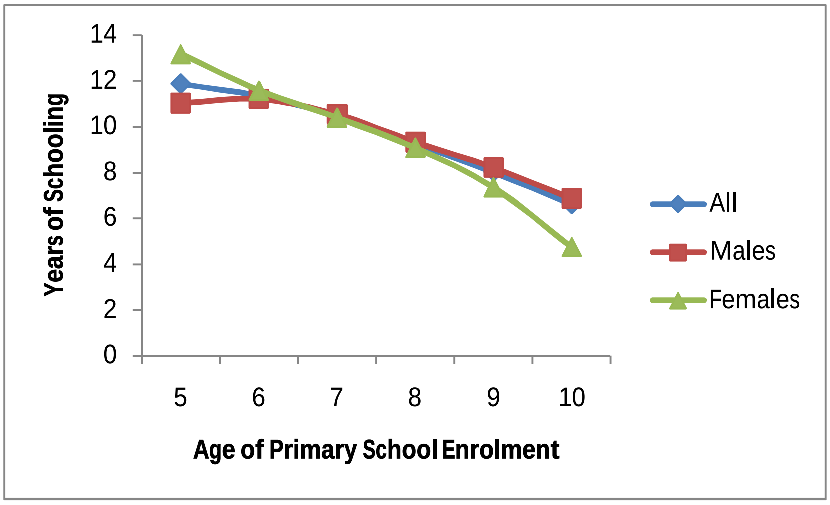
Figure 6.4: Pre-School Attendance and Monthly Earnings



Source: Author's calculation based on IFLS4 data set.

Figure 6.4 presents the average monthly earnings received by individuals with and without pre-school. Individuals with pre-school experience have average monthly earnings significantly higher than individuals without pre-school experience. Again, the argument for this positive association needs to be that it reflects an indirect relationship between pre-school attendance and earnings through schooling. That is, individuals with pre-school tend to stay at school longer than their counterparts without pre-school, and by having more years of schooling they tend to have higher earnings. For the pooled sample, individuals who never attended pre-school have average monthly earnings Rp446,080 below the earnings of individuals who attended pre-school. Male workers with pre-school experience earn Rp522,763 more than male workers who never attended pre-school. Female workers with no pre-school experience have average monthly earnings of Rp931,270, and this is well below the average monthly earnings of Rp1,372,214 for female workers who attended pre-school.

Figure 6.5: Age of Primary School Enrolment and Years of Schooling

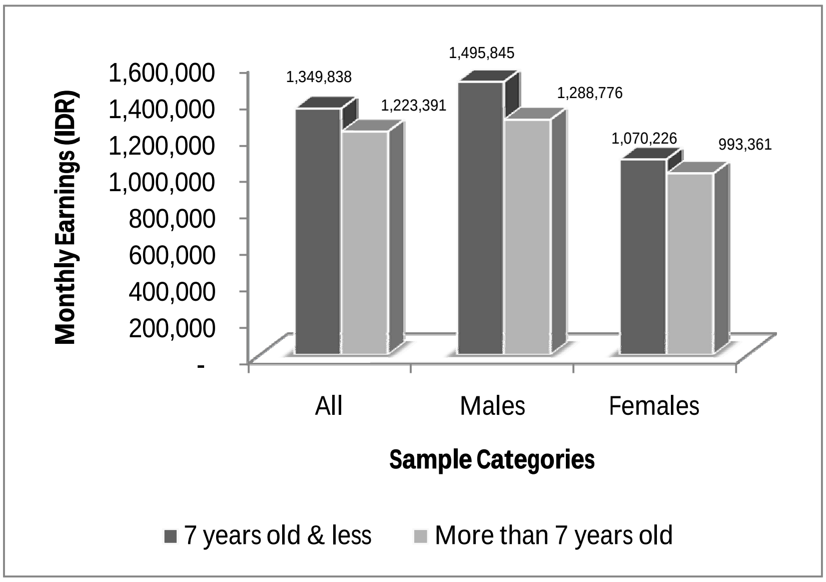


Source: Author's calculation based on IFLS4 data set.

Figure 6.5 portrays the relationship between delayed primary school enrolment and years of schooling for the three samples. Each of these three profiles has a negative slope, which indicates a negative correlation between delayed primary school enrolment and the years of schooling. That is, the older the individuals start their primary schooling the shorter their completed years of schooling. Individuals who enter primary school at 6 years of age tend to spend around 11 years at school, and there is little difference between males and females in this regard. Males who start primary school at the age of 10 tend to have only around 7 years of schooling. However, females who start primary school at this age (10 years) tend to have significantly lower completed years of schooling, specifically about 4 years.

Figure 6.6 presents the age of primary school enrolment - earnings profiles for the three samples. The ages of primary school enrolments are divided into two categories. The first category is for individuals who start primary school at the official age (7 years) or younger. The second category is for the individuals who first enrol in primary school older than the official age. Typically, individuals who start primary school when they are older than the official age receive slightly lower average monthly earnings. Thus the difference between the average monthly earnings received by male workers who start their primary school when they are older than the official age and who start primary school at the official age or younger is approximately 16 percent. The comparable earnings disparity among female workers is smaller, being about 8 percent.

Figure 6.6: Age of Primary School Enrolment and Monthly Earnings



Source: Author's calculation based on IFLS4 data set.

Comparing the average years of schooling between individuals who are assumed not affected and affected by the CSAL-1, the CSAL-2 and the INPRES program leads to the same general patterns except for the male sample with the CSAL-2. As expected, on average individuals who were affected by these three government education policies have slightly higher average years of schooling. The CSAL-1 appears to be associated with an increase in the average years of schooling from 10.38 to 10.91 years, or by 5.11 percent, for the pooled sample, from 10.45 to 10.73 years, or by 2.68 percent, for the male sample, and from 10.24 to 11.29 years, or by 10.25 percent, for the female sample. The CSAL-2 increases the average years of schooling from 10.60 to 10.87 years for the pooled sample, and from 10.57 to 11.36 years for the female sample. The average years of schooling for males who were not affected by the CSAL-2 is 10.62 years, and it is 10.56 years for males who were affected by that policy. There is no obvious reason for the counter-intuitive outcome for males from this policy change. Individuals who are assumed affected by the INPRES program have an average years of schooling of 10.98, 10.82, and 11.33 years for the pooled, male, and female samples, respectively. These mean schooling levels represent increases by 11.47, 8.09, and 18.76 percent for the pooled, male, and female samples, respectively in comparison to individuals who were not affected by the INPRES program. These comparisons show that the difference in years of schooling between individuals who were affected and not affected by the CSAL-1, the CSAL-2, and the INPRES program is higher for females than males. This indicates that these education policies have had a greater impact for females than for males.

The data on the average monthly earnings shows a pattern opposite that for the average years of schooling. Individuals who were affected by the CSAL-1, the CSAL-2, or the INPRES program have lower average monthly earnings than individuals who were not affected by these three policies. In particular, individuals who were affected by the CSAL-1 have average monthly earnings of Rp1,156,800, Rp1,280,208, and Rp1,203,099 for the pooled, male, and female samples, respectively. These are 26.82 (pooled sample), 26.23 (male sample), and 5.46 (female sample) percent lower than those of individuals who were not affected by the CSAL-1. The individuals who were not affected by the CSAL-2 (INPRES program) have average monthly earnings that are 32.04 (23.93), 29.33 (28.99), and 13.64 (10.36) percent higher than the earnings of individuals who were affected by these policies, for the pooled, male, and female samples, respectively. The explanation for this is most likely that individuals who were affected by these policies are in the younger cohorts, while individuals who were not affected by these policies are in older cohorts. Individuals from younger cohorts have lower potential work experience, and in Chapter 5 the data informed that average monthly earnings increase with potential work experience.

6.4. Results and Interpretations

As mentioned in the previous chapter, including proxies for ability directly in the earnings function is one way of handling the omitted ability variable problem. Unfortunately, very few datasets contain ability measures that are convincing. The IFLS4 in particular does not provide such data, and therefore this proxy variable approach cannot be adopted in this study. The main alternative approach to tackle the endogeneity problem is the IV method. As discussed previously, the IV approach is based on finding credible instruments that are correlated with schooling and ability but not correlated with the residual in the earnings function. This is the approach pursued in this section.

The discussion commences with instrumenting schooling with parental years of schooling for the standard and augmented Mincerian models, followed by instrumenting schooling with pre-school attendance and delayed primary school enrolment for the standard and augmented Mincerian models, instrumenting schooling with the CSAL-1 and the CSAL-2 for the standard and augmented Mincerian models, and instrumenting schooling with the INPRES program for the standard and augmented Mincerian models. Using these four alternative sets of instruments provides a basis for assessing the quality of the instruments and for establishing the robustness of the findings to the choice of instruments. Following the presentation of the empirical findings for each set of instruments the chapter turns to a general discussion of validity and relevance of all the instruments.

6.4.1 Instrumenting Schooling with Parental Education

Following Blackburn and Neumark (1991), Uusitalo (1999), and Levin and Plug (1999), the first set of instruments used in this study are based on parental education. Mother's and father's levels of education have become popular variables in instrumental variables studies of earnings determination. The earlier studies that utilise these variables as instruments assume that parents' levels of education are not correlated with their children's inherent abilities but influence their children's educational achievement (Li and Luo, 2004).[22] The view that more educated parents provide a better environment for their children has been the basis of many investigations. Generally, studies that examine the correlation between parental levels of education and children's educational attainment find that parents' levels of education have a significant influence on the educational achievement of their offspring (see Tansel, 1997; Liu and Lin, 2000; Hudson and Sessions, 2009; Lemke and Rischall, 2003). Much of this research has had a focus on developed countries.

[22] We tested whether parents' education is correlated with one's wages by including mother's and father's education in the wage equation, treating parental education as a proxy for unobserved ability variables. This test leads to ambiguous findings. Furthermore the exclusion restriction, that parental education has no direct effect on wages, was tested. This test leads to consistent results across specifications and samples: the exclusion test is satisfied.

Table 6.2: Instrumenting Schooling with Parental Education (Standard Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
									age proxying experience			
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	8.40798	4.82745	8.60605	4.92776	7.95033	4.60245	3.29939	4.72522	2.36074	4.92105	4.14650	4.50855
	(0.19366)***	(0.05349)***	(0.24778)***	(0.06692)***	(0.31163)***	(0.08436)***	(0.58927)***	(0.07482)***	(0.74833)***	(0.09052)***	(0.96449)***	(0.12479)***
Years of Schooling		0.07962		0.07862		0.08912		0.06839		0.06764		0.07745
		(0.00389)***		(0.00490)***		(0.00607)***		(0.00321)***		(0.00406)***		(0.00500)***
Experience	-0.03860	0.01812	-0.04474	0.01474	-0.01861	0.01697						
	(0.01458)***	(0.00195)***	(0.01877)**	(0.00239)***	(0.02344)	(0.00322)***						
Experience^2	-0.00177	-0.00020	-0.00141	-0.00013	-0.00263	-0.00016						
	(0.00032)***	(0.00004)***	(0.00041)***	(0.00005)**	(0.00053)***	(0.00007)**						
Age							0.19049	0.01951	0.24329	0.01296	0.13784	0.01862
							(0.03165)***	(0.00968)***	(0.03965)***	(0.00484)***	(0.05334)***	(0.00672)***
Age^2							-0.00277	-0.00017	-0.00325	-0.00009	-0.00244	-0.00015
							(0.00041)***	(0.00005)***	(0.00051)***	(0.00006)	(0.00071)***	(0.00009)**
Father's Schooling	0.32376		0.31700		0.33077		0.36728		0.35734		0.38045	
	(0.01777)***		(0.02208)***		(0.02985)***		(0.01894)***		(0.02319)***		(0.03261)***	
Mother's Schooling	0.20063		0.17174		0.26052		0.25071		0.21797		0.31750	
	(0.02040)***		(0.02494)***		(0.03524)***		(0.02174)***		(0.02623)***		(0.03838)***	
R^2	0.3547		0.3126		0.4328		0.2611		0.2344		0.3185	
Adjusted R^2	0.3541		0.3117		0.4313		2606		0.2334		0.3167	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality[23]												
F		578.197		328.687		254.635		733.108		425.292		310.516
P-Value		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***
Validity (Sargan test)												
Chi^2		1.09176		1.50852		0.02328		0.79617		1.28249		2.5e-06
P-Value		0.2961		0.2194		0.8787		0.3722		0.2574		0.9987
Relevance (Hausman test)												
F		45.9312		35.9206		22.9775		41.4677		34.5832		20.40520
P-Value		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

[23] The discussion about the quality, validity, and relevance of the instruments is presented in Section 6.4.5.

Research on the role of family background, and parental education in particular, in explaining earnings and the returns to schooling is less extensive for developing countries. The current study makes an effort to establish the contribution of parental schooling to the private return to schooling in Indonesia, and can be viewed as a pioneering effort in this regard. Separate variables are considered for father's and mother's years of schooling. Firstly parental levels of education will be utilised as instruments in the standard Mincerian model estimated using the IV approach. Then these instruments are used when the augmented Mincerian model is estimated using the IV approach.

The reduced-form regressions for the determinants of schooling, which is the first stage in the IV technique, and the IV earnings function estimates using parental education as instruments for the standard Mincerian model, are presented in Table 6.2. We commence the discussion with the specifications using experience (columns (a) to (f)). The relatively high first stage R^2 (ranges from 0.3126 to 0.4328) and significant *F*-statistic in all three samples are an indication of good correlation between the instruments and years of schooling.[24] Moreover, it is apparent that father's and mother's years of schooling are acceptable instruments since the value of the *F*-test allows us to reject the hypothesis that these variables do not determine the years of schooling. All of the coefficients of father's and mother's years of schooling variables are statistically significant at the 1 percent level of significance. Both the years of education of father and of mother impact positively on the completed years of education of the individuals. The coefficient on the father's years of schooling variable is greater than that on the mother's years of schooling variable in each of the three samples, specifically it is 0.324 of a year (pooled sample), 0.317 of a year (male sample), and 0.331 of a year (female sample) for the father's years of schooling and 0.201 of a year (pooled sample), 0.172 of a year (male sample), and 0.261 of a year (female sample) for the mother's years of schooling. This indicates the relatively more important role of father's education rather than mother's education in determining the educational outcomes of offspring, regardless of the gender of the children.

[24] The R^2 from the second stage regression has no statistical meaning in the context of 2SLS/IV (see Sribney *et al.*, 2011 at http://www.stata.com/support/faqs/stat/2sls.html). Accordingly, we do not discuss the R^2 from the earnings function in the IV approach.

The returns to schooling estimated using parental education as instruments clearly show that the figures are higher than the OLS estimates presented in Chapter 5. The returns to schooling obtained using OLS are 5.66 percent (pooled sample), 5.28 percent (male sample), and 6.46 percent (female sample). Using the IV approach with parental education levels as instruments, the return to schooling rises to 7.96 percent (pooled sample), 7.86 percent (male sample), and 8.91 percent (female sample). Thus, the average difference between the IV and OLS estimates is 2.44 percentage points. Thus, on average, the OLS estimates are 29.64 percent less than the IV estimates. All the major patterns in relation to the coefficients on the schooling variable found using OLS carry over to the IV results, with the return to schooling for females being greater than that for males. The difference between the return to schooling obtained using OLS and IV is economically important, and along with the results of the statistical testing via the Hausman test, shows that the endogeneity of schooling in the study of the returns to schooling in Indonesia warrants careful attention.

The results from the second part of Table 6.2 (columns (g) to (l)) are for the specification where the potential work experience variables are replaced by the age variables.[25] This change results in a slightly smaller first stage R^2, which now ranges from 0.2344 to 0.3185, though these, along with the significant *F*-statistic in all three samples, provide an indication of a good correlation between the instruments and the years of schooling variable. The value of the *F*-test allows us to reject the hypothesis that these variables do not determine the years of schooling. All of the coefficients of father's and mother's years of schooling variables are statistically significant at the 1 percent level of significance. The results show that the years of education of both father and mother have positive impact on the years of education of their children. In line with the results from the specification using experience, the father's years of schooling variable has a greater effect on the years of schooling of his children than does the mother's years of schooling variable. An additional year of schooling for the father tends to increase the years of schooling of his children by 0.37 years (pooled sample), 0.36 years (male sample), and by 0.38 years (female sample). On the other hand, an additional year of schooling for the mother tends to increase the years of

[25] Given the similarity of the general patterns obtained from the standard Mincerian model and the augmented Mincerian model, the estimates associated with the experience and age variables will not be discussed here. Discussions on these are provided when the augmented Mincerian model estimates are analysed.

schooling of her children by 0.25 years (pooled sample), 0.22 years (male sample), and by 0.32 years (female sample).

The results from the standard Mincerian model based on the age variables and estimated using IV support the finding discussed previously in this chapter, that the return to schooling obtained using the IV approach is higher than that obtained using OLS. The return to schooling obtained using OLS with the age-based specification of the standard Mincerian model is 5.07 percent (pooled sample), 4.70 percent (male sample), and 5.88 percent (female sample). Applying IV to the same model, with parental levels of education as instruments, sees the return to schooling increase to 6.84 percent (pooled sample), 6.76 percent (male sample), and 7.74 percent (female sample). The Hausman test rejects the null hypothesis of equality of the OLS and IV estimates.

Table 6.3 presents results from the augmented Mincerian earnings model estimated using IV. Similar to the ‘OLS augmented Mincerian specification’ in Chapter 5, this ‘IV augmented Mincerian model’ includes the five control variables, namely tenure and its square, marital status, urban area of residence, and gender (for the pooled sample only). The layout of this table is the same as that of Table 6.2.

The results from the specifications based on potential labour market experience (columns (a) to (f)) reveal that the additional variables to control for job tenure and its square, marital status, urban residence, and gender lift the first stage R^2 to 0.4140, 0.3697, and 0.5030 for the pooled, male, and female samples, respectively. Furthermore, all of the *F*-statistics in the first stage regressions suggest a good correlation between the instruments and the individuals’ years of schooling. Moreover, it seems that the father’s and mother’s years of schooling are acceptable instruments since the value of the *F*-test allows us to reject the hypothesis that these variables do not determine the years of schooling of the individual. Typical of the pattern established above, father’s and mother’s years of schooling have significant positive effects on the years of schooling of their children. Also similar to the results discussed above, the effect of father’s education exceeds that of the mother. An additional year of schooling for the father (mother) increases the years of schooling of their children by 0.29 (0.17), 0.28 (0.14), and 0.30 (0.23) years for the pooled, male, and female samples.

Table 6.3: Instrumenting Schooling with Parental Education (Augmented Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		Males		Females		All		Males		Females	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	7.52344	4.90386	7.52112	4.94377	7.41438	4.62127	3.01790	4.92460	1.98465	4.98520	4.23893	4.61875
	(0.20591)***	(0.05268)***	(0.26186)***	(0.06763)***	(0.32369)***	(0.08496)***	(0.61297)***	(0.07608)***	(0.76620)***	(0.09340)***	(1.01530)***	(0.13050)***
Years of Schooling		0.07790		0.07423		0.08317		0.06929		0.06608		0.07384
		(0.00436)***		(0.00580)***		(0.00668)***		(0.00351)***		(0.00476)***		(0.00522)***
Experience	-0.10657	0.01219	-0.10047	0.01150	-0.11559	0.01316						
	(0.01592)***	(0.00223)***	(0.02044)***	(0.00277)***	(0.02547)***	(0.00380)***						
Experience^2	-0.00114	-0.00011	-0.00093	-0.00011	-0.00154	-0.00012						
	(0.00035)***	(0.00005)**	(0.00044)**	(0.00006)*	(0.00056)***	(0.00008)						
Age							0.16620	0.00834	0.23870	0.00630	0.07690	0.01069
							(0.03552)***	(0.00437)*	(0.04414)***	(0.00547)	(0.06019)	(0.00751)
Age^2							-0.00251	-0.00008	-0.00309	-0.00006	-0.00200	-0.00010
							(0.00046)***	(0.00006)	(0.00056)***	(0.00007)	(0.00079)**	(0.00010)
Tenure	0.11740	0.01197	0.08837	0.00863	0.17201	0.01814	0.05169	0.01504	0.02096	0.01130	0.11368	0.02202
	(0.01528)***	(0.00212)***	(0.01876)***	(0.00248)***	(0.02622)***	(0.00400)***	(0.01687)***	(0.00205)***	(0.02009)	(0.00241)***	(0.03029)***	(0.00381)***
Tenure^2	-0.00080	-0.00025	-0.00058	-0.00014	-0.00137	-0.00046	-0.00143	-0.00025	-0.00127	-0.00014	-0.00179	-0.00047
	(0.00050)	(0.00007)***	(0.00061)	(0.00008)*	(0.00086)	(0.00012)***	(0.00055)***	(0.00007)***	(0.00066)*	(0.0008)*	(0.00099)*	(0.00012)***
Marital Status	0.66684	-0.02844	0.88521	0.00399	0.31556	-0.06570	-0.00564	-0.00221	-0.19636	0.04043	0.07152	-0.05081
	(0.13647)***	(0.01858)	(0.18919)***	(0.02514)	(0.19598)	(0.02814)**	(0.15099)	(0.01827)***	(0.20517)	(0.02461)	(0.22472)	(0.02793)*
Urban	1.31188	0.05266	1.45466	0.04100	1.03111	0.08897	1.48627	0.05677	1.53900	0.04706	1.36811	0.08805
	(0.09420)***	(0.01492)***	(0.11362)***	(0.01869)**	(0.16721)***	(0.02581)***	(0.10319)***	(0.01464)***	(0.12192)***	(0.01800)***	(0.18982)***	(0.02585)***
Female	-0.08109	-0.19495					-0.09906	-0.19633				
	(0.09105)	(0.01492)***					(0.09977)	(0.01207)***				
Father's Schooling	0.29080		0.27862		0.30036		0.34142		0.32262		0.36436	
	(0.01705)***		(0.02133)***		(0.02807)***		(0.01862)***		(0.02275)***		(0.03187)***	
Mother's Schooling	0.17169		0.14102		0.23339		0.21831		0.17805		0.29646	
	(0.01956)***		(0.02408)***		(0.03315)***		(0.02139)***		(0.02577)***		(0.03756)***	
R^2	0.4140		0.3697		0.5030		0.2948		0.2751		0.3538	
Adjusted R^2	0.4128		0.3680		0.5004		0.2934		0.2732		0.3504	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality												
F		470.416		249.088		228.044		593.348		317.171		283.715
P-Value		0.0000***		0.0000***		0.0000***		0.0000***		0.0000		0.0000***
Validity (Sargan test)												
Chi^2		0.79358		1.31205		0.00021		0.57412		1.17452		0.01054
P-Value		0.3730		0.2520		0.9884		0.4486		0.2785		0.9182

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
									age proxying experience			
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Relevance (Hausman test)												
F		55.4416		29.4551		25.9323		52.3454		28.3995		23.9579
P-Value		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The results from the earnings function show that the return to schooling obtained using the IV method exceeds the return obtained using OLS. Thus, the returns to schooling obtained using IV (OLS) are 7.79 (4.93) percent (pooled sample), 7.42 (4.59) percent (male sample), and 8.32 (5.26) percent (female sample). Thus, the average difference between the IV and OLS estimates is 2.92 percentage points. On the average, the OLS estimates are 37.21 percent less than the IV estimates. Again the Hausman test rejects the null hypothesis of equality of the OLS and IV estimates.

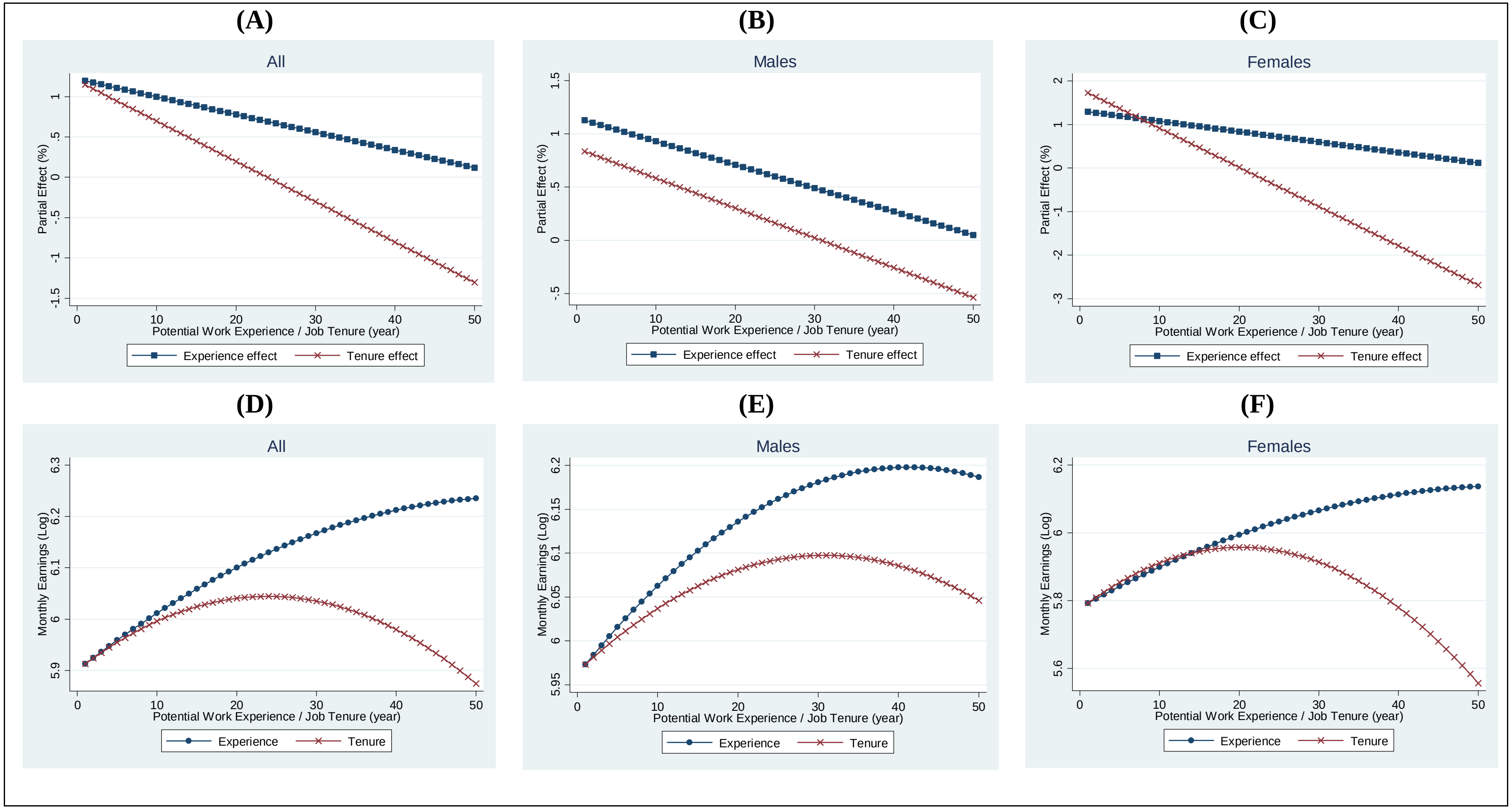
While most interest in the estimates in this chapter is in the change to the estimated return to schooling following the adoption of the IV technique, it is of interest to provide summary comments on the estimated effects of the various control variables. As these estimated effects are quite similar to those obtained using OLS, the discussion can be brief.

Figure 6.7 presents information on the relationship between the marginal or partial effects on earnings of experience (tenure) along with the corresponding experience (tenure)-earnings profiles for the various samples. In the first row, Panel A shows the partial effects of experience and tenure on earnings for the combined sample of males and females. Panel D presents the experience-earnings and tenure-earnings profiles. It is seen here that the partial effect of labour market experience is greater than the effect of job tenure for the entire work lifetime coverage in the sample. That is, the change in earnings associated an additional year of potential work experience is greater than the change in earnings associated with an additional year of tenure. For example the marginal effects of potential work experience (job tenure) are 0.10 (0.70), 0.78 (0.20), 0.56 (-0.30), and 0.34 (-0.80) percent after working for 10, 20, 30 and 40 years, respectively. Beyond 24 years the marginal effect of tenure on earnings is negative. The partial effect of potential labour market experience on earnings is positive over the range of experience relevant to the sample. The gap between these two effects initially is very narrow but it widens with additional years of experience or tenure. Workers reach the peak of their experience-earnings profile after approximately 55.41 years of labour market experience. In the case of the tenure-earnings profile, workers reach the peak after having job tenure of around 23.94 years. The experience-earnings profile is always above the tenure-earnings profile (see Panel D). This pattern is opposite to the findings in Chapter 5 when OLS was used. Using OLS showed that the tenure-earnings profile was above the experience-earnings profile.

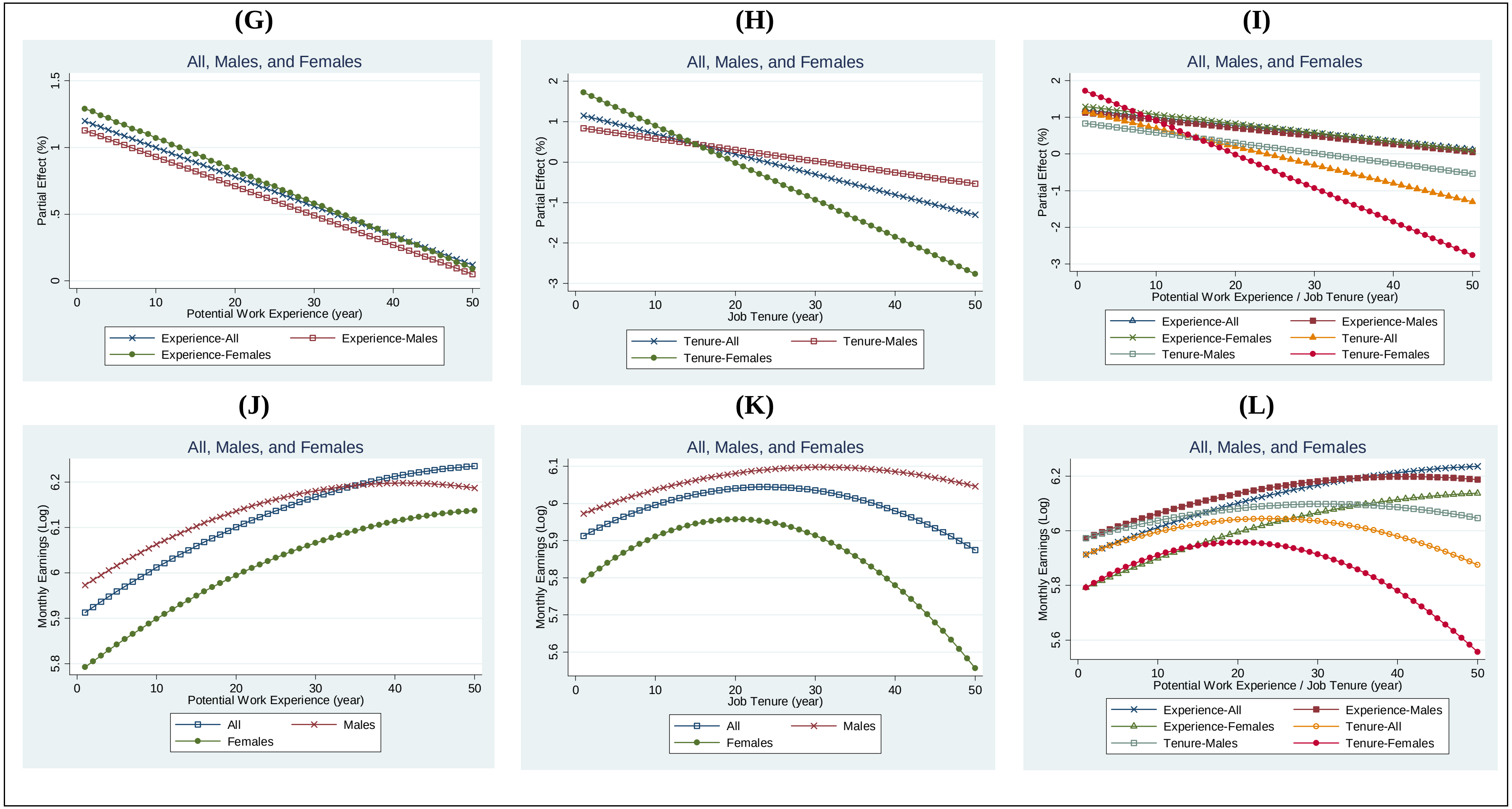
Panel B (E) portrays the marginal effect of experience and the marginal effect of tenure (experience-earnings and tenure-earnings profiles) for male workers. Similar to the pooled sample, the effect of experience on earnings is greater than the effect of tenure on earnings for the entire working period, and the partial effect of potential labour market experience on earnings is positive over the range of experience relevant to the sample. One difference compared to the findings for the pooled sample is that the gap between these two effects for the male sample is fairly constant. Consistent with the case of the pooled sample, the effect of tenure reaches its zero point earlier (after 31 years) than the effect of experience, thus the tenure-earnings profile also reaches the maximum point earlier than the experience-earnings profile. In line with the pattern for the pooled sample, the experience-earnings profile is above the tenure-earnings profile. Again this pattern is contrary to the finding from the OLS estimation for males.

For female workers the effects of experience (tenure) on earnings and the corresponding experience (tenure)-earnings profiles are described in Panels C and F. The patterns evident in the experience and tenure effects on earnings for females are clearly different from those for the pooled and male samples. The marginal effects for female workers (Panel C) show that, over the first seven years, the marginal effect of tenure on earnings is greater than the marginal effect of experience on earnings. Beyond this seven years threshold, however, the marginal effect of potential labour market experience for females exceeds that of job tenure, and the gap between these two marginal effects widens with additional years of experience and years of tenure. The marginal effect of tenure for female workers becomes negative earlier than that of male workers, specifically it turns negative around 20 years of tenure. This figure is about 10.67 years earlier than that of males. On the other hand, the experience-earnings profile reaches the turning point only after female workers have been in the labour market for about 54.83 years.

Figure 6.7: Partial Effect of Experience and Partial Effect of Tenure on Earnings and Experience-Earnings and Tenure-Earnings Profiles (IV Estimates with Parental Education as Instruments)[26]



[26] In order to avoid presentational problems due to comparing various groups, to construct the bottom three diagrams the mean log earnings is used as the initial level of earnings for both the experience and tenure profiles.



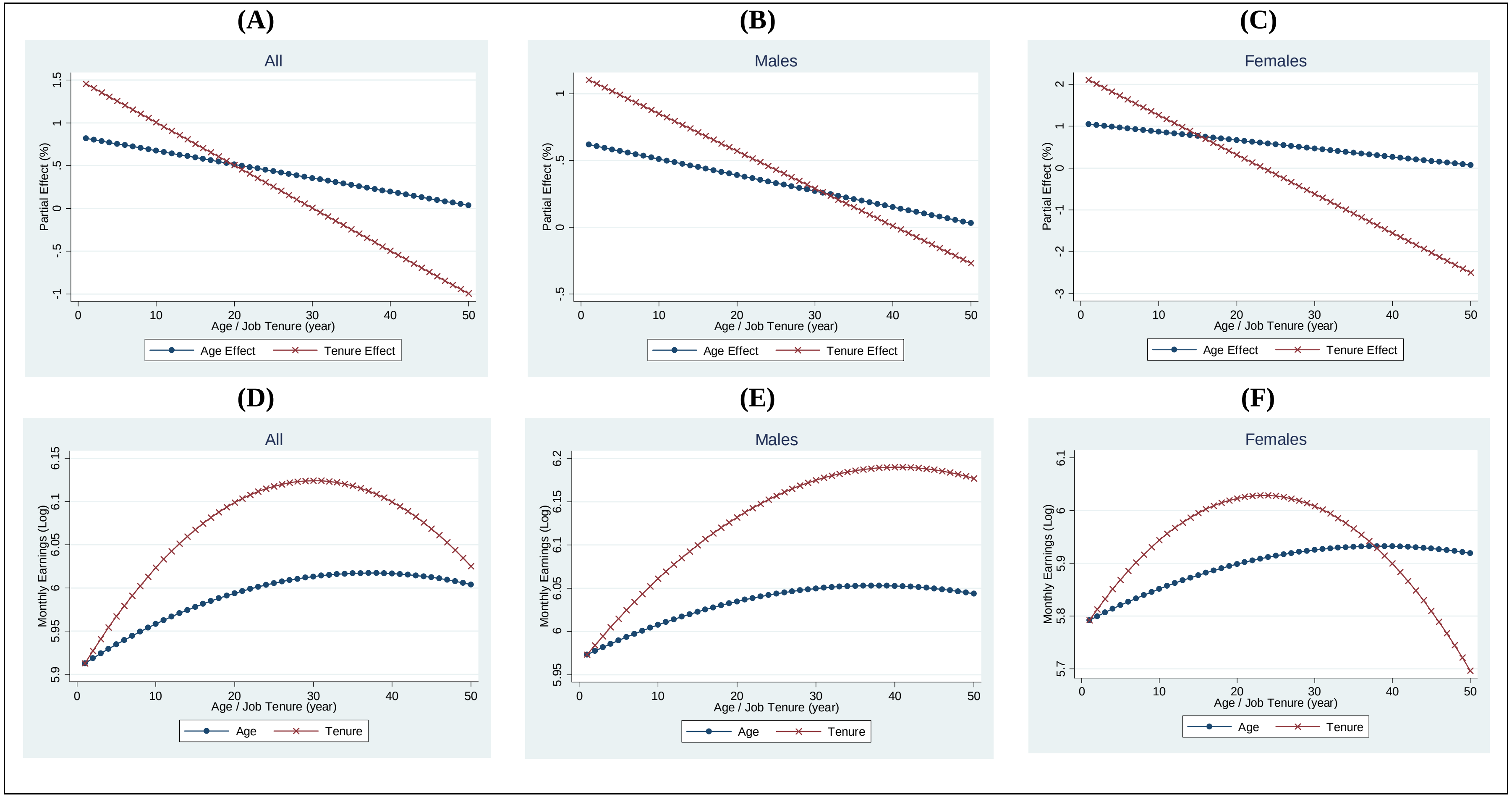
Source: Author's calculation based on Table 6.3.

The second part of Figure 6.7 (Panels G to L) compares the marginal effects of experience (tenure) across the pooled, male, and female samples, and relates these effects to the experience (tenure)-earnings profiles. Female workers have a higher marginal effect of experience for the entire working lifetime (see Panel G). This implies that potential work experience is more important for female workers than it is for male workers. In other words, the gender differences in the return to the general skills captured by the potential work experience variables are the same as found for the schooling variable. On the other hand, the marginal effect of tenure on earnings shows a different pattern (see Panel H). During the first 15 years, the marginal effect of tenure for female workers is greater than that of male workers. Beyond this tenure threshold, however, the marginal effect of tenure for female workers is less than that of male workers. Note, however, that as the mean of the tenure variable is around 8 years (standard deviation also 8 years), for most of the sample the effect of tenure for females will exceed that of males, and to this extent the situation is similar to the situation with respect to potential labour market experience. In addition it is noted that the maximum points for the tenure-earnings profile come earlier than is the case for the experience-earnings profiles for the pooled, male, and female samples (see Panel L). The tenure-earnings profile for female workers reaches its turning point earlier than that of male workers (see Panel K), but the experience-earnings profile for female workers reaches its maximum point later than that of male workers (see Panel J).

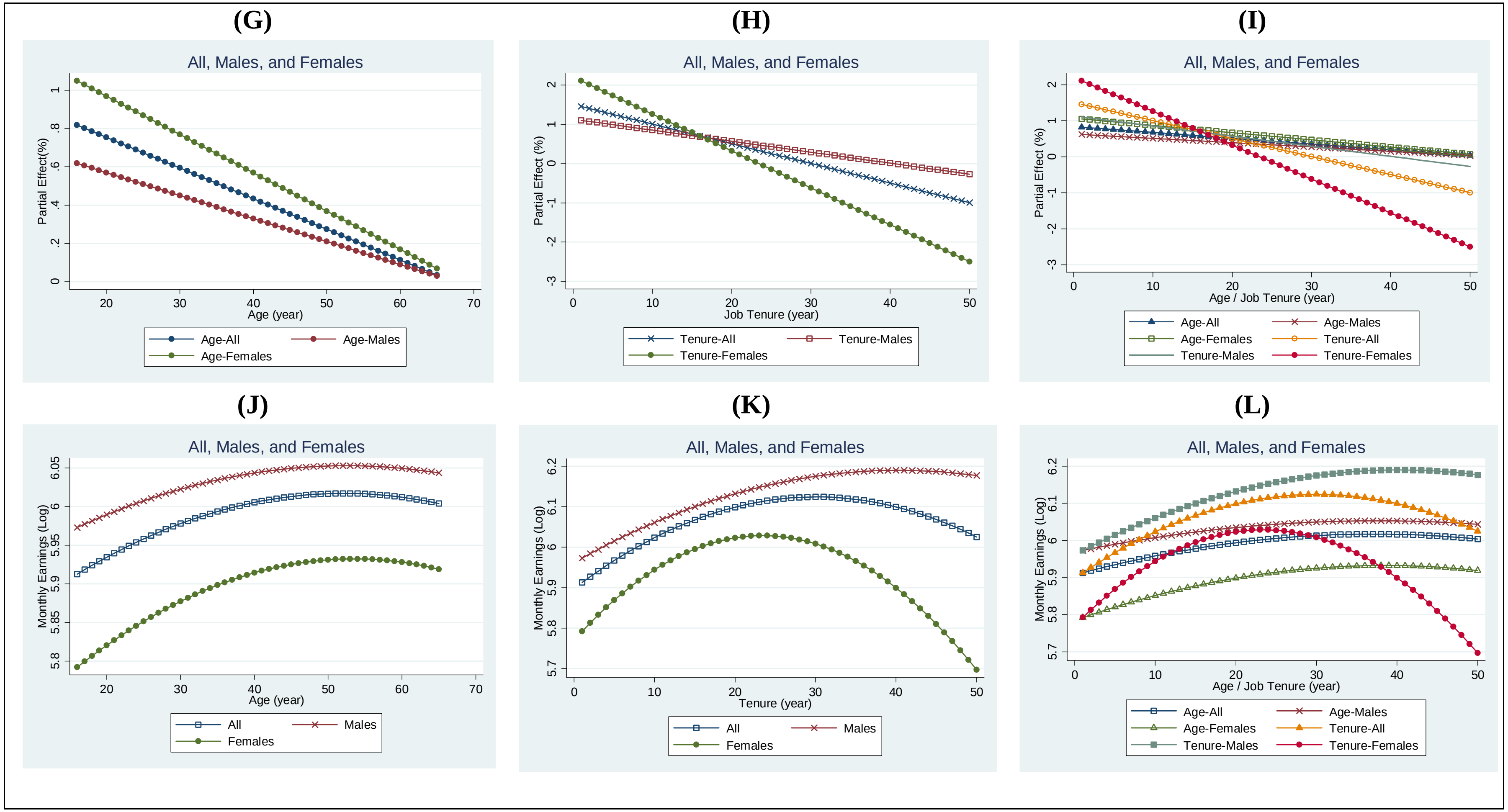
The estimates also suggest that, on average, residents of urban areas receive significantly higher earnings than individuals living in rural areas. Specifically, the findings show that workers from urban areas earn 5.27 (pooled sample), 4.10 (male sample), and 8.90 (female sample) percent more than workers from rural areas. Comparing the male and female samples, the coefficient of the urban dummy variable is higher for females than it is for males. This outcome supports the finding in Chapter 5 when the OLS method was used.

In line with the finding from the OLS model that the marital status variable is significant only for females, the IV results show that being married only has a significant negative effect on the wages of female workers. Married women tend to earn 6.79 percent less than unmarried women.

Figure 6.8: Partial Effect of Age and Partial Effect of Tenure (IV Estimates with Parental Education as Instruments)[27]



[27] In order to avoid presentational problems due to comparing various groups, to construct the bottom three diagrams the mean log earnings is used as the initial level of earnings for both the age and tenure profiles.



Note: In order to have a reasonable comparison, the age-earnings profile that starts from 15 years of age is compared to the tenure-earnings profile that starts from 0 year of job tenure.

Source: Author's calculation based on Table 6.3.

Columns (g) to (l) of Table 6.3 report the IV estimates of the augmented Mincerian model using age in place of potential work experience. Again, parental levels of education are used as instruments. With this specification the reduced-form schooling equation exhibits a lower explanatory power than with potential work experience, though it remains a good predictor of the schooling variables.[28] One additional year of father's (mother's) schooling tends to increase the individual's years of schooling by 0.34 (0.22) years (pooled sample), 0.32 (0.18) years (male sample), and 0.36 (0.30) years (female sample). All of these estimates are highly significant. Therefore, parental years of schooling are indeed correlated with individuals' years of schooling. This result reinforces the results that have been discussed earlier, where it has been concluded that parental education is a good instrument for schooling.

The estimate of the return to schooling is 6.93, 6.61, and 7.38 percent for the pooled, male, and female samples, respectively. These figures are higher than those obtained using OLS, but they are slightly lower compared to the results obtained from the augmented Mincerian model based on experience. The results from the standard Mincerian model using age estimated using IV also reveal a similar pattern, where the return to schooling was higher than that obtained from the application of OLS, but a little bit lower than that obtained when the standard Mincerian model based on the experience variable was estimated using IV. On the average, the OLS estimates are 31.55 percent less than the IV estimates. The average difference between the IV and OLS estimates is 2.19 percentage points. The Hausman test again confirms the necessity to use the IV approach.

Comparisons between the marginal effects of age and the marginal effects of tenure on earnings, and their relationship with the age-earnings and tenure-earnings profiles, can be seen in Figure 6.8. Panels A, B, and C provide comparisons between the marginal effects of age and the marginal effects of tenure on earnings for the pooled, male, and female samples, respectively. In order to capture the relationships between the marginal effects of age and tenure and the age-earnings and tenure-earnings profiles, Panels A, B, and C should be related to Panels D, E, and F, which present the age-earnings and tenure-earnings profiles for the pooled, male, and female

[28] The better explanatory power with the potential work experience variable presumably reflects the use of information on the years of schooling in the construction of that variable. The comparable IV results established using the age variables are therefore reassuring.

samples. The three figures in Panels A, B, and C have similar patterns in that at the beginning of the worker's career the marginal effect of tenure exceeds the marginal effect of age, but later on the marginal effect of age exceeds the marginal effect of tenure. The sole difference between males and females is that the crossing point between the marginal effect of age and the marginal effect of tenure for females comes earlier than that for males. Specifically, for females the crossing point happens after around 15 years of tenure while for males it occurs after around 30 years of tenure. The maximum point of the age-earnings profiles is reached at about 52.13 years of age (pooled sample), 52.50 years (male sample), and 53.45 years (female sample). In Figure 6.8 these points occur at around 37-38 years, since the age-earnings profile that starts from 15 years of age is plotted to start from the 0 point. The tenure-earnings profile reaches its maximum point at about 30.08 years (pooled sample), 40.36 years (male sample), and 23.43 (female sample) years of job tenure.

Panel G (H) compares the marginal effect of age (tenure) for the three samples used in this study. Panel I compares the marginal effects of age and tenure across the samples. The marginal effect of age (tenure) for females drops more rapidly than that of males. Hence, while for the first 37 years of the working period the marginal effect of age for females is greater than that for males, later on females have a smaller marginal effect than males (see Panel G). In Panel H, it can be seen that the marginal effect of tenure on earnings for female workers initially lies above that of male workers for about 16 years. Beyond that crossing point, however, the marginal effect of tenure on earnings for female workers is less than that for male workers.

Panel J (K) compares the age (tenure)-earnings profiles across the samples. Panel L compares the age-earnings and tenure-earnings profiles across the samples. The age-earnings profile for males in Panel J and the tenure-earnings profile for males in Panel K are higher than those for females for the entire work careers covered in the sample. It is seen in Panel L that the age-earnings profiles are much flatter than the tenure-earnings profiles, indicating that an additional year of tenure has a greater percentage impact on earnings than a one year increase in age.

Similar to the finding discussed before, residents of urban areas receive significantly higher earnings than individuals living in the rural areas. The urban effect on earnings is greater for females than it is for males. Female workers from urban areas tend to receive monthly earnings that are 8.81 percent greater than female workers from rural areas. Male workers from urban areas have monthly earnings that are 4.71 percent greater than their counterparts from rural areas. In terms of marital status, this variable has a significant effect for the pooled and females samples. For the pooled sample, being married has a positive impact on workers' earnings, but it has a negative impact on female workers' earnings. Married female workers tend to have monthly earnings that are 5.81 percent less than comparable unmarried female workers.

6.4.2 Instrumenting Schooling with Pre-School Attendance and Delayed Primary School Enrolment

The second set of instruments employed in this empirical study that vary across individuals in a given age category are the dummy variable for pre-school attendance and the variable for delayed primary school enrolment (age of primary school enrolment). The rationale for the pre-school attendance variable as an instrument is that pre-school experiences are linked to school success (Howes, 1988). Pre-school education is a useful preparation for primary schools and is highly effective in developing school readiness. In reading readiness and in number readiness, children with pre-school education are found to be superior to children without pre-school education (Muralidharan and Banerji, 1975). The more recent study by Schütz (2009) supports these findings.

The fact that delay in school enrolment could have an impact on a student's study length at school provides a basis for employing the entry age to primary school as an instrument in attempts to address ability variable bias in the earnings function. This sort of delay could be caused by financial limitations of the parent or malnutrition problems. Glewwe and Jacoby (1995) explained that malnutrition problems could be the reason why children delayed their enrolment in primary school, and in fact found that there was a strong positive effect of early childhood nutritional deficiencies on delayed enrolment. Moreover, students with malnutrition prior to school enrolment performed significantly worse on intelligence tests compared to their well-nourished counterparts. However, as children age the effect of malnutrition tends to decrease. Similarly, Moock and Leslie (1986) and Jamison (1986) conclude that better nourished children complete more grades in school. From this perspective, it is noted that the age of primary school enrolment varies among children in Indonesia. The sample data used in this analysis shows that the age of primary school enrolment ranges from age of 5 to 14, whereas the official age to start grade 1 is 7. For that reason, it seems useful to consider the entry age to primary school when analysing the return to schooling in Indonesia.

In the literature examining the returns to schooling, information on pre-school attendance and delayed primary school education has received little attention. Fortunately the IFLS4 provides data for these two variables and thus enables them to be adopted as instruments in this study. A set of reduced-form regressions for schooling and the IV earnings function using pre-school and delayed primary school enrolment as instruments is reported in Tables 6.4 and 6.5. Before discussing specific coefficients, however, it is worth noting some general points regarding the explanatory power of these regressions. The explanatory power for the first stage estimations is fairly high. For the specifications that employ age instead of experience the value of the R^2 for the first stage estimations is slightly low, with a range of 0.1142 to 0.2070 (range of 0.2070 to 0.3946 with experience). Nevertheless, the *F*-test on the excluded instruments allows us to reject the hypothesis that these variables do not determine the years of schooling, and confirm that those two variables are acceptable instruments.

Instrumenting schooling using pre-school attendance and delayed primary school enrolment for both the standard and the augmented Mincerian models results in an increase in the estimate of the return to schooling, but the increase is lower than those documented for the IV approach using parental levels of education as instruments. The evidence from the Hausman test suggests, however, that instrumenting is necessary, except for standard Mincerian model for the pooled sample.

Based on the standard Mincerian model with, alternatively, the experience and age variables, the return to schooling using IV (OLS) is 6.78 (5.66) and 5.93 (5.07) percent for the pooled sample, 7.67 (5.28) and 6.50 (4.70) percent for male sample, and 8.30 (6.46) and 7.19 (5.88) percent for female sample. In the case of the augmented Mincerian model with, alternatively, the experience and age variables, the return to schooling using IV (OLS) is 7.24 (4.93) and 6.24 (4.72) percent for the pooled sample, 7.08 (4.59) and 6.04 (4.36) percent for male sample, and 7.51 (5.43) and 6.57 (5.26) percent for female sample. Again these results support the finding noted previously that Indonesian female workers receive a higher return to schooling than their male counterparts.

By comparing the marginal effects of potential work experience and that of tenure on earnings, the results from the pooled sample show that the marginal effect of experience is greater than that of tenure on earnings. That is, an additional year of potential labour market experience raises earnings more than an additional year of job tenure does. For example, an additional year of potential work experience (job tenure) increases earnings by 1.013 (1.020), 0.773 (0.520), and 0.533 (0.020) percent after individuals work for 5, 15, and 25 years, respectively.

The marginal effects of experience and tenure on earnings for males follow the same pattern as discussed above for the pooled sample, where the marginal effect of experience is consistently greater than the marginal effect of tenure. For females, the marginal effect of experience exceeds the marginal effect of tenure in the later years only. For example, after working for 10 years an additional year of experience increases earnings by around 0.91 percent, while an additional year of tenure increases earnings by about 1.027 percent. Five years later, which is after working for 15 years, an additional year of potential work experience increases earnings by about 0.78 percent, while an extra year of tenure increases earnings by approximately 0.547 percent.

Similar to the estimations using the parents' years of schooling as instruments, females reach the maximum point of their experience-earnings, age-earnings, and tenure-earnings profiles earlier than males. Using the data in Table 6.5, columns (d) and (f), it can be found that males reach the turning point of their experience-earnings profile when they have 50 years of potential work experience, whereas females reach their turning point five years earlier. After working for about 29.90 years, males reach the maximum point of their tenure-earnings profiles, while females reach the peak of their tenure-earnings profile after working for about 20.70 years.

Table 6.4: Instrumenting Schooling with Pre-School Attendance and Delayed Primary School Enrolment (Standard Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	15.35993	4.97989	14.84314	4.95255	16.66054	4.68170	10.77418	4.78865	9.32669	4.93670	13.01922	4.55216
	(0.44170)***	(0.09387)***	(0.53224)***	(0.11849)***	(0.80352)***	(0.14871)***	(0.75024)***	(0.07831)***	(0.92453)***	(0.09405)***	(1.30878)***	(0.13211)***
Years of Schooling		0.06782		0.07668		0.08304		0.05929		0.06497		0.07192
		(0.00713)***		(0.00908)***		(0.01119)***		(0.00485)***		(0.00613)***		(0.00766)***
Experience	-0.05163	0.01705	-0.06240	0.01456	-0.02247	0.01659						
	(0.01591)***	(0.00200)***	(0.02021)***	(0.00250)***	(0.02622)	(0.00325)***						
Experience^2	-0.00181	-0.00022	-0.00133	-0.00013	-0.00290	-0.00018						
	(0.00035)***	(0.00004)***	(0.00044)***	(0.00005)**	(0.00059)***	(0.00008)**						
Age							0.28993	0.02179	0.32603	0.01374	0.27128	0.01993
							(0.03444)***	(0.00403)***	(0.04268)***	(0.00500)***	(0.05928)***	(0.00681)***
Age^2							-0.00392	-0.00021	-0.00420	-0.00010	-0.00403	-0.00018
							(0.00045)***	(0.00005)***	(0.00055)***	(0.00006)	(0.00078)***	(0.00009)*
Pre-School	1.63510		1.60028		1.67438		2.23412					
	(0.11520)***		(0.14438)***		(0.17431)***		(0.12138)***					
Delayed PS Enrolment	-0.50457		-0.42717		-0.71182		-0.83609					
	(0.06356)***		(0.07505)***		(0.11922)***		(0.06852)***					
R^2	0.2390		0.2076		0.2983		0.1265		0.1142		0.1571	
Adjusted R^2	0.2384		0.2066		0.2964		0.1257		0.1130		0.1549	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality												
F		141.5820		82.5818		59.4900		266.4090		159.9710		104.9960
P-Value		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***
Validity (Sargan test)												
Chi^2		0.00894		0.26696		0.02182		0.76064		0.89377		0.31342
P-Value		0.9247		0.6054		0.8826		0.3831		0.3445		0.5756
Relevance (Hausman test)												
F		2.63995		7.65251		2.99720		3.52364		9.77395		3.37684
P-Value		0.1043		0.0057***		0.0084***		0.0606*		0.0018***		0.0663*

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 6.5: Instrumenting Schooling with Pre-School Attendance and Delayed Primary School Enrolment (Augmented Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	13.38732	4.96300	12.46717	4.98039	15.21565	4.71381	9.22612	4.96191	7.41855	5.00967	12.26908	4.67690
	(0.43893)***	(0.09483)***	(0.52669)***	(0.12308)***	(0.77087)***	(0.14907)***	(0.76607)***	(0.07868)***	(0.92612)***	(0.09555)***	(1.34271)***	(0.13682)***
Years of Schooling		0.07244		0.07076		0.07507		0.06243		0.06040		0.06570
		(0.00848)***		(0.01134)***		(0.01264)***		(0.00547)***		(0.00727)***		(0.00824)***
Experience	-0.12495	0.01133	-0.11753	0.01099	-0.13834	0.01170						
	(0.01714)***	(0.00249)***	(0.02170)***	(0.00310)***	(0.02819)***	(0.00422)***						
Experience ^{2}	-0.00106	-0.00012	-0.00084	-0.00011	-0.00145	-0.00013						
	(0.00037)***	(0.00005)**	(0.00046)*	(0.00006)*	(0.00062)**	(0.00008)						
Age							0.27273	0.00997	0.33044	0.00799	0.21044	0.01207
							(0.03817)***	(0.00444)**	(0.04675)***	(0.00566)	(0.06667)***	(0.00750)
Age ^{2}							-0.00370	-0.00010	-0.00409	-0.00008	-0.00354	-0.00013
							(0.00049)***	(0.00006)*	(0.00060)***	(0.00007)	(0.00088)***	(0.00010)
Tenure	0.12848	0.01270	0.09177	0.00897	0.20350	0.01987	0.03684	0.01533	0.00375	0.01135	0.10885	0.02299
	(0.01640)***	(0.00233)***	(0.01978)***	(0.00264)***	(0.02889)***	(0.00457)***	(0.01812)**	(0.00203)***	(0.02126)	(0.00239)***	(0.03356)***	(0.00384)***
Tenure ^{2}	-0.00097	-0.00025	-0.00062	-0.00015	-0.00198	-0.00048	-0.00126	-0.00026	-0.00105	-0.00014	-0.00187	-0.00049
	(0.00054)***	(0.00007)***	(0.00065)	(0.00008)*	(0.00095)**	(0.00012)***	(0.00060)**	(0.00007)***	(0.00070)	(0.00008)*	(0.00110)*	(0.00012)***
Marital Status	0.78516	-0.02390	0.97477	0.00751	0.47256	-0.06135	-0.11709	-0.00285	-0.36058	0.03843	0.02786	-0.05024
	(0.14636)***	(0.01938)	(0.19999)***	(0.02687)	(0.21615)**	(0.12838)**	(0.16211)	(0.01807)	(0.21676)*	(0.02446)	(0.24895)	(0.02758)
Urban	1.74112	0.06326	1.89853	0.04794	1.37516	0.10176	1.96210	0.07278	2.00502	0.06044	1.80106	0.10588
	(0.09959)***	(0.02049)***	(0.11771)***	(0.02759)*	(0.18374)***	(0.03065)***	(0.10917)***	(0.01753)***	(0.12635)***	(0.02209)***	(0.20909)***	(0.02916)***
Female	-0.09910	-0.19472					-0.15832	-0.19591				
	(0.09812)	(0.01205)***					(0.10763)	(0.01194)***				
Pre-School	1.31002		1.25815		1.37365		1.92411		1.81373		2.06842	
	(0.10990)***		(0.13767)***		(0.18068)***		(0.11889)***		(0.14561)***		(0.20335)***	
Delayed PS Enrolment	-0.45570		-0.35614		-0.68010		-0.74255		-0.63293		2.06842	
	(0.06017)***		(0.07116)***		(0.11092)***		(0.06656)***		(0.07702)***		(0.20335)***	
R^2	0.3249		0.2935		0.3946		0.1859		0.1879		0.2070	
Adjusted R^2	0.3236		0.2916		0.3914		0.1843		0.1858		0.2028	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality												
F		105.7840		57.3667		50.9191		207.2860		118.9620		90.3308
P-Value		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***		0.0000***
Validity (Sargan test)												
Chi ^{2}		0.53469		0.43996		0.28999		1.04707		0.69927		0.56629
P-Value		0.4646		0.5071		0.5902		0.3062		0.4030		0.4517

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
									age proxying experience			
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Relevance (Hausman test)												
F		8.08242		5.21976		2.95308		8.61055		5.90990		2.86310
P-Value		0.0045***		0.0222**		0.0859*		0.0034***		0.0151**		0.0908*

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Comparing the age-earnings and tenure-earnings profiles based on the data in Table 6.5, columns (j) and (l), the results suggest that males (females) reach the peak of their age-earnings profile at the age of 50 (46.42) years. Females reach the peak of their tenure-earnings profile after working for about 23.46 years, and around 17 years later males reach the peak of their tenure-earnings profile, that is after they work for around 40.54 years.

Urban area of residence has a significant effect on earnings in all 6 estimations in favour of workers who live in urban areas. The magnitude of the urban area of residence effect on earnings ranges from about 4.79 percent to 10.59 percent. This result supports the finding discussed previously, both in Chapter 5 and the earlier part of this chapter.

Marital status is statistically significant only for females in the estimation based on the experience variables. The result suggests that married females earn 6.24 percent less than unmarried females.

6.4.3 Instrumenting Schooling with Compulsory School Attendance Laws

The next category of instruments used in this study are variables that are the same for all individuals in a given age category. These comprise dummy variables for the compulsory school attendance laws and the INPRES program. Compulsory school attendance laws have been employed as instruments by many researchers. These researchers usually utilise changes in compulsory education laws directly as an instrument in the form of a dummy variable, or they focus on the specific number of years of compulsory study or the age of children who must stay at school. In this empirical study, compulsory school attendance laws are treated as dummy variables. A 6 years compulsory school attendance law was launched in 1984. Ten years after the first compulsory school attendance law was implemented, a 9 years compulsory school attendance law was introduced in 1994. Hence, there are two dummy variables for compulsory school attendance laws for this analysis. Individuals who were born in 1977 and later are assumed as the persons who were affected by the first compulsory education policy. Then these individuals are given a value of 1 for the dummy variable of the first compulsory school attendance law (CSAL-1), and all other individuals are assigned a value of zero. The 1977 threshold is derived from the year when the first compulsory school attendance law was launched (1984) minus the official age to start primary education (7 year). The dummy variable for the second compulsory school attendance law (CSAL-2) is derived using the same logic as with CSAL-1, where 1 is for individuals who were born in 1987 and later and a 0 is assigned to all other individuals. If compulsory schooling laws forced people to get more schooling than they would have chosen otherwise then individuals who spent their teens after the compulsory school attendance laws were implemented should have more years of schooling. Although compulsory school attendance laws have been adopted in many previous studies (Levin and Plug, 1999; Leigh and Ryan, 2005 and 2006) this is the first attempt to employ these instruments in the study of the returns to schooling in Indonesia.

Tables 6.6 and 6.7 present estimates from the specification that uses the compulsory school attendance laws as instruments. Using these instruments, there are some major points that need to be noted. First, the R squareds of the first stage of the estimation based on experience are relatively high. This suggests that there have been major changes in schooling attainment over time, and the compulsory school law variables capture much of these changes. Second, the compulsory school attendance dummy variables both appear, at first glance, to have an unexpected sign. In particular, both the variables, which are thought to be associated with greater educational attainment, have negative estimated coefficients. However, this appears to be simply an artifact of the control for potential labour market experience. Hence, consider two workers of adjacent ages at the time of survey in 2007/2008, where the older worker was not affected by the compulsory school attendance in 1994 and the younger worker was. To have the same potential labour market experience, which is held constant in the schooling regression, the younger worker must have attended school for fewer years. This is confirmed when the schooling equation is estimated replacing potential labour market experience by age. In this set of estimations the variables for the two compulsory school attendance laws have positive coefficients, although only that in the equation for females is statistically significant. Third, in the case of the estimations using age, the R squareds of the first stage are fairly high, yet the values of the *F*-test on the instruments indicate that the dummy variables for compulsory education are not valid instruments for the pooled and male samples. Fourth, while the relationship between years of schooling and earnings is statistically significant for all estimations based on the potential labour market experience variables, the schooling variable is not significant in any of the estimations using age as the proxy for experience. Given these apparent deficiencies, the results based on the compulsory school attendance laws as instruments will not be discussed further here.

Table 6.6: Instrumenting Schooling with Compulsory School Attendance Laws (Standard Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		Males		Females		All		Males		Females	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	25.16895	5.12178	25.30784	5.29942	25.13737	4.73604	4.96995	4.55508	4.43603	3.87379	3.62177	5.58830
	(0.27961)***	(0.04173)***	(0.34618)***	(0.04875)***	(0.48803)***	(0.07394)***	(1.36008)***	(0.41659)***	(1.72627)***	(1.23458)***	(2.27073)	(0.58323)***
Years of Schooling		0.05684		0.04959		0.07887		0.09280		0.24646		-0.05933
		(0.00291)***		(0.00337)***		(0.00523)***		(0.05876)		(0.20837)		(0.07040)
Experience	-0.76904	0.01605	-0.79420	-0.79420	-0.73612	0.01632						
	(0.01950)***	(0.00190)***	(0.02416)***	(0.02416)***	(0.03410)***	(0.00317)***						
Experience^2	0.00749	-0.00024	0.00822	-0.00016	0.00634	-0.00019						
	(0.00036)***	(0.00004)***	(0.00044)***	(0.00005)***	(0.00063)***	(0.00007)***						
Age							0.33484	0.01341	0.35066	-0.03896	0.41020	0.05103
							(0.05969)***	(0.01526)	(0.07552)***	(0.06132)	(0.10028)***	(0.01939)***
Age^2							-0.00469	-0.00008	-0.00473	0.00064	-0.00576	-0.00071
							(0.00066)***	(0.00023)	(0.00083)***	(0.00087)	(0.00114)***	(0.00031)**
CSAL-1	-4.80266		-4.78421		-4.87563		0.09012		0.07209		0.34846	
	(0.12946)***		(0.15352)***		(0.24069)***		(0.20436)		(0.24524)		(0.37340	
CSAL-2	-4.38260		-4.29310		-4.59882		0.44273		0.29315		0.91005	
	(0.13818)***		(0.16156)***		(0.26178)***		(0.22885)*		(0.27248)		(0.42134)**	
R^2	0.4709		0.4610		0.4920		0.0259		0.0219		0.0443	
Adjusted R^2	0.4705		0.4603		0.4906		0.0251		0.0206		0.0418	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality												
F		1209.63		840.804		373.041		1.87207		0.57893		2.48784
P-Value		0.0000***		0.0000***		0.0000***		0.1539		0.5606		0.0834*
Validity (Sargan test)												
Chi^2		2.46881		1.85955		2.99415		2.04907		0.02973		4.87454
P-Value		0.1161		0.1727		0.0836*		0.1523		0.8631		0.0273**
Relevance (Hausman test)												
F		0.00784		1.38727		11.319		0.59447		4.36491		6.51706
P-Value		0.9294		0.2389		0.0008***		0.4407		0.0368**		0.0108**

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 6.7: Instrumenting Schooling with Compulsory School Attendance Laws (Augmented Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		Males		Females		All		Males		Females	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	22.79847	5.19023	22.71940	5.27480	22.90201	4.78000	3.16191	4.96365	2.71972	4.31638	2.53854	5.60343
	(0.29876)***	(0.04015)***	(0.36676)***	(0.04750)***	(0.51020)***	(0.07459)***	(1.33256)***	(0.28151)***	(1.66312)	(0.78000)***	(2.25941)	(0.50154)***
Years of Schooling		0.05149		0.04287		0.06752		0.06211		0.22143		-0.06402
		(0.00306)***		(0.00364)***		(0.00569)***		(0.04997)		(0.17665)		(0.06533)
Experience	-0.77043	0.00803	-0.77377	0.00691	-0.77361	0.01034						
	(0.01962)***	(0.00211)***	(0.02427)***	(0.00261)***	(0.03393)***	(0.00367)***						
Experience^2	0.00725	-0.00013	0.00762	-0.00012	0.00683	-0.00014						
	(0.00036)***	(0.00004)***	(0.00045)***	(0.00006)**	(0.00064)***	(0.00008)*						
Age							0.33293	0.01004	0.36333	-0.03985	0.35393	0.03400
							(0.06095)***	(0.01261)	(0.07587)***	(0.05344)	(0.10456)***	(0.01557)**
Age^2							-0.00456	-0.00010	-0.00464	0.00056	-0.00522	-0.00057
							(0.00069)***	(0.00019)	(0.00085)***	(0.00071)	(0.00120)***	(0.00027)**
Tenure	0.04682	0.01554	0.02469	0.01168	0.09442	0.02149	0.04406	0.01535	0.00897	0.01003	0.12290	0.03840
	(0.01388)***	(0.00203)***	(0.01651)	(0.00238)***	(0.02532)***	(0.00385)***	(0.01896)**	(0.00295)***	(0.02209)	(0.00480)**	(0.03562)***	(0.00953)***
Tenure^2	0.00102	-0.00028	0.00110	-0.00017	0.00059	-0.00049	-0.00148	-0.00026	-0.00123	0.00005	-0.00222	-0.00076
	(0.00045)**	(0.00007)***	(0.00054)**	(0.00008)***	(0.00082)	(0.00012)***	(0.00062)**	(0.00010)***	(0.00073)*	(0.00026)	(0.00117)*	(0.00023)***
Marital Status	0.99603	-0.00643	1.04785	0.03579	0.88180	-0.05729	-0.11659	-0.00288	-0.36439	0.09503	-0.00990	-0.04115
	(0.12365)***	(0.01790)	(0.16743)***	(0.02404)	(0.18738)***	(0.02749)**	(0.17127)	(0.01866)	(0.22789)	(0.07765)	(0.26639)	(0.04131)
Urban	1.35290	0.10398	1.46076	0.10619	1.09016	0.11366	2.33299	0.07353	2.35296	-0.31874	2.18527	0.38998
	(0.08372)***	(0.01334)***	(0.09789)***	(0.01578)***	(0.15821)***	(0.02475)***	(0.11233)***	(0.11729)	(0.12906)***	(0.41683)	(0.21826)***	(0.14708)***
Female	-0.12586	-0.19385					0.06416	-0.19589				
	(0.08372)	(0.01182)***					(0.11190)	(0.01231)***				
CSAL-1	-4.51541		-4.52750		-4.38997		0.15902		0.11926		0.50652	
	(0.12551)***		(0.14831)***		(0.23420)***		(0.19835)		(0.23543)		(0.36595)	
CSAL-2	-4.03935		-3.90868		-4.33606		0.46327		0.29935		0.88423	
	(0.13260)***		(0.15587)***		(0.24849)***		(0.21878)**		(0.25808)		(0.40697)**	
R^2	0.5243		0.5134		0.5507		0.1132		0.1251		0.1162	
Adjusted R^2	0.5234		0.5121		0.5483		0.1115		0.1228		0.1115	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality												
F		1111.42		773.934		333.027		2.28047		0.68834		2.85966
P-Value		0.0000***		0.0000***		0.0000***		0.1024		0.5025		0.0576*
Validity (Sargan test)												
Chi^2		3.45884		2.43180		1.29281		5.34534		0.22819		1.84850
P-Value		0.0629*		0.1189		0.2555		0.0208**		0.6329		0.1740

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
									age proxying experience			
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Relevance (Hausman test)												
F		0.76210		1.01695		7.85956		0.09063		3.81439		7.19283
P-Value		0.3827		0.3133		0.0051***		0.7634		0.0509*		0.0074***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

6.4.4 Instrumenting Schooling with the INPRES Program

We turn now to the last instrument exploited in this analysis - the INPRES program. The Indonesian government received considerable revenue from the oil boom in the 1970s, and it used part of this revenue to finance centrally administered development programs, called the presidential instruction (INPRES). The *Sekolah Dasar* (Primary School) INPRES program was launched in 1973-1974. More than 61,800 new primary schools were constructed, and this represented about one school per 500 children aged 5 to 14. This program was reported as the fastest primary school construction program ever undertaken in the world (Duflo, 2001).

It is believed that investment in schooling infrastructure has an impact on educational attainment for the more recent cohorts in Indonesia. More specifically it is assumed that the presence of more schools raises the probability of enrolment. Based on this argument, the INPRES program is utilised as an instrument when estimating the returns to schooling. A dummy variable is formed. It is assumed that this program has an impact on the education attainment for individuals who were born in 1967 (1974 - 7) and later. The year of 1974 refers to the year when the primary school buildings were completely constructed by the INPRES program and 7 is the official age to start primary education. Hence, the variable for the INPRES program is 1 if individuals were born after 1967 and zero for all other individuals.

Table 6.8 (Table 6.9) presents the estimates of the earnings equation using the INPRES program as an instrument based on the standard (augmented) Mincerian model. Instrumenting schooling using the INPRES program leads to some inconsistent results. The specifications employing experience have reasonable R squareds in the first stage estimation, which are 0.3076 (0.3824), 0.2912 (0.3720), and 0.3391 (0.4116) for the pooled, male, and female samples. However, the INPRES program variable has an unexpected sign in each of these three samples. In the case of the specification using age in place of experience, the dummy variable for the INPRES program has the expected positive sign, nevertheless the R squareds of the first stage in the standard Mincerian model are very low, being 0.0277, 0.0228, and 0.0481 for the pooled, male, and female samples, respectively. Hence the correlations between this instrument and schooling are questionable, and we therefore do not discuss these results further.

Table 6.8: Instrumenting Schooling with a Dummy Variable for the INPRES Program (Standard Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	18.45375	4.98875	18.53952	5.01570	18.22468	4.87494	6.08515	5.44098	5.21815	6.38918	6.47860	4.81773
	(0.24665)***	(0.06142)***	(0.30896)***	(0.07088)***	(0.41805)***	(0.11275)***	(0.71198)***	(0.28401)***	(0.89176)***	(0.76421)***	(1.20090)***	(0.27670)***
Years of Schooling		0.06713		0.07175		0.06821		-0.03429		-0.18304		0.03828
		(0.00454)***		(0.00524)***		(0.00837)***		(0.03863)		(0.12547)		(0.03166)
Experience	-0.17090		-0.18529	0.01408	-0.13755	0.01564						
	(0.01529)***		(0.01932)***	(0.00237)***	(0.02565)***	(0.00317)***						
Experience^2	-0.00309		-0.00259	-0.00013	-0.00416	-0.00022						
	(0.00034)***		(0.00042)***	(0.00005)***	(0.00058)	(0.00007)***						
Age							0.24021	0.04517	0.28533	0.08574	0.21499	0.02790
							(0.03635)***	(0.01083)***	(0.04481)***	(0.03813)**	(0.06315)***	(0.01002)***
Age^2							-0.00331	-0.00056	-0.00379	-0.00112	-0.00311	-0.00031
							(0.00049)***	(0.00016)***	(0.00059)***	(0.00054)**	(0.00088)***	(0.00015)**
INPRES Program	-4.64872		-4.70941		-4.49362		0.76871		0.52434		1.32520	
	(0.16796)***		(0.20167)***		(0.30243)***		(0.21878)***		(0.26107)**		(0.39682)***	
R^2	0.3076		0.2912		0.3391		0.0277		0.0228		0.0481	
Adjusted R^2	0.3072		0.2905		0.3378		0.0271		0.0219		0.0462	
Observations	4596	4596	3065	3065	1531	1531	3065	3065	3065	3065	1531	1531
Test Results												
Quality												
F		766.077		545.341		220.771		12.3451		4.03372		11.1525
P-Value		0.0000***		0.0000***		0.0000***		0.0004***		0.0447**		0.0009***
Relevance (Hausman test)												
F		6.29776		15.9523		0.21343		8.00219		20.3375		0.43927
P-Value		0.0121**		0.0001***		0.6442		0.0047***		0.0000***		0.5076

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 6.9: Instrumenting Schooling with a Dummy Variable for the INPRES Program (Augmented Mincerian Model)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
							age proxying experience					
	All		**Males**		**Females**		**All**		**Males**		**Females**	
Variable	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings	Reduced-Form Schooling	IV-Earnings
Constant	15.91274	5.07360	15.88886	5.01554	15.71235	5.02911	4.47174	5.53319	3.66807	6.10877	5.46893	4.68936
	(0.26619)***	(0.05845)***	(0.32347)***	(0.06622)***	(0.45230)***	(0.12511)***	(0.72532)***	(0.21557)***	(0.88932)***	(0.58450)***	(1.24147)***	(0.22086)***
Years of Schooling		0.06225		0.06743		0.04747		-0.04255		-0.19488		0.06396
		(0.00497)***		(0.00567)***		(0.01048)***		(0.03560)		(0.12597)		(0.02566)**
Experience	-0.23415	0.00972	-0.23898	0.01050	-0.22954	0.00672						
	(0.01652)***	(0.00221)***	(0.02070)***	(0.00273)***	(0.02776)***	(0.00399)*						
Experience^2	-0.00198	-0.00012	-0.00172	-0.00011	-0.00231	-0.00016						
	(0.00036)***	(0.00005)***	(0.00044)***	(0.00006)*	(0.00062)***	(0.00008)**						
Age							0.23056	0.03492	0.29479	0.08384	0.14427	0.01236
							(0.03976)***	(0.01010)***	(0.04841)***	(0.03950)**	(0.07019)**	(0.00854)
Age^2							-0.00311	-0.00048	-0.00369	-0.00109	-0.00237	-0.00013
							(0.00053)***	(0.00015)***	(0.00063)***	(0.00053)**	(0.00096)**	(0.00013)
Tenure	0.11126	0.01409	0.07992	0.00929	0.17921	0.02578	0.04597	0.01985	0.00961	0.01344	0.12734	0.02320
	(0.01570)***	(0.00211)***	(0.01865)***	(0.00245)***	(0.02858)***	(0.00427)***	(0.01890)**	(0.00304)***	(0.02206))	(0.00585)**	(0.03534)***	(0.00480)***
Tenure^2	-0.00104	-0.00027	-0.00066	-0.00015	-0.00206	-0.00054	-0.00149	-0.00041	-0.00124	-0.00045	-0.00219	-0.00049
	(0.00051)**	(0.00007)***	(0.00061)	(0.00008)*	(0.00093)**	(0.00012)***	(0.00062)**	(0.00010)***	(0.00073)*	(0.00024)*	(0.00116)*	(0.00013)***
Marital Status	1.10092	-0.01540	1.38934	0.01089	0.69160	-0.04651	-0.15077	-0.01273	-0.40062	-0.05129	0.00884	-0.05012
	(0.14028)***	(0.01829)	(0.18913)***	(0.02482)***	(0.21325)***	(0.02778)*	(0.16960)	(0.02369)	(0.22608)*	(0.07354)	(0.26219)**	(0.02758)*
Urban	1.69167	0.08308	1.82836	0.05490	1.35575	0.14532	2.33019	0.31789	2.34846	0.66157	2.20114	0.10970
	(0.09481)***	(0.01541)***	(0.11029)***	(0.01838)***	(0.18061)***	(0.02830)***	(0.11217)***	(0.08456)***	(0.12897)***	(0.29853)**	(0.21740)***	(0.06066)*
Female	-0.04242	-0.19430					0.08223	-0.18948				
	(0.09343)	(0.01189)***					(0.11175)	(0.01564)***				
INPRES Program	-4.14861		-4.35347		-3.60358		0.81929		0.51532		1.57306	
	(0.16173)***		(0.19251)***		(0.29535)***		(0.21015)***		(0.24856)**		(0.38385)***	
R^2	0.3824		0.3720		0.4116		0.1152		0.1259		0.1225	
Adjusted R^2	0.3813		0.3706		0.4089		0.1137		0.1239		0.1185	
Observations	4596	4596	3065	3065	1531	1531	4596	4596	3065	3065	1531	1531
Test Results												
Quality												
F		657.986		511.431		148.862		15.1989		4.29825		16.7947
P-Value		0.0000***		0.0000***		0.0000***		0.0001***		0.0382**		0.0000***
Relevance (Hausman test)												
F		7.86419		17.5227		0.46422		10.9754		21.5211		0.19955
P-Value		0.0051***		0.0000***		0.4958		0.0009***		0.0000***		0.6552

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

6.4.5 Instruments Quality, Validity, and Relevance

To evaluate whether the *instruments* used in this analysis are appropriate the quality, validity, and relevance criteria of the instruments are introduced. Table 6.10 collates the information on the quality, validity, and relevance of the instruments that has been presented in the lower panel of each table (Tables 6.2, 6.3, 6.4, 6.5, 6.6, 6.7, 6.8, and 6.9). The first test is for the quality of the instruments. This can be assessed by examining the correlation between the instruments and schooling. The ***F***-test of the joint significant of the respective instrument sets in their first stage equation has been undertaken. The results show that parental education as well as pre-school attendance and delayed primary school enrolment prove to be satisfactorily correlated with schooling for all specifications and samples. Furthermore the R squareds from the first stage equations are at a reasonable level, which ranges from 11 percent (the lowest) to 41 percent (the highest). With INPRES programs, although the *F*-tests show that these instruments seem correlated with schooling, some of the R squareds from the first stage equations are very low, specifically they are around 2 percent. The compulsory school attendance laws appear well correlated with schooling for all samples using experience, but only two of the six estimations using age are characterised by a significant correlation between these instruments and schooling.

The second criterion is the validity of the instruments. An instrument is categorised as a valid instrument if it affects earnings through schooling only. This can be assessed using the over-identification restriction test (Sargan or Basmann test). The results suggest that there is no over-identification problem in any of the specifications that employ parents' years of schooling and pre-school attendance and delayed primary school enrolment as instruments. These test results therefore confirm that these instruments are valid. An over-identification problem is found in the standard Mincerian model using age for the pooled sample and in the augmented Mincerian model using either experience or age for the pooled sample when compulsory schooling attendance laws are employed as instruments. These results, that support a direct influence of compulsory school attendance laws on earnings, thus suggest these instruments are of dubious value.

The final criterion is relevance. The relevance of the instrument is to answer the most essential question, whether instrumenting the schooling variable is necessary or not?

To answer this question, the Hausman test can be applied (Hausman, 1978). This study finds that when using parents' education as instruments, the results for all samples and specifications show that the endogeneity of schooling significantly affects the estimated return to schooling, meaning that the IV approach is necessary. When pre-school attendance and delayed primary school enrolment are used as instruments, the results suggest that adopting the IV approach is necessary for almost all specifications and samples, except for the standard Mincerian model based on experience for the pooled sample. When instrumenting schooling using the compulsory school attendance laws, the Hausman test confirms the necessity to use an IV approach for the female sample in the standard and the augmented Mincerian models based on experience, and in the pooled and male samples when using the standard and the augmented Mincerian models based on age. When using the INPRES program as an instrument, the Hausman test rejects the null hypothesis of equality of the OLS and IV estimates for the pooled and male samples.

The CSAL-1, the CSAL-2, and the INPRES program variables apparently do not perform well as instruments in this study. The following reason may explain this. When instrumenting schooling, the CSAL-1, the CSAL-2, and the INPRES program variable are formed into dummy variables based on the birth year of the individuals. This form for these variables appears to create a correlation between these instruments and the age and potential work experience variables, so that what is captured in the estimations is simply a shift in the age-schooling or experience-schooling relationships rather than the independent effect of the particular laws and program.

Based on these quality, validity, and relevance criteria, it can be summarised that the variables that vary across individuals in a given age category perform better as instruments for schooling than the variables that are the same for all individuals in a given age category. More specifically, it can be concluded that among all the instruments utilised in this analysis, parents' levels of education perform the best and appear to be the most consistent instruments. This result is in line with research by Levin and Plug (1999), Li and Luo (2004), and Lemke and Rischall (2003).

Table 6.10: Quality, Validity, and Relevance of the Instruments

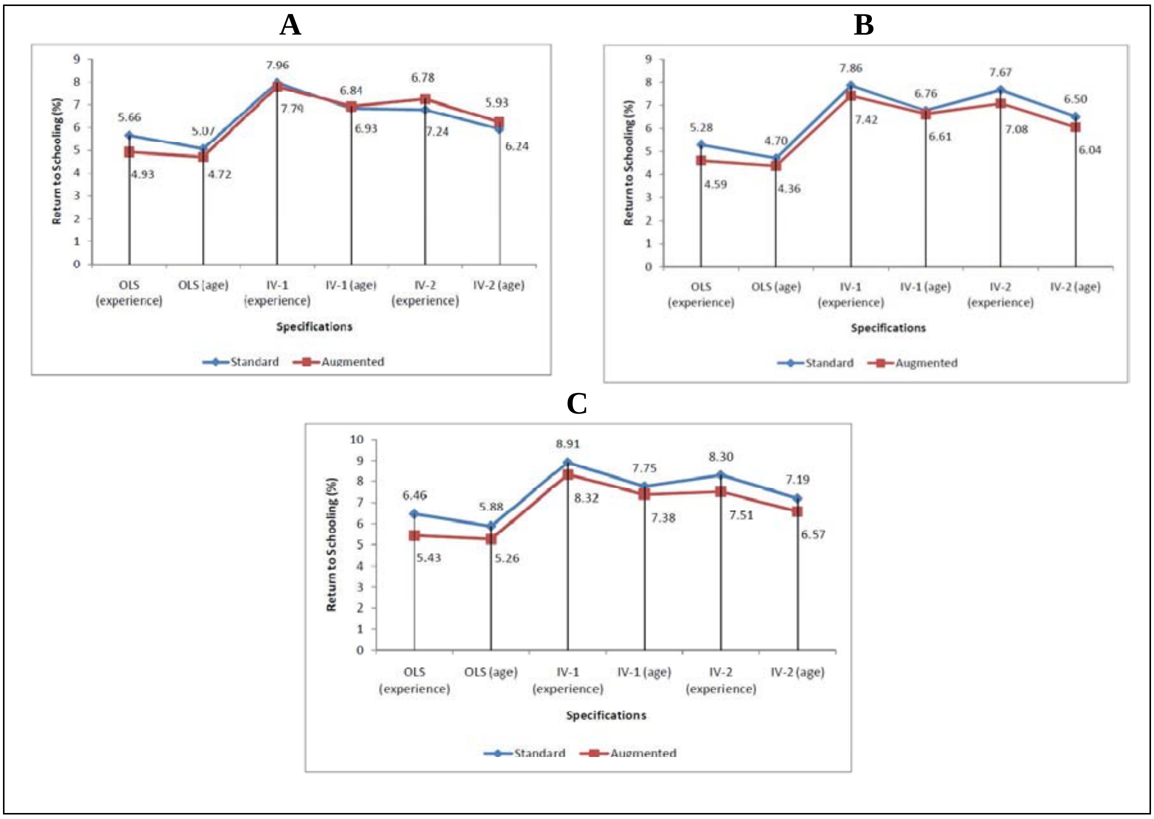
		Standard Mincerian						Augmented Mincerian					
					age proxying experience						age proxying experience		
		All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Parents' years of schooling as instruments													
Quality													
	R^2	0.3547	0.3126	0.4328	0.2611	0.2344	.0.3185	0.4140	0.3697	0.1689	0.2948	0.2751	0.3538
	F	578.197	328.687	254.635	733.108	425.292	310.516	470.416	249.088	228.044	593.348	317.171	283.715
	P-Value	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Validity													
	Chi^2	1.09176	1.50852	0.02328	0.79617	1.28249	2.5e-06	0.79358	1.31205	0.00021	0.57412	1.17452	0.01054
	P-Value	0.2961	0.2194	0.8787	0.3722	0.2574	0.9987	0.3730	0.2520	0.9884	0.4486	0.2785	0.9182
Relevance													
	F	45.9312	35.9206	22.9775	41.4677	34.5832	20.4052	55.4416	29.4551	25.9323	52.3454	28.3995	23.9579
	P-Value	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Pre-School Attendance and Delayed Primary School Enrolment as instruments													
Quality													
	R^2	0.2390	0.2076	0.2983	0.1265	0.1142	0.1571	0.3249	0.2935	0.3946	0.1859	0.1879	0.2909
	F	141.582	82.5818	59.49	266.409	159.971	104.996	105.784	57.3667	50.9191	207.286	118.962	90.3308
	P-Value	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Validity													
	Chi^2	0.00894	0.26696	0.02182	0.76064	.89377	0.31342	0.53469	0.43996	0.28999	1.04707	0.69927	0.56629
	P-Value	0.9247	0.6054	0.8826	0.3831	0.3445	0.5756	0.4646	0.5071	0.5902	0.3062	0.4030	0.4517
Relevance													
	F	2.63995	7.65251	2.9972	3.52364	9.77395	3.37684	8.08242	5.21976	2.95308	8.61055	5.9099	2.8631
	P-Value	0.1043	0.0057***	0.00836***	0.0606*	0.0018***	0.0663*	0.0045***	0.0222**	0.0859*	0.0034***	0.0151**	0.0908*
Compulsory School Attendance Laws as instruments													
Quality													
	R^2	0.4709	0.4610	0.4920	0.0259	0.0219	0.0443	0.5243	0.5134	0.5507	0.1132	0.1251	0.1162
	F	1209.63	840.804	373.041	1.87207	0.57893	2.48784	1111.42	773.934	333.027	2.28047	0.68834	2.85966
	P-Value	0.0000***	0.0000***	0.0000***	0.1539	0.5606	0.0834*	0.0000***	0.0000***	0.0000***	0.1024	0.5025	0.0576*
Validity													
	Chi^2	2.46881	1.85955	2.99415	2.04907	0.02973	4.87454	3.45884	2.4318	1.29281	5.34534	0.22819	1.8485
	P-Value	0.1161	0.1727	0.0836*	0.1523	0.8631	0.0273**	0.0629*	0.1189	0.2555	0.0208**	0.6329	0.1740
Relevance													
	F	0.00784	1.38727	11.319	0.59447	4.36491	6.51706	0.76210	1.01695	7.85956	0.09063	3.81439	7.19283
	P-Value	0.9294	0.2389	0.0008***	0.4407	0.0368**	0.0108**	0.3827	0.3133	0.0051***	0.7634	0.0509*	0.0074***
INPRES Program as an instrument													
Quality													
	R^2	0.3076	0.2912	0.3391	0.0277	0.0228	0.0481	0.3824	0.3720	0.4116	0.1152	0.1259	0.1225
	F	766.077	545.341	220.771	12.3451	4.03372	11.1525	657.986	511.431	148.862	15.1989	4.29825	16.7947
	P-Value	0.0000***	0.0000***	0.0000***	0.0004***	0.0447**	0.0009***	0.0000***	0.0000***	0.0000***	0.0001***	0.0382**	0.0000***
Relevance													
	F	6.29776	15.9523	0.21343	8.00219	20.3375	0.43927	7.86419	17.5227	0.46422	10.9754	21.5211	0.19955
	P-Value	0.0121**	0.0001***	0.6442	0.0047***	0.0000***	0.5076	0.0051***	0.0000***	0.4958	0.0009***	0.0000***	0.6552

Sources: Tables 6.2, 6.3, 6.4, 6.5, 6.6, 6.7, and 6.8.

6.4.6 All Estimates Compared: OLS versus IV

Figure 6.9 provides an overview of the estimated return to schooling obtained using the OLS and IV approaches. Panels A, B, and C present the comparison of the return to schooling obtained using the OLS and IV approaches based on the standard and augmented Mincerian models for the combined, male, and female samples, respectively. Based on Figure 6.9, three characteristics of the estimated return to schooling in Indonesia can be readily identified.

Figure 6.9: Return to Schooling: OLS versus IV



Notes: IV-1 is the IV approach using parental education as instruments; IV-2 is the IV approach using pre-school attendance and delayed primary school enrolment as instruments.
Source: Author's calculation based on Tables 5.4, 5.5, 6.2, 6.3, 6.4, and 6.5.

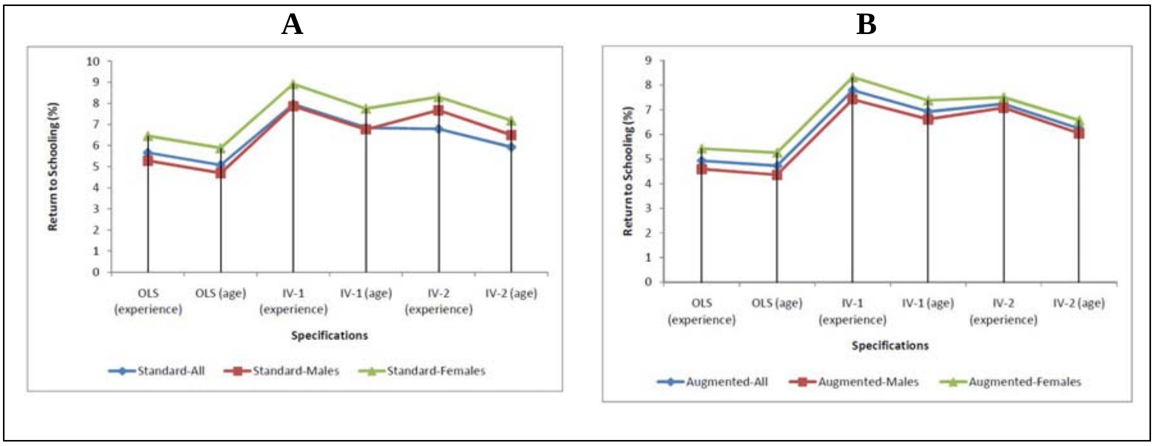
Firstly, in general the return to schooling based on the augmented Mincerian model is higher than that based on the standard Mincerian model. There are three modest exceptions to this general finding, namely the estimate obtained using the IV approach based on age with parental education as instruments and the IV approach based on experience and age with pre-school attendance and delayed primary school enrolment as instruments for the pooled sample. On average the return to schooling based on the augmented Mincerian model is 0.42, 0.45, and 0.67 percentage points lower than that obtained from the standard Mincerian model for the pooled, male and female samples, respectively.

Secondly, adopting the IV approach leads to a higher return to schooling than that obtained using the OLS approach. The return to schooling obtained from applying OLS to the standard Mincerian model based on experience (age) is 5.66 (5.07), 5.28 (4.70), and 6.46 (5.38) percent for the combined, male, and female samples, respectively. Applying the IV approach with parental education as instruments, the return to schooling increases by around 2.30 (1.77), 2.58 (2.06), and 2.45 (1.87) percentage points to 7.96 (6.84), 7.86 (6.76), and 8.91 (7.75) percent for the pooled, male, and female samples, respectively. When the parental schooling instruments are replaced by pre-school attendance and delayed primary school enrolment the return to schooling appears to be 6.78 (5.93), 7.67 (6.50), and 8.30 (7.19) percent for the combined, male and female samples, respectively. That is, the return to schooling increases by about 1.12 (0.86), 2.39 (1.80), and 1.84 (1.31) percentage points, respectively, for the combined, male, and female samples.

For the augmented Mincerian model based on experience (age) the return to schooling obtained using the OLS approach is 4.93 (4.72), 4.59 (4.36), and 5.43 (5.26) percent, respectively for the full, male, and female samples. Using the IV approach with parental education as instruments the return to schooling increases by approximately 2.86 (2.21), 2.83 (2.25), and 2.89 (2.12) percentage points to 7.79 (6.93), 7.42 (6.61), and 8.32 (7.38) percent, respectively, for the full, male, and female samples. Utilising pre-school attendance and delayed primary school enrolment as instruments for the IV approach with this augmented model, the return to schooling for the combined, male and female samples increases to 7.24 (6.24), 7.08 (6.04), and 7.51 (6.57) percent, respectively. All of the above patterns confirm the existence of downward bias on the OLS estimate of the return to schooling. In other words, this finding is in line with a stylised fact in the mainstream literature that the return to schooling derived using OLS may be biased downward (Angrist and Krueger, 1991; Levin and Plug, 1999; Plug, 2002; Li and Luo, 2004; Lemke and Rischall, 2003).

Thirdly, all of the estimations based on age lead to a somewhat lower return to schooling compare to that of the comparable estimations based on experience. This result is consistent with Blinder's (1976) finding. On average the estimated return to schooling based on age obtained using the OLS method is about 0.39 percentage point lower than that based on experience. The IV estimations based on age are also associated with a smaller estimated return to schooling than the estimations based on experience, by approximately 1.01 percentage points.

Figure 6.10: Return to Schooling by Gender



Notes: IV-1 is the IV approach using parental education as instruments; IV-2 is the IV approach using pre-school attendance and delayed primary school enrolment as instruments.
Source: Author's calculation based on Tables 5.4, 5.5, 6.2, 6.3, 6.4, and 6.5.

Figure 6.10 compares the estimated return to schooling across the specifications and methods of estimation by gender. Panel A (B) of Figure 6.10 compares the estimated return to schooling across the specifications and methods of estimation based on the standard (augmented) Mincerian model for the pooled, male, and female samples. It is clearly seen from these two figures that the estimated returns to schooling for females are higher than those of males for all the specifications and methods of estimation. The differences in returns to schooling between males and females are not very large, however. They range from 0.43 to 1.18 percentage points. This result reinforces the result in Chapter 5 and it is akin to the results of the study by Behrman and Deolalikar

(1993, 1995) in Indonesia, Miller *et al.* (1997) in Australia, Flanagan (1998) in the Czech Republic, Brunello *et al.* (2000) in Italy, Lopez-Avecedo (2001) in Mexico, and Asadullah (2006) in Bangladesh.

6.4.7 Financial Gain from an Extra Year at School

So far the discussion on the rate of return to schooling in this chapter has focused only on the benefits of an additional year of schooling, ignoring, other than to the extent that it is implicitly recognised in the theoretical development of the Mincerian model, the costs of schooling. To explore an alternative framework for assessing the present value of the financial gains from an extra year of schooling, this study follows Oreopolous (2003) and Leigh and Ryan (2005, 2008).

First, we need to derive the age-earnings profiles for two individuals with one year difference in their years of schooling over their entire working period.[29] Figure 6.11 presents the projected earnings of individuals with, respectively, 9 and 10 years of schooling using "the IV augmented Mincerian model" with parental education as instruments.[30] Panels A, B, and C present projected lifetime earnings for such individuals across the three samples used in this study. The monthly earnings used in the regression analysis are converted to annual equivalents for this analysis.[31] Based on the projected earnings, it can be estimated that individuals who left school at age 16 with 9 years of schooling and who work until the age of 65 could expect lifetime earnings of Rp329,085,491 for the combined sample, Rp318,375,620 for the male sample, and Rp204,879,267 for the female sample. Individuals who left school at age 17 with 10 years of schooling and who work until the age of 65 could expect lifetime earnings of Rp379,558,948, Rp364,231,840, and Rp239,032,514 for the full, male, and female

[29] Any years of schooling can be chosen, however, this study uses individuals with 9 years of schooling as a baseline and individuals with 10 years of schooling as the comparison group.

[30]a) The IV approach using parents' years of schooling is chosen to derive the projected yearly earnings in this analysis as these variables perform best as instruments. b) Since the official age to start primary school is 7 years, to derive the projected earnings profile for workers with 9 years of schooling we start at an age of 16 years (7 + 9 = 16). The projected earnings profiles start at 17 years (7 + 10 = 17) for workers with 10 years of schooling.

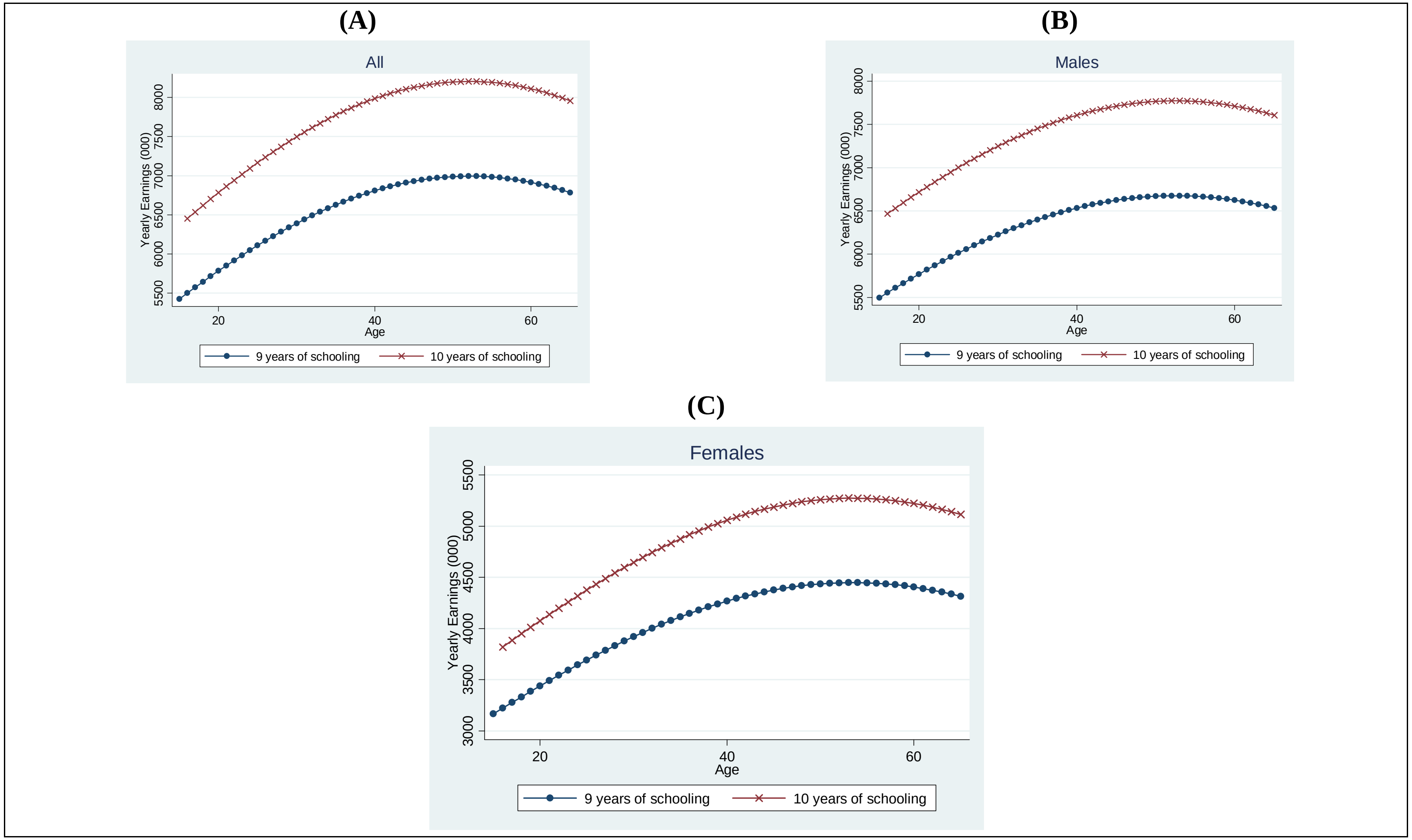
[31] The earnings data used in this study are monthly earnings, so that to obtain projected yearly earnings we need to multiply each of the projected monthly earnings by 12.

samples, respectively. The difference between the lifetime incomes for those with 10 and 9 years of schooling represents the monetary gains from the extra year of schooling.

All these amount are in 2007/2008 IDR. Moreover, they place equal value on amounts received in each year. However, as money received in the future is worth less than money received today, the future benefits need to be discounted. Table 6.11 converts the annual earnings differences for each sample (all, males, and females) using discount rates of 3, 5, and 7 percent. This table also uses eight different rates of return that have been estimated earlier in this chapter to compute the future income gains associated with the extra year of schooling.[32] For example, at the lowest returns in the table, and using a zero discount rate, the monetary gains from the extra year of schooling are Rp21,049,140, Rp20,635,591, Rp14,625,104 for the combined, male and female samples, respectively (see the first row of each panel for column (b)). With the highest annual earnings gains in the table, of 7.96 percent (all), 7.86 percent (males), and 7.51 percent (females), the average present value gain from leaving school a year later is Rp28,254,832, Rp26,853,600, and Rp16,717,584 under a 0 percent discount rate, for the pooled, male, and female samples, respectively (see column (i)). These monetary benefits decline as higher discount rates are applied. For example, applying a 5 percent discount rate to the highest returns in panel (i), the present value of the monetary benefit of the extra year of schooling falls to Rp10,043,753, Rp9,636,825, Rp5,849,722 for the combined, male and female samples, respectively.

[32] The eight rates of return to schooling used to calculate the financial gain from continuing at school for one extra year are the rates of return to schooling obtained by the IV approach based on the standard and augmented Mincerian models with parental education as well as pre-school attendance and delayed primary school enrolment as instruments.

Figure 6.11: Projected Yearly Earnings Profiles for Individuals Leaving School at Grades 9 and 10 (2007/2008 IDR)[33]



Source: Author's calculation based on Table 6.2.

[33] Unlike the studies by Oreopolous (2003) and Leigh and Ryan (2005, 2008) that projected the income profiles using a quartic age function, this study utilises the quadratic in age form from the previous regression equations.

Table 6.11: Discounted Present Value of an Additional Year of Schooling (in 2007/2008 IDR)

All									
	Rate of Return to Schooling								
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
Discount Rate	**5.93%**	**6.24%**	**6.78%**	**6.84%**	**6.93%**	**7.24%**	**7.79%**	**7.96%**	**Baseline Foregone Earnings**
0%	Rp21,049,140	Rp22,149,517	Rp24,066,302	Rp24,279,278	Rp24,598,742	Rp25,699,119	Rp27,651,400	Rp28,254,832	Rp5,499,855
3%	Rp10,680,702	Rp11,239,053	Rp12,211,663	Rp12,319,731	Rp12,481,833	Rp13,040,183	Rp14,030,805	Rp14,373,019	Rp5,499,855
5%	Rp7,482,344	Rp7,873,495	Rp8,554,855	Rp8,630,562	Rp8,744,122	Rp9,135,273	Rp9,829,251	Rp10,043,753	Rp5,499,855
7%	Rp5,583,024	Rp5,874,885	Rp6,383,288	Rp6,439,778	Rp6,524,512	Rp6,816,373	Rp7,334,191	Rp7,494,244	Rp5,499,855
Males									
	Rate of Return to Schooling								
Discount Rate	**6.04%**	**6.50%**	**6.61%**	**6.76%**	**7.08%**	**7.42%**	**7.67%**	**7.86%**	**Baseline Foregone Earnings**
0%	Rp20,635,591	Rp22,207,175	Rp22,582,989	Rp23,095,462	Rp24,188,739	Rp25,350,345	Rp26,511,951	Rp26,853,600	Rp5,553,174
3%	Rp10,530,177	Rp11,332,145	Rp11,523,919	Rp11,785,430	Rp12,343,321	Rp12,936,079	Rp13,528,837	Rp13,703,178	Rp5,553,174
5%	Rp7,405,398	Rp7,969,385	Rp8,104,251	Rp8,288,160	Rp8,680,499	Rp9,097,359	Rp9,514,220	Rp9,636,825	Rp5,553,174
7%	Rp5,545,425	Rp5,967,759	Rp6,068,752	Rp6,206,469	Rp6,500,267	Rp6,812,426	Rp7,124,586	Rp7,216,398	Rp5,553,174
Females									
	Rate of Return to Schooling								
Discount Rate	**6.57%**	**7.38%**	**7.74%**	**8.30%**	**8.32%**	**8.91%**	**7.19%**	**7.51%**	**Baseline Foregone Earnings**
0%	Rp14,625,104	Rp16,428,199	Rp17,229,574	Rp18,476,158	Rp18,520,679	Rp19,834,045	Rp16,005,250	Rp16,717,584	Rp3,220,559
3%	Rp7,350,284	Rp8,256,484	Rp8,659,239	Rp9,285,747	Rp9,308,123	Rp9,968,194	Rp8,043,918	Rp8,401,923	Rp3,220,559
5%	Rp5,117,533	Rp5,748,462	Rp6,028,875	Rp6,465,072	Rp6,480,651	Rp6,940,216	Rp5,600,466	Rp5,849,722	Rp3,220,559
7%	Rp3,797,433	Rp4,265,609	Rp4,473,688	Rp4,797,366	Rp4,808,925	Rp5,149,943	Rp4,155,790	Rp4,340,749	Rp3,220,559

Notes: Projected earnings profile for adults with 9 and 10 years of schooling are shown in Figure 6.16. Foregone earnings are obtained from the initial (age of 16 years) projected annual earnings for workers who have 9 years of schooling.
Source: Author's calculation.

Second, we need to find the foregone earnings from staying on at school for an extra year. This study obtains foregone earnings from the initial projected yearly earnings for individuals with 9 years of schooling. Based on the projected yearly earnings the foregone earnings from continuing at school for the extra year are Rp5,499,855, Rp5,553,174, and Rp3,220,559, for the pooled, male, and female samples, respectively. Table 6.11 includes these figures in the last column. To calculate the financial gain from an additional year of schooling, these foregone earnings should be compared with the discounted increase in future earnings.

The profitability of continuing at school into year 10 can be assessed by comparing the discounted future gains with the foregone earnings. At the lowest rate of return in the table, recorded in the first column, and using a zero discount rate, the present value of the gain is 3.83, 3.72, and 4.54 times as high as expected foregone earnings for the combined, male and female samples, respectively. At a 5 percent discount rate with these low returns to schooling the benefit-cost ratios for the three samples are 1.36, 1.33, and 1.59 respectively. At the highest rates of return in the Table (in the second last column) the present value of the gain is 5.14, 4.84, and 5.19 times as large as expected foregone earnings for the combined, male, and female samples, respectively when a zero discount rate is used. Even with a higher discount rate (5 percent), the present value of the lifetime gain from continuing at school for the extra year is Rp10,043,753 for the pooled sample, Rp9,636,825 for the male sample, and Rp5,849,722 for the female sample. These amounts remain considerably higher than the estimated foregone earnings.

One of the advantages of the framework provided by Table 6.11 is that it permits costs of schooling other than foregone earnings to be incorporated into the analysis. Examples of such cost would be the cost of books or private tuition. Consider males with a rate of return to schooling of 6.04 percent, and a discount rate of 5 percent. These other cost would need to be as high as (Rp7,405,398 - Rp5,553,174 = Rp1,852,224) during the extra year of schooling to drive to benefit-cost ratio less than one. This magnitude of extra cost seems unlikely.

Table 6.12: Benefits to Education with Growth of the Real Lifetime Earnings

Discount Rate	All		Males		Females	
	Zero growth rate	3.82% growth rate	Zero growth rate	3.82% growth rate	Zero growth rate	3.82% growth rate
0%	Rp24,598,742	Rp229,168,957	Rp22,582,989	Rp203,725,432	Rp17,229,574	Rp159,179,899
3%	Rp12,481,833	Rp70,019,109	Rp11,523,919	Rp63,387,945	Rp8,659,239	Rp47,586,296
5%	Rp8,744,122	Rp31,490,220	Rp8,104,251	Rp28,736,240	Rp6,028,875	Rp21,191,820
7%	Rp6,524,512	Rp14,159,632	Rp6,068,752	Rp12,999,782	Rp4,473,688	Rp9,456,913

Source: Author's calculation.

The framework provided by Table 6.11 is based on the cross-sectional analysis of earnings. It therefore makes no allowance for growth in real earnings over time due to productivity improvements. The addition of such growth enhances the profitability of the investment in education. Table 6.12 presents the calculation for 3.82 percent growth in real earnings overtime.[34] At this 3.82 percent growth in real earnings over time and a 3 percent discount rate, the monetary benefit of the extra year of schooling is Rp70,019,109, Rp63,387,945, and Rp47,586,296 for the combined, male and female samples, respectively. When a higher discount rate is considered, for example a 5 percent discount rate, the lifetime gain in earnings is Rp31,490,220, Rp28,736,240, and Rp21,191,820 for the pooled, male, and female sample, respectively.

6.5 Conclusion

This chapter presents evidence on the returns to schooling in Indonesia and highlights some important points. In this study we have compared four sets of instruments when using twelve different estimating equations (3 (3) IV standard Mincerian models using experience (age) and 3 (3) IV augmented Mincerian models using experience (age)), separating the causal effect of education on earnings from any ability bias. In conventional IV, the corrected estimates of the return to schooling indicate the presence of some downward bias in the OLS estimates, in line with a number of recent studies. This study finds evidence that instruments that vary across individuals

[34] We assume 3.82 percent growth based on the average growth of 2000-2008 real GDP per capita. To calculate the benefit of the extra year of schooling with growth of real lifetime earnings we use the following formula:

$$\sum_{t=1}^{38} \frac{Y_{10}(1+g)^t}{(1+r)^t} - \sum_{t=1}^{39} \frac{Y_9(1+g)^t}{(1+r)^t}.$$

The calculations in Table 6.12 are for the returns to schooling in columns (f), (d), and (c) of Table 6.11 for the combined, male and female samples, respectively.

in a given age category perform better, in that they provide more reliable, and more consistent, findings than instruments that do not vary across individuals in a given age category. The estimated coefficients for the preferred equations are precisely estimated, and the differences are statistically significant. In line with Ashenfelter and Zimmerman (1997) and Lemke and Rischall (2003), this study finds that considering endogeneity bias via the IV method is important, and draws attention to family background factors being useful instruments.

When the returns to schooling are estimated through applying OLS to the standard Mincerian model, the estimated results are lower than the estimates of the returns to schooling in other Asian countries. After taking into account the endogeneity problem by employing the IV approach, the return to schooling increases by a moderate amount, which is by about 0.86 percentage point to about 2.89 percentage points. Using OLS, the returns to schooling range from 4.36 percent to 6.45 percent across the different samples and estimating equations. When the IV approach is applied, the returns to schooling vary from 4.59 percent to 8.92 percent across the different sample groups and estimating equations. Although adopting the IV approach has increased the return to schooling for Indonesia, the estimated returns remain low compared to other Asian countries and less developed countries. This result supports the finding in the previous chapter that the return to schooling in Indonesia is quite low, and even lower than the return to schooling obtained using older data (see Duflo, 2001).

Controlling for tenure and its square shows that labour market experience is more important than job tenure. This result is in contrast with the finding in Chapter 5. Comparing the marginal effect of age and the marginal effect of tenure on earnings, it is seen that over the early period of the worker's career, the effects of tenure on earnings for the three different samples considered are greater than the effects of age on earnings. During the later periods in the labour market, the marginal effect of age exceeds the marginal effect of tenure on earnings. This pattern is also contrary to the finding in Chapter 5 where the OLS approach was applied. Marital status has a negative impact on earnings for females. In relation to urban area of residence, the results reinforce the finding in Chapter 5, where workers from urban areas were shown to have higher earnings than their counterparts from rural areas of residence.

Another finding from this study that needs to be highlighted is that the benefit of continuing at school for an extra year is quite high. Based on the alternative scenarios in Table 6.11, the lifetime gain to staying on at school for an extra year typically exceeds the estimated foregone earnings, even when a high discount rate is used. This result is in agreement with the finding from the study by Oreopolous (2003) for the United States, Canada, and the United Kingdom, and the study by Leigh and Ryan (2005, 2008) for Australia. The results provide a sound basis for evaluating school leaving decisions. Recognising a foregone benefit from dropping out will assist to quantify a cost-benefit analysis of the dropout decision.

The private return to schooling is the focus for the study in this chapter and Chapter 5. However, it is widely perceived that education not only has private economic effects but also externalities for individuals and society at large. It would be a valuable contribution to the literature if we estimate the externalities of human capital in Indonesia. For this reason, the following chapter investigates the human capital externalities in Indonesia.

Chapter 7

Estimating Human Capital Externalities: An Empirical Study for Indonesia

7.1 Introduction

Evidence in relation to the private return to schooling in Indonesia is documented in Chapters 5 and 6. Given that evidence, which shows that the return to schooling in Indonesia is low in comparison with other Asian countries, it is important to evaluate the effect of education in terms of externalities for individuals and society at large. Therefore, this chapter sheds light on the human capital externalities in Indonesia. In particular, we attempt to evaluate the existence and the magnitude of local human capital externalities in Indonesia, taking the province as the territorial unit of analysis. Such study has broader relevance, as research for a less developed country will complement the empirical studies on this topic that are dominated by case studies of developed countries, the US in particular.

This chapter develops a framework for estimating the external returns by investigating the effect of the average level of human capital in a province on the individual earnings of workers residing in that province. That effect is evaluated while controlling for the effect of the individual's schooling. Rudd (2000) considers this phenomenon as a "human capital spillover." Chapter 3 has noted that there are two types of these human capital spillovers, namely pecuniary and non-pecuniary spillovers. This study focuses on the first type of spillover - pecuniary spillover.

This study attempts to estimate the external effect of human capital at the individual level employing a variety of data and combinations of variables, as well as different methods of estimation. The framework adopted can be viewed as an extension of the research of Chapters 5 and 6, whereby the Mincerian earnings equation is augmented with the average levels of education in the provinces.

Four alternative measures of the aggregate-level human capital are proposed here: the average years of schooling, the average years of schooling based on the industrial sector within each province, the percentage of workers who graduated with higher education qualifications, and the percentage of workers who graduated with higher education qualifications based on the industrial sector within each province.

The rest of the chapter is organised as follows. The next section discusses the empirical models and estimation methods. Section 3 briefly introduces the data set used in the empirical work. Results and interpretations are reported in Section 4. This section is divided into five sub-sections. First, we examine the human capital externalities using the OLS method. This is followed by an evaluation of the human capital externalities using the IV method. Next the impact of the aggregate-level human capital on individual earnings is considered separately for male and female workers. In this sub-section the OLS and IV approaches are both employed. The existence of human capital externalities can also be examined by testing the imperfect substitutability between low-skilled and high-skilled workers. Thus the next sub-section is devoted to discuss this issue. All results are collated in the last sub-section of Section 4. The final section summarises the main results and conclusions.

7.2 Empirical Models and Estimation Methods

Similar to the analysis in the two previous chapters (Chapters 5 and 6), the model adopted here is a Mincerian wage equation that includes an aggregate-level human capital measure. The external effect of human capital can be internalised within a small group, such as a firm, or a bigger group, such as a city, province, or state. However, it seems reasonable to have a different kind of interaction depending on whether or not people work in the same industry or occupation. It can be assumed that the closer the interaction the stronger the effect. Also the effect of the aggregate-level human capital may be greater within the same industrial sector than it is in the remaining industrial sectors in the economy. For example, a higher level of human capital in the manufacturing sector may have an effect on productivity in this sector but is likely to have only a very small effect on productivity in other sectors.[35]

Based on the above rationale, two approximations for the aggregate-level human capital measure are used in this study. The first aggregate-level human capital

[35] It is important to be noted that this study employs individual-level survey data and provincial-level data. However, given the small number of provinces this study does not address the issue of clustering observations (Primo *et al.*, 2007)

measure is based only on administrative and geographical boundaries, or more specifically it is based only on the province of residence. The second aggregate-level human capital measure is based on industrial sector within the province. In particular, it is measured as the average level of human capital in the province in the worker's particular industry of employment. Within each of these aggregate-level human capital measures two types of variables are constructed, based on the average years of schooling of the workers and on the percentage of workers with higher education qualifications. Thus, the aggregate-level human capital measures for each province can be defined as follows: The first variable records the average years of schooling among all the workers in province *j* (*AveSchool*); the second records the average years of schooling among all the workers in industrial sector *n* in province *j* (*AveSchool-Ind*); the third variable is for the percentage of college or higher-degree holders among all the workers in province *j* (*PerHE*); and the fourth variable is for the percentage of college or higher-degree holders among all the workers in industrial sector *n* in province *j* (*PerHE-Ind*).[36] Referring to Fu's (2007) definition for the depth or quality of the human capital stock, *AveSchool* and *PerHE* are proxies for the quality of human capital stock in province *j*, while *AVeSchool-Ind* and *PerHE-Ind* are proxies for the quality of human capital stock of the industrial sector in province *j*.

The OLS and IV approaches are utilised to analyse the effects on the earnings of individual workers of human capital externalities. Equation (7.1) below represents a general form of the model estimated in this chapter.

$$\ln\left(earnings_{inj}\right) = \beta_0 + \beta X_{inj} + \gamma P_j + \mu_{inj} \tag{7.1}$$

where $earnings_{inj}$ is the monthly earnings of individual *i* who worked in industrial sector *n* in province *j*, X_{inj} is the vector of characteristics for this individual *i*, P_j is a measure of aggregate-level human capital, and μ_{inj} is an error term.

The variables for individual characteristics employed in equation (7.1) in this chapter are the same as those utilised in Chapters 5 and 6. Hence, *X* for the Mincerian model

[36] Since the data available on workers' education based on the province and industrial sector within province provided by BPS - Statistics Indonesia and the Ministry of Manpower and Transmigration (MoMT) are only based on the highest education level completed, and there is no information on highest grade completed, to calculate the average years of schooling and the average years of schooling based on the industrial sector within the province this study only considers the highest education level completed.

without additional variables for individual characteristics represents years of schooling, experience and its square (or age and its square). In the case of the Mincerian model with additional variables for individual characteristics the X vector consists of years of schooling, experience and its square (or age and its square), tenure and its square, marital status, urban area of residence, and gender status. As noted above, the measures of the aggregate-level human capital considered below are the average years of schooling (or percentage of workers with higher education) and average years of schooling for each industrial sector in province j (percentage of workers with higher education for each industrial sector in province j).[37]

Similar to the analysis in Chapters 5 and 6, in this chapter age is also utilised as a proxy for potential work experience in order to check the robustness of the estimations. Additionally, in order to ascertain whether there are any non-linear effects of education on earnings, this study measures individual education by dummy variables for the level of education in addition to the conventional continuous years of schooling variable. This may be important because Rudd (2000) found that allowing for a non-linear relationship between earnings and education changes noticeably the aggregate-level education effect on an individual's labour productivity.

Estimating external returns to schooling using the OLS approach invites the question of whether the estimation results will suffer from omitted variables bias. The unobserved characteristics of individuals and provinces could be correlated with the average years of schooling or the percentage of higher education graduates and thus could raise individuals' earnings, biasing the coefficient on the aggregate human capital measure. To address the problem of potential endogeneity bias, this study adopts an IV approach. The following two equations model, describing the natural logarithm of monthly earnings ($\ln(earnings_{inj})$), and the generation of the aggregate-level human capital variable (P_j), is applied to handle this potential endogeneity problem:

$$\ln(earnings_{inj}) = \beta_0 + \delta X_{inj} + \gamma P_j + \mu_{inj} \tag{7.2}$$

$$P_j = \varphi Z_{inj} + \varepsilon_{inj} \tag{7.3}$$

[37] There are 9 industrial sector categories used in this study: (1) agriculture, forestry, fishing, and hunting, (2) mining and quarrying, (3) manufacturing, (4) electricity, gas, and water, (5) construction, (6) wholesale, retail, restaurant and hotel, (7) transportation, storage, and communications, (8) finance, insurance, real estate and business services, and (9) social services.

where X and Z are vectors of observed variables, Pj is either the average years of schooling (*AveSchool*j) or the percentage of workers with higher education qualifications ($PerHE_j$), and $E(X_{inj}\ \mu_{inj}) = E(Z_{inj}\ \varepsilon_{inj}) = 0$. The explanatory variables employed in equation (7.2) are the same as those utilised in (7.1).

The key to the IV approach is to identify instruments that are highly correlated with the educational attainment at the provincial level but uncorrelated with the error term. Based on this principle, this study proposes the following instruments for the average years of schooling and the percentage of workers with higher education: the percentage of the population below the poverty line (*PerPoverty*) and the number of senior secondary schools per 1000 people (*SSS-Population*).

It is assumed that these two instruments indirectly impact the individuals' earnings only through the average years of schooling or the percentage of workers with higher education, which seems reasonable. Poverty has an important effect on education, since to invest in education someone needs to provide appropriate resources. For poor families, investing their resources in education probably is not a priority since they need to spend their resources to fulfill the basic needs that are more urgent. It follows that an area with a high number of poor families will tend to have a low average years of schooling and also a low percentage of workers with higher education.

In order to check the robustness of the estimations using the percentage of the population below the poverty line as an instrument, the analysis in this chapter employs the number of senior secondary schools per 1000 people as a second instrument. This second instrument used is inspired by Heuermann (2008), who employed the number of public schools in a region as an instrument for the share of highly qualified workers. Instead of using the number of public schools, this study utilises the ratio of the number of senior secondary schools per 1000 people as an instrument. Senior secondary schools are not evenly available in every area in terms of quality and quantity. Some areas have relatively more and some areas have fewer schools. This means that for an area that has fewer senior secondary schools, people need to move to other areas to be able to attend this type of school. Many such individuals may have to move to another province. Some of these students may remain in this new province at the completion of their senior secondary school, either to work or to continue their study at college or university. Based on this intuition we believe that the ratio of the number of senior secondary schools to the population is a relevant instrument for the aggregate human capital measure in terms of the average years of schooling and the percentage of workers with higher education.

7.3 Data

The data used in this chapter are taken from four sources. Individual-level data are taken from the IFLS4. Average provincial-level data are taken from the BPS-Statistics Indonesia and the Ministry of Manpower and Transmigration (MoMT). The variables to instrument the average years of schooling and the percentage of workers with higher education variables are based on data from the BPS - Statistics Indonesia and the Ministry of National Education (MoNE).

Compared to Chapters 5 and 6, the number of observations here is 68 fewer. These 68 individuals are dropped from the samples because these individuals have missing data on their industry of employment which prevents a match of their individual data with the aggregate-level data based on industrial sector.

To construct all the variables for individual's characteristics, such as years of schooling, potential work experience, tenure, marital status, urban areas of residence, and gender status, the same approach as in Chapters 5 and 6 is applied in this chapter.

Table 7.1 shows the summary statistics for the variables used in this chapter. The mean total monthly earnings in log form is 5.908 across the workers. The mean years of schooling is relatively low, specifically 10.669 years, or just one year higher than the 9 years of compulsory study. The workers in the sample have mean work experience and age of approximately 17.869 years and 35.262 years, respectively. The mean length of job tenure is 7.890 years.

Table 7.1: Summary Statistics of Variables

Variables	Mean	Standard Deviation	Variables	Mean	Standard Deviation
Monthly earnings (Log)	5.908	0.437	Tenure	7.890	8.142
Years of schooling	10.669	3.751	$Tenure^2$	128.525	248.365
Primary school	0.181	0.386	Married	0.868	0.339
Junior secondary school	0.165	0.371	Urban	0.674	0.469
Vocational senior secondary school	0.157	0.364	Female	0.334	0.472
General senior secondary school	0.237	0.426	Average years of schooling	8.744	0.770
College	0.068	0.251	Average years of schooling based on industrial sector[38]	9.370	1.493
Master	0.006	0.080	Percentage of workers with higher education	7.731	3.139
Experience	17.869	10.604	Percentage of workers with higher education based on industrial sector	12.348	12.406
$Experience^2$	431.715	480.584	Percentage of population under the poverty line	13.524	5.357
Age	35.262	9.741	Ratio of the number of senior secondary schools to population (per 1000 people)	0.072	0.037
Age^2	1338.281	752.392			

Source: Author's calculation based on IFLS4, BPS's, MoMT's, and MoNE's databases.

Table 7.2 presents some characteristics of the provincial-level data. It shows a substantial variation in the number of people - between 1,114.60 thousand and 40,623.70 thousand - across the provinces. There are four provinces in the sample with a population of over 10 million. Three of these provinces are located in Java Island, namely Jawa Barat, Jawa Tengah, and Jawa Timur. Jawa Barat is the most populated province among these (population of 40,623.70 thousand), followed by Jawa Timur, Jawa Tengah, and Sumatera Utara, which have populations of 36,995.20 thousand, 32,503.35 thousand, and 12,938.35 thousand, respectively. The province

[38] To construct this variable we calculate total years of schooling of workers for each industrial sector within each province, and then this amount is divided by the number of workers in that particular industrial sector.

with the smallest population is Kepulauan Bangka Belitung, with 1,114.60 thousand inhabitants.

In terms of the average years of schooling for workers in each province, Daerah Istimewa Yogyakarta (DIY) has the highest average years of schooling, with 12.22 years of schooling. However, this figure is not impressive, because it is just equal to an individual who completed senior high school (grade 12). The province with the lowest average years of schooling for its workers is Riau, which is 9.42 years of schooling, and this is just equal to an individual who completed basic education (grade 9).

Table 7.2: Characteristics of Provincial-Level Data

Province	2007/2008 population (thousands)	Average years of schooling	Percentage of workers with higher education	Average monthly earnings (IDR)	2007/2008 percentage of population below the poverty line	Ratio of the number of senior secondary schools to population (per 1000 people)
Sumatera Utara	12,938.35	10.11	6.38	1,177,003	6.00	0.118
Sumatera Barat	4,730.45	9.85	8.46	1,414,498	6.50	0.089
Kepulauan Bangka Belitung	1,114.60	10.85	5.83	1,390,355	7.00	0.096
Kepulauan Riau	1,423.00	9.56	10.71	1,464,333	8.00	0.088
Riau	5,130.10	9.42	7.75	813,473	9.00	0.073
DKI	9,105.40	11.12	16.20	1,782,441	15.50	0.121
Jawa Barat	40,623.70	11.01	7.31	1,455,023	16.00	0.053
Jawa Tengah	32,503.35	9.98	5.68	916,528	16.50	0.011
DIY	3,451.50	12.22	10.43	1,317,787	17.00	0.099
Jawa Timur	36,995.20	10.72	5.49	1,110,402	17.50	0.059
Banten	9,512.90	11.06	7.89	1,419,919	18.00	0.058
Bali	3,497.90	11.14	8.64	1,458,574	25.50	0.077
NTB	4,328.15	11.46	5.04	1,137,382	26.00	0.066
Kalimantan Selatan	3,421.65	10.05	5.50	1,665,274	6.75	0.061
Sulawesi Selatan	3,421.65	11.09	7.80	1,400,063	17.88	0.191

Source: Author's calculation based on IFLS4, BPS's, MoMT's, and MoNE's databases.

The percentage of the workers with higher education is low. Only three provinces in the sample have a percentage of their workers with higher education of more than 10 percent, namely Daerah Khusus Ibukota (DKI), Kepulauan Riau, and DIY, with

16.20, 10.71, and 10.43 percent, respectively. Nusa Tenggara Barat (NTB) is the province with the lowest percentage of workers with higher education, with only 5.04 percent.

Turning to the average monthly earnings, DKI is the province that has the highest average monthly earnings, with Rp1,782,441. Apparently Riau not only has the lowest average years of schooling of its workers, but also has the lowest average monthly earnings for its workers, with an average of just Rp813,473.

Among the 15 provinces in the sample, there are 6 provinces that have a percentage of their population below the poverty line in 2007/2008 of less than 10 percent. These provinces are Sumatera Utara (6 percent), Sumatera Barat (6.5 percent), Kalimantan Selatan (6.75 percent), Kepulauan Bangka Belitung (7 percent), Kepualauan Riau (8 percent), and Riau (9 percent). None of these provinces is situated in Java Island. There are 2 provinces that have a percentage of population below the poverty line in 2007/2008 of more than 25 percent, which are Bali (25.50 percent) and its nearest neighbour province, Nusa Tenggara Barat or NTB (26.00 percent).

The largest ratio of the number of senior secondary schools (vocational senior secondary schools and general senior secondary schools) per 1,000 people is for the province of Sulawesi Selatan, with a ratio of 0.191. On the other hand, the province with the lowest ratio is Jawa Tengah, with a ratio of 0.011.

7.4 Results and Discussions

This section reports results from the estimation of equations (7.1), (7.2) and (7.3).[39] The discussion commences with the analysis based on the OLS approach. This part first examines the results from the estimation of the importance of human capital externalities using the Mincerian model with average years of schooling as the aggregate-level human capital measure. Then the importance of human capital externalities based on the Mincerian model with the percentage of workers with higher education as the aggregate-level human capital measure is canvassed.

The second part of this section discusses the estimation results based on the IV approach. Firstly we discuss the estimation results based on the IV approach with the

[39] The terms of human capital externalities, external returns to schooling, and external returns to education are used interchangeably in this chapter.

share of the population below the poverty line as an instrument. Then the estimations based on the IV approach with the ratio of the number of senior secondary schools to the population are analysed. Similar to the discussion based on the OLS approach, in this sub-section the analysis is divided into two categories, which are for the Mincerian model with the average years of schooling as the aggregate-level human capital measure, and for the Mincerian model with the percentage of workers with higher education as the aggregate-level human capital measure.

This study also analyses differences in the magnitude of the external return to schooling for male and female workers. This issue is discussed in the third part of this section. These analyses are followed by discussion on imperfect substitutability between low-skilled and high-skilled workers to assess the existence of human capital externalities.

7.4.1 OLS Approach

7.4.1.1 OLS Estimates Using the Average Years of Schooling of Workers as the Aggregate-Level Human Capital Measure

Table 7.3 shows the results from the estimation of equation (7.1) for the Mincerian model with the average years of schooling and the average years of schooling based on the industrial sector within each province as the aggregate-level human capital measures. In these estimates the variables for individual characteristics are years of schooling (level of education), potential work experience and its quadratic term (age and its quadratic term).

The results reported in Table 7.3 can be considered satisfactory, as more than 20 percent of the variance in earnings is explained. The estimates of the private returns to education are very comparable for the two specifications (experience-based and age-based) in columns (a) and (c). The estimated coefficient for the years of schooling variables are 0.05057 (based on experience) and 0.04455 (based on age), indicating that one extra year of schooling is expected to increase individual earnings by around 5.06 and 4.46 percent, respectively. These estimated effects are similar to those reported in Chapter 5. The similarity between the estimates based on the work experience and age variable carries over to the estimates of the private return to schooling using levels of education. The returns to schooling from the model based on potential work experience are 1.43, 4.06, 5.15, 5.25, 4.80, 6.36, and 13.87 percent for primary school, junior secondary school, vocational senior secondary school, general senior secondary school, college, undergraduate, and master, respectively. When the age variable is utilised the returns to schooling are 1.56, 3.68, 4.46, 4.48, 4.05, 5.76, and 13.52 percent for primary school, junior secondary school, vocational senior secondary school, general senior secondary school, college, undergraduate, and master, respectively. Again, these results are comparable to the findings in Chapter 5. The estimated coefficients on potential work experience (age) and their squared terms conform to theoretical expectation and are also in line with those reported in Chapter 5.

Table 7.3: OLS Estimates Using the Average Years of Schooling of Workers (without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)
			age proxying experience	
Constant	4.37517	4.60501	4.08941	4.30296
	(0.07374)***	(0.07691)***	(0.09710)***	(0.10149)***
Years of schooling	0.05057		0.04455	
	(0.00183)***		(0.00169)***	
Primary school		0.08563		0.09381
		(0.02591)***		(0.02540)***
Junior secondary school		0.20730		0.20407
		(0.02725)***		(0.02611)***
Vocational senior secondary school		0.36181		0.33782
		(0.02813)***		(0.02656)***
General senior secondary school		0.36466		0.33840
		(0.02687)***		(0.02521)***
College		0.50876		0.45991
		(0.03346)***		(0.03183)***
Undergraduate		0.61913		0.56883
		(0.03054)***		(0.02882)***
Master		0.89662		0.83918
		(0.07569)***		(0.07508)***
Experience	0.01617	0.01615		
	(0.00187)***	(0.00189)***		
Experience^2	-0.00024	-0.00026		
	(0.00004)***	(0.00004)***		
Age			0.02444	0.02256
			(0.00005)***	(0.00385)***
Age^2			-0.00024	-0.00023
			(0.00005)***	(0.00005)***
AveSchool	0.05669	0.05863	0.05691	0.05905
	(0.00747)***	(0.00749)***	(0.00748)***	(0.00750)***
AveSchool-Ind	0.03340	0.03309	0.03328	0.03330
	(0.00422)***	(0.00424)***	(0.00422)***	(0.00425)***
Adj-R^2	0.2299	0.2290	0.2282	0.2270
Observations	4528	4528	4528	4528

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The estimates of the human capital externalities are all positive and statistically significant at the 1 percent level of significance. The effects of human capital depth are decomposed into two components: the depth of the overall human capital stock and the depth of the same industrial sector human capital stock. The estimated effect of each of these variables is very much the same across the four estimations presented in Table 7.3.

Using *AveSchool* as the aggregate-level human capital measure, the coefficient of the average years of schooling is 0.05669 and 0.05863 in the estimation based on experience, and 0.05691 and 0.05905 in the estimation based on age, implying that an increase by one in the average years of schooling in the province is expected to increase the individual's monthly earnings by 5.67 to 5.91 percent. These results are in line with those estimated by Liu (2007) in China, where an increase in the average years of schooling by one year led to an increase in individual earnings by 4.90 to 6.67 percent.

The similarity of the results using years of schooling and the dummy variables for the level of education in the estimations contrasts with Rudd's (2000) finding. Rudd (2000) reported that there was no evidence of human capital spillovers when a years of schooling variable was used in the estimation, while such spillovers were evident when dummy variables for educational attainment were utilised in the model.

The results discussed above show that there is evidence of human capital externalities based on the depth of the overall human capital stock. Now we examine the human capital externalities based on the depth of human capital stock in the worker's specific industrial sector. The *AveSchool-Ind* variable has coefficients that vary from 0.03309 to 0.03340, suggesting that an increase by one in the average years of schooling in each worker's industrial sector tends to increase the worker's monthly earnings by between 3.31 percent and 3.34 percent. Based on the above results it can be seen that the effects of human capital depth within the worker's industrial sector of employment are significantly smaller than the effects of the overall human capital depth. This is in agreement with Fu's (2007) finding using Boston metropolitan data. A potential reason behind this fact is measurement error. The survey data involved a massive number of respondents containing measurement error. According to Fu (2007), data obtained from a smaller area tend to have greater measurement error problems. Measurement errors in explanatory variables tend to be associated with underestimated coefficients.

Rauch (1993) argued that a difference between the social and private returns to schooling follows from the presence of positive externalities from formal education. In other words, the social return to schooling consists of both the private and external returns to schooling. Then, based on the results in columns (a) and (c) of Table 7.3, it can be seen that the social return exceeds the private return by a factor of between (0.05057 + 0.05669 + 0.03340)/0.05057 and (0.04455 + 0.05691 + 0.03328)/0.04455, or by between about 2.78 and 3.02. These figures are higher than the finding of Rauch (1993), based on US data. Rauch (1993) found that the social return exceeds the private return by a factor of 1.7. The social return to schooling based on education levels tends to increase by level of schooling. The specification based on experience (age) generates a social return to schooling of 10.60 (10.80), 13.23 (12.91), 14.32 (13.69), 14.32 (13.71), 13.98 (13.29), 15.53 (15.00) and 23.05 (22.75) percent for primary school, junior secondary school, vocational senior secondary school, general senior secondary school, college, undergraduate and master degree, respectively. The social return to schooling for workers with general senior secondary school is larger than for workers with vocational senior secondary school. Using a cost benefit analysis method, McMahon and Boediono (1992) reported a similar finding, whereby workers who graduated from general senior secondary school possess a greater social return to schooling than that of workers who graduated from vocational senior secondary schools. In particular, the magnitude of the social return to schooling for workers with general secondary school (vocational senior secondary school) is 22 (16), 16 (15), 13 (10), and 11 (6) percent in 1982, 1986, 1988, 1989, respectively.

Now we expand the estimation by including the tenure, marital status, urban area of residence, and gender status variables. The results are reported in Table 7.4. While the adjusted-R squareds rise moderately relative to the previous results in Table 7.3, the coefficients of interest decrease slightly. This pattern also occurs in Chapter 5 when comparing estimates based on the standard and augmented Mincerian models.

The estimated earnings effect associated with the individual characteristics (years of schooling, dummies for level of education, experience and its square, and age and its square) in the estimations based on this expanded Mincerian model are comparable with the results reported for the augmented Mincerian model in Chapter 5.

The results suggest that an extra year of schooling leads to an increase in the monthly earnings by about 4.39 percent for the estimation based on experience, and by 4.18 percent for the estimation based on age. In terms of the level of educational attainment, the return to schooling for the estimation based on potential work experience (age) is 0.92 (1.12) percent, 3.33 (3.31) percent, 3.77 (3.55) percent, 4.03

(3.81) percent, 5.50 (5.25) percent, 6.46 (6.31) percent, and 12.91 (12.92) percent for primary school, junior secondary school, vocational secondary school, general senior secondary school, college, undergraduate, and master, respectively.

Table 7.4: OLS Estimates Using the Average Years of Schooling of Workers (with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)
Variable			**age proxying experience**	
Constant	4.49422	4.72749	4.32482	4.57470
	(0.07156)***	(0.07436)***	(0.09573)***	(0.09959)***
Years of schooling	0.04389		0.04182	
	(0.00183)***		(0.00165)***	
Primary school		0.05518		0.06707
		(0.02484)**		(0.02423)***
Junior secondary school		0.15504		0.16650
		(0.02625)***		(0.02498)***
Vocational senior secondary school		0.26804		0.27313
		(0.02744)***		(0.02565)***
General senior secondary school		0.27600		0.28066
		(0.02617)***		(0.02429)***
College		0.44090		0.43822
		(0.03250)***		(0.03047)***
Undergraduate		0.53435		0.53296
		(0.02977)***		(0.02764)***
Master		0.79302		0.79145
		(0.07258)***		(0.07169)***
Experience	0.00739	0.00750		
	(0.00205)***	(0.00207)***		
$Experience^2$	-0.00013	-0.00016		
	(0.00004)***	(0.00005)***		
Age			0.01346	0.01063
			(0.00417)***	(0.00420)**
Age^2			-0.00016	-0.00013
			(0.00005)***	(0.00005)**
Tenure	0.01611	0.01573	0.01618	0.01063
	(0.00197)***	(0.00197)***	(0.00197)***	(0.00197)***
$Tenure^2$	-0.00028	-0.00026	-0.00028	-0.00028
	(0.00006)***	(0.00006)	(0.00006)***	(0.00006)
Marital status	-0.00177	-0.00282	-0.00209	0.00121
	(0.01767)	(0.01762)	(0.01777)	(0.01775)
Urban	0.07602	0.08271	0.07605	0.08223
	(0.01258)***	(0.01264)***	(0.01258)***	(0.01265)***
Female	-0.20078	-0.20967	-0.20188	-0.21072
	(0.01176)***	(0.01181)***	(0.01175)***	(0.01181)***
AveSchool	0.05235	0.05470	0.05234	0.05498
	(0.00719)***	(0.00718)***	(0.00719)***	(0.00719)***
AveSchool-Ind	0.03610	0.03460	0.03616	0.03490
	(0.00413)***	(0.00413)***	(0.00413)***	(0.00414)***
$Adj\text{-}R^2$	0.2965	0.3005	0.2963	0.2995
Observations	4528	4528	4528	4528

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

In the case of the depth of overall effects of the human capital stock, the *AveSchool* variable has a statistically significant effect on monthly earnings in each of the estimations. The effect of the average years of schooling on monthly earnings ranges from 5.23 percent to 5.50 percent. These numbers are slightly lower than the results obtained using the OLS approach without the additional control variables, where the numbers ranged from 5.67 to 5.91 percent.

When using the industrial sector level variable the results suggest that an increase by one in the average years of schooling in each industrial sector will generate an increase in monthly earnings from about 3.46 to 3.62 percent. These results support the earlier findings in Table 7.3, that the average years of schooling based on the industrial sector has a positive impact on an individual's monthly earnings.

A comparison between the social return and the private return reveals a pattern similar to the results reported in Table 7.3. Here, the social return exceeds the private return by a factor of between 3.02 and 3.12 for the specification based on years of schooling. The social return to schooling based on education level ranges from the lowest of 9.85 to the highest of 21.86 percent, and it increases with the level of education (details on the social return to schooling for each level of education and each specification can be found in Tables A7.25 and A7.26). Supporting the earlier results, workers with vocational secondary school have a lower social return to schooling than workers with general senior secondary school

The results from Tables 7.3 and 7.4 provide strong evidence of human capital externalities in Indonesia. This is in line with the findings from the previous studies conducted by Rakova and Vaillancourt (2005) in Canada, Liu (2007) in China, Sanroma and Ramos (2007) in Spain, and Muravyev (2008) in Russia. However, the results from Tables 7.3 and 7.4 should be considered with caution due to the potential endogeneity of the average years of schooling.

7.4.1.2 OLS Estimates Using the Percentage of Workers with Higher Education as the Human Capital Measure

To check the robustness of the OLS estimates considered above, the models of Tables 7.3 and 7.4 are re-estimated using an alternative measure for the provincial level education, namely the percentage of workers with higher education. The results are reported in Tables 7.5 and 7.6.

Including an aggregate-level human capital measure based on the percentage of workers with higher education leads to lower coefficients compared to those obtained using the average years of schooling. Using this new variable, the coefficients vary from 0.011670 to 0.01225, implying that an increase in the percentage of workers with higher education by one percentage point can be expected to increase an individual's monthly earnings by between about 1.17 percent and 1.23 percent.[40] These results are very similar to the OLS estimates of 1.02 percent to 1.42 percent reported by Morreti (2004) based on US data, and the 1.10 percent to 1.45 percent reported by Liu (2007) based on Chinese data.

Table 7.5: OLS Estimates Using the Percentage of Workers with Higher Education (without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)
Variable			**age proxying experience**	
Constant	5.04382	5.29995	4.75888	5.00343
	(0.03105)***	(0.03340)***	(0.07198)***	(0.07570)***
Years of schooling	0.05277		0.04680	
	(0.00185)***		(0.00170)***	
Primary school		0.08421		0.09290
		(0.02612)***		(0.02560)***
Junior secondary school		0.21248		0.21015
		(0.02743)***		(0.02628)***
Vocational senior secondary school		0.37307		0.35020
		(0.02828)***		(0.02667)***
General senior secondary school		0.38167		0.35657
		(0.02698)***		(0.02528)***
College		0.52996		0.48228
		(0.03375)***		(0.03205)***
Undergraduate		0.64297		0.59391
		(0.03087)***		(0.02907)***
Master		0.92069		0.86463
		(0.07637)***		(0.07574)***
Experience	0.01600	0.01605		
	(0.00188)***	(0.00191)***		
Experience^2	-0.00024	-0.00026		
	(0.00004)***	(0.00004)***		
Age			0.02437	0.02241
			(0.00385)***	(0.00388)***
Age^2			-0.00025	-0.00023
			(0.00005)***	(0.00005)***
PerHE	0.01167	0.01212	0.01176	0.01225
	(0.00184)***	(0.00185)***	(0.00184)***	(0.00185)***
PerHE-Ind	0.00224	0.00207	0.00225	0.00212
	(0.00050)***	(0.00051)***	(0.00051)***	(0.00051)***
Adj-R^2	0.2176	0.2161	0.2160	0.2142
Observations	4528	4528	4528	4528

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Consider now the estimates based on the variables constructed using the percentage of workers with higher education based on the industrial sector within each province. These results show that an increase in the percentage of workers with higher education in each industrial sector by one percentage point leads to an increase in an individual's monthly earnings by approximately 0.21 to 0.23 percent. Similar to the results reported earlier in Tables 7.3 and 7.4, the external returns to schooling from

[40] Note that the *PerHE* and *PerHE-Ind* variables are measured as a percent whereas *AveSchool*, *AveSchool-Ind* and years of schooling are in years. Comparisons of estimated impacts might be more useful if undertaken using an elasticity measure. In the semi-logarithmic specification of the earnings equation, the elasticity is found by multiplying the regression coefficient by the mean of the variable of interest. However, as the means are comparable (for example, the mean of *AveSchool* is 8.74 and the mean of *PerHE* is 7.73, the regression coefficients provide a good basis for comparisons from this respective.

aggregate-level human capital in the same industrial sector within the province are lower than those from the overall-level of human capital within the province.

The social returns to schooling associated with the percentage of workers with higher education exceed the private returns by a factor between 1.26 and 1.30 for the specification based on years of schooling. The social return to schooling based on education levels varies from 2.82 to 15.31 percent, and it also increases with the level of education, which is consistent with the earlier results. These are lower than those reported in Tables 7.3 and 7.4. The results in Table 7.5, however, confirm the main finding in Tables 7.3 and 7.4, that there are sizeable human capital externalities in Indonesia.

Comparing the social return to schooling for workers with general and vocational senior secondary school, the results obtained using OLS based on experience are consistent with the findings presented in Tables 7.3 and 7.4, where the social return for the former level of schooling exceeds that for the latter level. Nevertheless, the opposite pattern is found in the results obtained using OLS based on age, where workers with vocational secondary school have a smaller social return to schooling than those with general senior secondary school.

Table 7.6 shows the results from the estimation of equation (7.1) for the Mincerian model with the additional variables for individual characteristics. These estimations again utilise the percentage of workers with higher education and the percentage of workers with higher education based on the industrial sector within each province as the aggregate-level human capital measures.

Most of the individual characteristics variables are statistically significant and have the expected signs in each model. In particular, the results for the variables related to the individual's schooling and potential work experience conform to the conventional wisdom. Marital status is the sole variable that is not statistically significant.

In the case of the depth of the overall level of the human capital stock, the *PerHE* variable significantly affects the monthly earnings across the estimations. The coefficients of this variable are statistically significant at the 1 percent level. The contribution of the stock of higher educated workers to monthly earnings varies from 3.46 to 5.50 percent. These numbers are slightly lower than the results obtained using the OLS approach without the additional control variables reported in Table 7.4, where the figures range from 5.67 to 5.91 percent.

Table 7.6: OLS Estimates Using the Percentage of Workers with Higher Education (with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)
Variable			age proxying experience	
Constant	5.15447	5.40690	4.97610	5.24954
	(0.03150)***	(0.03400)***	(0.07320)***	(0.07662)***
Years of schooling	0.04602		0.04387	
	(0.00186)***		(0.00167)***	
Primary school		0.05443		0.06717
		(0.02508)**		(0.02446)***
Junior secondary school		0.15953		0.17198
		(0.02647)***		(0.02519)***
Vocational senior secondary school		0.27904		0.28484
		(0.02765)***		(0.02583)***
General senior secondary school		0.29273		0.29805
		(0.02635)***		(0.02445)***
College		0.46266		0.46018
		(0.03285)***		(0.03080)***
Undergraduate		0.55885		0.55767
		(0.03016)***		(0.02802)***
Master		0.81715		0.81580
		(0.07336)***		(0.07247)***
Experience	0.00770	0.00787		
	(0.00207)***	(0.00209)***		
Experience^2	-0.00013	-0.00017		
	(0.00004)***	(0.00005)***		
Age			0.01415	0.01122
			(0.00421)***	(0.00424)***
Age^2			-0.00016	-0.00014
			(0.00005)***	(0.00005)**
Tenure	0.01578	0.01539	0.01584	0.01605
	(0.00199)***	(0.00199)***	(0.00199)***	(0.00199)***
Tenure^2	-0.00028	-0.00015	-0.00028	-0.00028
	(0.00006)***	(0.00007)***	(0.00007)***	(0.00007)***
Marital status	-0.00525	-0.00641	-0.00576	-0.00227
	(0.01783)	(0.01779)	(0.01794)	(0.00007)
Urban	0.09039	0.09691	0.09040	0.09643
	(0.01268)***	(0.01274)***	(0.01268)***	(0.01275)***
Female	-0.19609	-0.20496	-0.19609	-0.20605
	(0.01185)***	(0.01190)***	(0.01185)***	(0.01191)***
PerHE	0.00959	0.01017	0.00961	0.01025
	(0.00180)***	(0.00180)***	(0.00180)***	(0.00180)***
PerHE-Ind	0.00242	0.00201	0.00243	0.00206
	(0.00049)***	(0.00049)***	(0.00049)***	(0.00049)***
Adj-R^2	0.2829	0.2864	0.2843	0.2854
Observations	4528	4528	4528	4528

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

For the industrial sector level, the results suggest that a one percentage point increase in the percentage of workers with higher education in each industrial sector tends to increase an individual's monthly earnings by around 0.96 to 1.03 percent. These figures are also slightly lower than those obtained using the OLS approach without the additional controls considered here, which are from about 1.17 to 1.23 percent.

Compared to the results in Table 7.5, the findings in terms of how large the social return exceeds the private return suggest a comparable pattern, where the social return associated with the percentage of workers with higher education and the percentage of workers with higher education based on the industrial sector within each province exceeds the private return by a factor of 1.26 and 1.27. Again, these are lower than those reported in Tables 7.3 and 7.4. The results from the specification based on the level of education also have a similar pattern, where the social returns to schooling are slightly lower than those reported in Tables 7.3 and 7.4. The pattern of the social return to schooling for workers with vocational and general senior secondary school qualifications is consistent with the result presented in Table 7.5.

Summing up, these OLS estimates reveal six points of interest. First, the estimates of the private returns to schooling are stable across all specifications. Second, all estimates of the external returns to schooling are positive and statistically significant, both for the overall level and for the industrial sector level. Third, using either years of schooling or the level of education for the individual's education, and either potential work experience or age, generates the same results, where the coefficients for each of the aggregate-level human capital measures is positive and statistically significant. Fourth, adding variables for tenure and its square, marital status, urban area of residence, and gender status leads to a slight increase in the coefficient of the average years of schooling measure and a slight decrease in the coefficient of the variable for the percentage of workers with higher education. Fifth, the social return to schooling increases with the level of education. Sixth, six of the eight specifications discussed in this sub-section show that the social return to schooling for workers with general senior secondary schooling is greater than that of workers with vocational senior secondary schooling. The other two specifications provide a contrary pattern.

7.4.2 IV Approach

In this sub-section the IV approach is adopted to address the issue of omitted variable bias that may arise because of unobserved factors being correlated with the provincial level human capital. The first part of this sub-section will discuss the results from the IV estimates using the percentage of the population below the poverty line as an instrument (*PerPoverty*). The second part will discuss the results from the IV estimates using the number of senior secondary schools per 1000 people as an instrument (*SSS-Population*).

Ideally the omitted variable bias that may arise because of unobserved factors being correlated with the human capital measure based on the industrial sector within each province should also be evaluated. Unfortunately there is no suitable instrument for this disaggregated measure of the human capital stock within each province.

7.4.2.1 Using the Percentage of the Population below the Poverty Line as an Instrument

Equations 7.2 and 7.3 portray the relationship between individual productivity and the provincial level of human capital using the IV approach. The results obtained using *PerPoverty* as an instrument are presented in Tables 7.7 (Mincerian model without additional variables for individual characteristics and using *AveSchool* as an aggregate-level human capital measure), 7.8 (Mincerian model with additional variables for individual characteristics and using *AveSchool* as an aggregate-level human capital measure), 7.9 (Mincerian model without additional variables for individual characteristics and using *PerHE* as an aggregate-level human capital measure), and 7.10 (Mincerian model with additional variables for individual characteristics and using *PerHE* as an aggregate-level human capital measure).

We begin with the discussion of the IV estimates reported in Table 7.7. Columns (a), (c), (e), and (g) report findings for the first-stage regression that includes the instrument and all the exogenous variables contained in the earnings equation. Conforming to expectation, the estimate associated with the instrument is negative and statistically significant at 1 percent level in all four specifications. The Hausman test of the endogeneity of *AveSchool* indicates that the null hypothesis of exogeneity is rejected at the 1 percent level for all four specifications. This result suggests that it is necessary to adopt an IV approach. Moreover, the R squareds for the first stage equation are all moderate in size, being around the 0.20 mark.[41]

The results presented in columns (b), (d), (f), and (h) of Table 7.7 show that all the individual variables (years of schooling or level of education, potential work experience or age and its square) included to control for individual effects on earnings

[41] The R^2 from the second stage regression has no statistical meaning in the context of 2SLS/IV (see Sribney *et al.*, 2011 at http://www.stata.com/support/faqs/stat/2sls.html). Accordingly, we do not discuss the R^2 from the earnings function in the IV approach.

are significant and have the expected sign and magnitude, except for the variable of age in column (h) that is not significant.

Similar to the results obtained using the OLS approach, estimating human capital externalities, whether using years of schooling or level of education, and whether using potential work experience or age to control for individual's characteristics, generate results that show evidence of a highly significant and positive relationship at the 1 percent level of significance between the average years of schooling in the worker's province and their monthly earnings. The magnitudes of the effect of the average years of schooling in the worker's province on their monthly earnings are almost equal across the four estimations. Applying the IV approach leads to higher estimated external returns to schooling compared to those obtained using the OLS approach. An increase by one in the average years of schooling in the province increases the individual's monthly earnings by from 22.62 to 23.33 percent. These results are very similar to the study using 1990 Canadian data conducted by Rakova and Vaillancourt (2005). They found that an increase by a year in their average education variable has an effect on labour productivity of 23 percent. Our results indicate that human capital externalities are sizeable and much higher than the return to own schooling. The magnitude of the externalities suggests that fostering education should be a priority of the government's policy agenda.

To put these results into perspective, an increase of one year in the average level of schooling in the province would be the equivalent of a move from Jawa Tengah province (mean years of schooling of 9.98) to Jawa Timur province (mean years of schooling of 10.72), or from Sumatera Utara province (mean years of schooling of 10.11) to Bali province (mean years of schooling of 11.14). The first two of these provinces differ in terms of mean monthly earnings by 21.15 percent. The final two provinces differ in terms of mean monthly earnings by 23.92 percent.

For the industrial sector level variable, the coefficients of *AveSchool-Ind* are 0.02272, 0.02174, 0.02273, and 0.02189, implying that a one percent increase in the percentage of workers with higher education in each industrial sector leads to an increase in an individual's monthly earnings by around 2.27, 2.17, 2.27, and 2.19 percent. These externalities are lower than those obtained using the OLS approach (which range from 3.46 to 3.62).

Table 7.7: Instrumenting Average Years of Schooling with Population below the Poverty Line (Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.24960	3.00532	9.32230	3.18970	8.80868	2.78071	8.83327	2.95986
	(0.08502)***	(0.15403)***	(0.09310)***	(0.15872)***	(0.14399)***	(0.16354)***	(0.15354)***	(0.16844)***
Years of schooling	0.01511	0.05029			0.01159	0.04439		
	(0.00332)***	(0.00194)***			(0.00305)***	(0.00178)***		
Primary school			-0.02021	0.10540			-0.00105	0.10979
			(0.04662)	(0.02746)***			(0.04563)	(0.02687)***
Junior secondary school			0.00315	0.22465			0.01875	0.21718
			(0.04904)	(0.02885)***			(0.04692)***	(0.02761)***
Vocational senior secondary school			0.10402	0.36213			0.10177	0.33558
			(0.05065)**	(0.02974)***			(0.04772)***	(0.02806)***
General senior secondary school			0.11503	0.36375			0.11012	0.33519
			(0.04839)**	(0.02840)***			(0.04531)**	(0.02663)***
College			0.09318	0.52483			0.07075	0.47523
			(0.06038)	(0.03540)***			(0.05731)	(0.03366)***
Undergraduate			0.10176	0.64590			0.07661	0.59486
			(0.05541)*	(0.03238)***			(0.05215)	(0.03055)***
Master			0.24040	0.88122			0.21195	0.82309
			(0.13604)*	(0.08001)***			(0.13473)	(0.07933)***
Experience	0.01598	0.01444	0.01639	0.01416				
	(0.00336)***	(0.00198)***	(0.00340)***	(0.00201)***				
Experience^2	-0.00031	-0.00020	-0.00032	-0.00021				
	(0.00031)***	(0.00004)***	(0.00008)***	(0.00004)***				
Age					0.03303	0.02042	0.03331	0.01815
					(0.00686)***	(0.00405)***	(0.00691)***	(0.00409)
Age^2					-0.00040	-0.00019	-0.00040	-0.00017
					(0.00009)***	(0.00005)***	(0.00009)***	(0.00005)***
AveSchool		0.22661		0.23328		0.22619		0.23300
		(0.01827)***		(0.01859)***		(0.01828)***		(0.01860)***
AveSchool-Ind	0.00392	0.02272	0.00610	0.02174	0.00402	0.02273	0.000675	0.02189
	(0.00775)	(0.00457)***	(0.00779)	(0.00461)***	(0.00775)	(0.00457)***	(0.00779)	(0.00462)***
PerPoverty	-0.06340		-0.00610		-0.06341		-0.06283	
	(0.00197)***		(0.00198)***		(0.00197)***		(0.00198)***	
R^2	0.1999		0.2008		0.2003		0.2012	
Adjusted R^2	0.1990		0.1988		01994		0.1992	
Observations	4528	4528	4528	4528	4528	4528	4528	4528

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
						age proxying experience		
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Test Results								
Quality								
F		1031.86		1001.42		1032.65		1002.64
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		121.335		123.705		120.176		122.497
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.8: Instrumenting Average Years of Schooling with Population below the Poverty Line (Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.21033	3.22751	9.26738	3.41666	8.85396	3.10855	8.87019	3.32568
	(0.08685)***	(0.14923)***	(0.09506)***	(0.15273)***	(0.15011)***	(0.15955)***	(0.15957)***	(0.16328)***
Years of schooling	0.01123	0.04426			0.00790	0.04250		
	(0.00345)***	(0.00193)***			(0.00312)**	(0.00174)***		
Primary school			-0.01301	0.07265			0.00178	0.08179
			(0.04675)	(0.02622)***			(0.04556)	(0.02555)***
Junior secondary school			-0.01300	0.17465			-0.00167	0.18345
			(0.04940)	(0.02770)***			(0.04699)	(0.02635)***
Vocational senior secondary school			0.07010	0.27598			0.06609	0.28038
			(0.05170)	(0.02891)***			(0.04828)	(0.02702)***
General senior secondary school			0.08625	0.28141			0.07999	0.28566
			(0.04932)*	(0.02757)***			(0.04574)*	(0.02558)***
College			0.05878	0.46009			0.03737	0.45893
			(0.06130)	(0.03428)***			(0.05742)	(0.03215)***
Undergraduate			0.06706	0.56432			0.04344	0.56460
			(0.05645)	(0.03149)***			(0.05238)	(0.02927)***
Master			0.18087	0.78893			0.15417	0.78929
			(0.13645)	(0.07642)***			(0.13465)	(0.07547)***
Experience	0.01346	0.00566	0.01370	0.00554				
	(0.00385)***	(0.00217)***	(0.00389)***	(0.00219)**				
Experience^2	-0.00256	-0.00009	-0.00026	-0.00012				
	(0.00008)***	(0.00005)**	(0.00008)***	(0.00005)**				
Age					0.02731	0.00973	0.02742	0.00656
					(0.00781)***	(0.00440)**	(0.00787)***	(0.00444)
Age^2					-0.00033	-0.00011	-0.00033	-0.00008
					(0.00010)***	(0.00006)*	(0.00010)***	(0.00006)
Tenure	0.00256	0.01660	0.00236	0.01629	0.00235	0.01670	0.00224	0.01695
	(0.00370)	(0.00207)***	(0.00371)	(0.00208)***	(0.00370)	(0.00207)***	(0.00370)	(0.00207)***
Tenure^2	-0.00013	-0.00028	-0.00011	-0.00026	-0.00011	-0.00028	-0.00010	-0.00028
	(0.00012)	(0.00007)***	(0.00012)	(0.00007)***	(0.00012)	(0.00007)***	(0.00012)	(0.00007)***
Marital status	0.07606	-0.00778	0.07756	-0.00926	0.07237	-0.00753	0.07372	-0.00467
	(0.03311)**	(0.01857)	(0.03313)**	(0.01857)	(0.03330)**	(0.01868)	(0.03333)**	(0.01869)
Urban	0.13466	0.04558	0.13277	0.05277	0.13472	0.04562	0.13238	0.05240
	(0.02349)***	(0.01357)***	(0.02368)***	(0.01365)***	(0.02349)***	(0.01357)***	(0.02368)***	(0.01365)***
Female	0.03404	-0.19565	0.03680	-0.20551	0.03194	-0.19644	0.03561	-0.20635
	(0.02212)***	(0.01236)***	(0.02227)*	(0.01244)***	(0.02209)	(0.01235)***	(0.02226)	(0.01244)***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
AveSchool		0.20962		0.21680		0.20951		0.21683
		(0.01770)***		(0.01789)***		(0.01770)***		(0.01790)***
AveSchool-Ind	-0.00440	0.02794	-0.00244	0.02578	-0.00431	0.02800	-0.00192	0.02601
	(0.00790)	(0.00441)***	(0.00794)	(0.00444)***	(0.00790)	(0.00441)***	(0.00794)	(0.00444)***
PerPoverty	-0.06293		-0.06248		-0.06292		-0.06249	
	(0.00199)***		(0.00199)***		(0.00199)***		(0.00199)***	
R^2	0.2070		0.2077		0.2071		0.2079	
Adjusted R^2	0.2053		0.2049		0.2054		0.2051	
Observations	4528	4528	4528	4528	4528	4528	4528	4528
Test Results								
Quality								
F		1004.37		981.124		1004.4		981.627
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		109.071		113.564		108.898		113.073
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The social return to schooling associated with the *AveSchool* and *AveSchool-Ind* variables is 4.96 and 5.61 times as high as the private return (see columns (b) and (f) of Table 7.7). Consistent with the results obtained using OLS, the social returns to schooling tend to increase with the level of education. For example, the social return to schooling based on experience is 27.26, 29.48, 30.08, 30.14, 30.87, 32.56, and 37.27 percent for primary school, junior secondary school, vocational senior secondary school, general senior secondary school, college, undergraduate, and master degree, respectively. These social returns to schooling obtained using the IV approach are much greater than those obtained using OLS. When the age variable is utilised, the results show similar patterns.

Table 7.8 presents the results following the addition of the extra controls for individual characteristics (tenure and its square, marital status, urban area of residence, and gender status) to the equations. Similar to the earlier results reported in Table 7.7, here all of the *F*-statistics in the first stage regressions suggest a good correlation between the instrument and the average years of schooling. Moreover, the Hausman test confirms the endogeneity of *AveSchool*. Typical of the pattern established above, *PerPoverty* has a significant negative effect on the average years of schooling.

Most the individual characteristic variables are significant, in particular, the variables related to individual schooling and potential work experience fall into this category. In line with the earlier results reported in Table 7.7, the results presented in Table 7.8 show that all the individual variables (years of schooling or level of education, potential work experience or age and its square) included to control for individual effects on earnings are significant and have the expected sign and magnitude, except for the variable of age in column (h) that is not significant.

Estimating the numerical importance of the average years of schooling externalities at the level of the province using the IV approach with this extended specification, and adopting *PerPoverty* as instrument, also yields statistically significant externalities. The estimates of the external effect from an increase by one in the average years of schooling in the province on an individual’s monthly earnings range from around 20.95 to 21.68 percent (statistically significant at the 1 percent level). These results are, on average, around 7.23 percent lower than the results reported in Table 7.7.

However these figures are 3.69 times as high as those obtained using the OLS approach reported in Table 7.4. These external returns associated with average years of schooling are comparable with Rakova and Vaillancourt's (2005) finding for Canada, where an increase by one year in the average level of education was associated with an 18.7 percent increase in private sector labour productivity.

The measure of the aggregate-level human capital given by the average years of schooling based on the industrial sector is statistically significant in all four specifications at the 1 percent level. The values of the coefficient on this variable indicate that an increase of one year in the average schooling increases the individual's monthly earnings by approximately 2.58 to 2.80 percent. On average these external returns from the average years of schooling based on the industrial sector are 0.46 percentage points higher than those obtained using the IV approach without the additional variables for individual characteristics. However these figures remain lower, by around 1.70 percentage points, compared to those obtained using the OLS approach. It has been discussed in Chapter 4 that in the study of human capital externalities, the direction of bias in the OLS estimate could go either way (upward or downward bias). The direction of bias in the OLS estimates, or the effect of endogeneity, is influenced by the relative importance of unobserved heterogeneity in the demand and supply for labour. The OLS estimate will be upward biased if average education variation across regions is pushed by unobserved *demand* shocks. On the other hand, if variation in average education across regions is driven by unobserved *supply* shocks, the OLS estimate is biased down (Moretti, 1998).

The comparison between the social return and the private return is similar to the earlier result presented in Table 7.7. The social return to schooling is 5.37 and 5.59 times as high as the private return (see columns (b) and (f) of Table 7.8). This type of similarity in the finding across specifications is also found for the models based on education levels. The results support the earlier results reported in Tables 7.3 to 7.7, that generally the higher the education level the higher is the social return.

Next the variables of *AveSchool* and *AveSchool-Ind* are replaced by *PerHE* and *PerHE-Ind*. The estimated results of the Mincerian model without (with) additional variables for individual characteristics are presented in Table 7.9 (7.10). Columns (a), (c), (e), and (g) of Table 7.9 report that the estimate associated with the instrument in the reduced form first-stage regression is negative and statistically significant at the 1 percent level in all four specifications. The Hausman test rejects at the 1 percent level the null hypothesis of equality of the OLS and IV estimates for all four specifications.

All variables for individual characteristics - years of schooling or level of education and potential work experience or age and its square - are statistically significant at the 1 percent level and are associated with sensible estimated impacts. More experience in terms of potential work experience or age implies greater earnings. Moreover, the private return to schooling is between 4.84 and 4.28 percent (see columns (b) and (f) of Table 7.9)).

Replacing *AveSchool* with *PerHE* as the aggregate-level human capital measure results in much lower estimates of the human capital externalities, of 7.04 to 7.27 percent (also statistically significant at the 1 percent level). However, the external return to schooling remains positive and significant, and also remains higher than the private return to schooling.

Using the *PerHE-Ind* variable instead of *AveSchool-Ind* is similarly associated with a lower estimate of the external return to schooling. A one percentage point increase in the share of workers with higher education at the industrial sector level can be expected to increase a worker's monthly earnings by approximately 0.13 to 0.37 percent. The social return associated with the *PerHE* and *PerHE-Ind* variables is 12.06 and 11.49 percent for the models based on years of schooling. In the models based on levels of education the social return varies from 9.05 to 17.04 percent for the models based on experience, and from 9.14 to 16.71 percent for the models based on age.

Based on the results in Tables 7.7, 7.8, 7.9, and 7.10, it can be seen that *PerPoverty* performs very well as the sole instrument in the first-stage regressions, being significant and having the expected sign.

Table 7.9: Instrumenting the Percentage of Workers with Higher Education with Population below the Poverty Line (Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	9.09992	4.65898	9.43190	4.88027	7.70906	4.43161	7.81058	4.65711
	(0.23388)***	(0.04761)***	(0.24877)***	(0.05154)***	(0.53848)***	(0.08439)***	(0.56417)***	(0.08907)***
Years of schooling	0.09697	0.04844			0.08274	0.04275		
	(0.01384)***	(0.00208)***			(0.01265)***	(0.00191)***		
Primary school			0.07184	0.09838			0.12336	0.10347
			(0.19533)	(0.02904)***			(0.19121)	(0.02843)***
Junior secondary school			0.31390	0.21056			0.34028	0.20483
			(0.20506)	(0.03047)***			(0.19621)*	(0.02918)***
Vocational senior secondary school			1.13425	0.31780			1.08983	0.29404
			(0.21095)***	(0.03177)***			(0.19858)***	(0.03000)***
General senior secondary school			0.79807	0.34689			0.74385	0.32114
			(0.20146)***	(0.03012)***			(0.18843)***	(0.02823)***
College			0.89716	0.50048			0.77178	0.45461
			(0.25236)***	(0.03758)***			(0.23926)***	(0.03566)***
Undergraduate			0.80711	0.63227			0.67133	0.58502
			(0.23167)***	(0.03431)***			(0.21770)***	(0.03229)***
Master			1.83796	0.82483			1.68682	0.77088
			(0.56995)***	(0.08525)***			(0.56443)***	(0.08446)***
Experience	0.05600	0.01399	0.05983	0.01355				
	(0.01412)***	(0.00209)***	(0.01425)	(0.00213)***				
Experience^2	-0.00102	-0.00019	-0.00110	-0.00021				
	(0.00031)***	(0.00005)***	(0.00031)***	(0.00005)***				
Age					0.10795	0.02014	0.11447	0.01739
					(0.02879)***	(0.00427)***	(0.02896)***	(0.00433)***
Age^2					-0.00128	-0.00019	-0.00134	-0.00016
					(0.00037)***	(0.00006)***	(0.00037)***	(0.00006)***
PerHE		0.07045		0.07278		0.07037		0.07275
		(0.00543)***		(0.00557)***		(0.00544)***		(0.00557)***
PerHE-Ind	0.00079	0.00173	0.00328	0.00133	0.00092	0.00174	0.00369	0.00137
	(0.00379)	(0.00056)***	(0.00384)	(0.00057)**	(0.00379)	(0.00056)***	(0.00384)	(0.00057)**
PerPoverty	-0.21976		-0.21677		-0.21967		-0.21680	
	(0.00808)***		(0.00811)***		(0.00808)***		(0.00811)***	
R^2	0.1510		0.1549		0.1509		0.1550	
Adjusted R^2	0.1501		0.1529		0.1500		0.1529	

	(a)	(b)	(c)	(d)	(e)	f)	(g)	(h)
						age proxying experience		
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Observations	4528	4528	4528	4528	4528	4528	4528	4528
Test Results								
<u>Quality</u>								
F		739.867		714.848		739.078		714.989
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
<u>Relevance (Hausman test)</u>								
F		173.092		176.5		171.437		175.1
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.10: Instrumenting the Percentage of Workers with Higher Education with Population below the Poverty Line (Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	8.41277	4.80594	8.59189	5.03601	7.35563	4.68227	7.34386	4.94799
	(0.24681)***	(0.04637)***	(0.26510)***	(0.04965)***	(0.56674)***	(0.08520)***	(0.59358)***	(0.08930)***
Years of schooling	0.05547	0.04438			0.04494	0.04261		
	(0.01434)***	(0.00207)***			(0.01291)***	(0.00186)***		
Primary school			0.07937	0.06782			0.12324	0.07733
			(0.19387)***	(0.02799)**			(0.18893)	(0.02728)***
Junior secondary school			0.11533	0.17131			0.14256	0.18090
			(0.20461)	(0.12953)***			(0.19459)	(0.02809)***
Vocational senior secondary school			0.76117	0.25097			0.73441	0.25653
			(0.21354)***	(0.03092)***			(0.19934)***	(0.02890)***
General senior secondary school			0.46423	0.28181			0.43066	0.28718
			(0.20364)**	(0.02940)***			(0.18874)**	(0.02726)***
College			0.51110	0.45683			0.42264	0.45709
			(0.25398)**	(0.03663)***			(0.23794)**	(0.03433)***
Undergraduate			0.40469	0.57324			0.31118	0.57482
			(0.23402)*	(0.03365)***			(0.21728)	(0.03127)***
Master			1.23479	0.76225			1.13113	0.76391
			(0.56611)**	(0.08193)***			(0.55879)**	(0.08090)***
Experience	0.04463	0.00552	0.04732	0.00529				
	(0.01598)***	(0.00231)**	(0.01613)***	(0.00234)**				
Experience^2	-0.00083	-0.00009	-0.00089	-0.00011				
	(0.00034)**	(0.00005)*	(0.00035)**	(0.00005)**				
Age					0.04463	0.00552	0.04732	0.00529
					(0.01598)***	(0.00231)**	(0.01613)***	(0.00234)**
Age^2					0.08335	0.00991	0.08896	0.00633
					(0.03245)***	(0.00469)**	(0.03265)***	(0.00474)
Tenure	0.01827	0.01585	0.01770	0.01554	-0.00100	-0.00011	-0.00106	-0.00008
	(0.01536)	(0.00221)***	(0.01538)	(0.00222)***	(0.00042)**	(0.00006)*	(0.00042)**	(0.00006)
Tenure^2	-0.00060	-0.00027	-0.00057	-0.00024	0.01899	0.01587	0.01829	0.01615
	(0.00050)	(0.00007)***	(0.00050)	(0.00007)***	(0.01537)	(0.00221)***	(0.01537)	(0.00222)***
Marital status	0.35645	-0.01744	0.35912	-0.01914	-0.00057	-0.00026	-0.00056	-0.00027
	(0.13750)***	(0.01982)	(0.13740)***	(0.01987)	(0.00050)	(0.00007)***	(0.00050)	(0.00007)***
Urban	1.10749	0.00849	1.07928	0.01577	0.35677	-0.01800	0.35541	-0.01500
	(0.09643)***	(0.01579)	(0.09704)***	(0.01584)	(0.13831)***	(0.01579)	(0.13828)***	(0.02001)
Female	0.14858	-0.19389	0.17128	-0.20471	1.10789	0.00852	1.07889	-0.20549

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
	(0.09157)***	(0.01315)***	(0.09210)*	(0.01327)***	(0.09643)***	(0.01579)	(0.09704)***	(0.01327)***
PerHE		0.06815		0.07033		0.06814		0.07039
		(0.00549)***		(0.00558)***		(0.00550)***		(0.00558)***
PerHE-Ind	-0.00224	0.00211	-0.00029	0.00153	-0.00216	0.00212	0.00002	0.00157
	(0.00376)	(0.00054)***	(0.00381)	(0.00055)***	(0.00376)	(0.00054)***	(0.00381)	(0.00055)***
PerPoverty	0.21129		-0.20945		-0.21122		-0.20949	
	(0.00806)***		(0.00808)***		(0.00806)***		(0.00808)***	
R^2	0.1767		0.1794		0.1766		0.1793	
Adjusted R^2	0.1749		0.1765		0.1748		0.1764	
Observations	4528	4528	4528	4528	4528	4528	4528	4528
Test Results								
<u>Quality</u>								
F		687.359		671.388		686.814		671.559
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
<u>Relevance (Hausman test)</u>								
F		167.105		172.564		166.78		172.216
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

7.4.2.2 Using the Ratio of the Number of Senior Secondary Schools to Population as an Instrument.

In this sub-section the human capital externalities are investigated by utilising *SSS-Population* as the sole instrument. The analysis is divided into the same four parts as in the earlier sub-section. In the first two parts we discuss the IV analysis of human capital externalities using the *AveSchool* and *AveSchool-Ind* variables as aggregate-level human capital measures in the Mincerian model, with and without the tenure, marital status, area of residence and gender variables. The results of these analyses are presented in Tables 7.11 and 7.12. The remaining parts of this sub-section elaborate the IV analysis of human capital externalities using the *PerHE* and *PerHE-Ind* variables as aggregate-level human capital measures for the Mincerian model with and without the additional variables for individual characteristics. The results of these analyses are reported in Tables 7.13 and 7.14. All the results for the IV estimations using *SSS-Population* as an instrument are consistent with the findings from the IV estimations using *PerPoverty* as an instrument. The results point to the existence of sizeable human capital externalities.

The results presented in columns (a), (c), (e), and (g) of Table 7.11 show that the estimate associated with the instrument is statistically significant at the 1 percent level in all four specifications. This suggests that *SSS-Population* is an acceptable instrument. The *SSS-Population* variable impacts positively on the average years of schooling, which is the expected direction of effect. The Hausman test rejects at the 1 percent level the null hypothesis of the equality between the OLS and IV estimates for all four specifications. The R squareds for the first-stage equation are all moderate in size, being around the 0.13 mark. These goodness of fit measures are, however, around six percentage points lower than those obtained with the alternative instrument in the earlier analyses.

All of the variables in the earnings equation are statistically significant and have the expected signs. The effect of a one year increase in the average years of schooling ranges from around an 11.22 to 12.41 percent increase in labour productivity. These are 11.44 and 10.89 percentage points lower than those of the IV estimates using *PerPoverty* as an instrument reported in Table 7.7. Nevertheless, these figures remain greater than both the private return and the external return associated with the average years of schooling obtained by using OLS that were reported in Table 7.3.

Supporting the earlier OLS and IV results obtained using the *PerPoverty* variable as an instrument, the effect from a one year increase on the average years of schooling at the industrial sector level is substantially weaker than that from the overall average years of schooling.

Compared to the results obtained using IV with *PerPoverty* as an instrument, the social return to schooling derived from Table 7.11 is substantially smaller for all specifications, based both on years of schooling and levels of education. Using years of schooling in the model, the social return to schooling is 19.26 and 18.79 percent. Based on education level, the social return to schooling varies from 16.78 to 28.33 percent.

Including additional control variables for individual characteristics into the estimating equation (see Table 7.12) decreases the effect of the provincial level average years of schooling on individual earnings, but it increases the estimated size of the human capital externalities associated with the average years of schooling based on the industrial sector within each province. Compared to the results reported in Table 7.11, the spillover effect from the average years of schooling to earnings is estimated at approximately 9.46, 10.71, 9.51, and 10.79 percent for the estimation based on years of schooling and potential work experience, the estimation based on the education levels and potential work experience, the estimation based on years of schooling and age, and the estimation based on the education levels and age, respectively. These effects are 1.76, 1.64, 1.85, and 1.62 percentage points less than those reported in Table 7.11.

The effect that comes from a one year increase in the average years of schooling based on the industrial sector within each province ranges from about 3.18 to 3.39 percent, and shows a pattern similar to the earlier results whereby these effects are significantly smaller than those associated with the average years of schooling for the province as a whole. However, these effects are slightly higher than those obtained using the specification that does not include the additional individual characteristics. The differences range from the lowest of 0.29 to the highest of 0.42 percentage points.

Including tenure, marital status, urban area of residence, and gender variables lowers the social return to schooling by 2.22 (based on experience) and 1.95 (based on age) percentage points in the models using years of schooling. On average, the social return to schooling based on the level of education is 1.72 percentage points smaller than the results from the model that excluded the tenure, marital status, urban area of residence, and gender variables.

Table 7.13 presents the IV estimates using the *SSS-Population* variable as the sole instrument and *PerHE* and *PerHE-Ind* as the aggregate-level human capital measures for the Mincerian model without additional individual characteristics. The first-stage regression for all estimations show that the estimate associated with the instrument is positive and statistically significant at the 1 percent level, indicating that *SSS-Population* is acceptable instrument. Moreover, the Hausman test rejects, at the 1 percent level, the null hypothesis of the equality between the OLS and IV estimates for all four specifications.

The results from the earnings equation estimations show that all the individual variables are highly significant and have the expected sign. The external return produced by *PerHE-Ind* is positive and highly significant for all specifications. More importantly, the external return to schooling associated with the *PerHE* variable is also positive and significant, and it is even greater than the private return to schooling (see columns (b) and (f)).

Table 7.11: Instrumenting Average Years of Schooling with the Ratio of the Number of Senior Secondary School to Population (Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	8.00577	3.92637	8.08542	4.07966	7.65945	3.65106	7.70308	3.80059
	(0.08002)***	(0.18639)***	(0.08843)***	(0.19102)***	(0.14632)***	(0.19089)***	(0.15593)***	(0.19535)***
Years of schooling	0.01087	0.05048			0.00849	0.04450		
	(0.00347)***	(0.02250)***			(0.00319)***	(0.00170)***		
Primary school			-0.04939	0.09297			-0.03448	0.09979
			(0.04861)	(0.02621)***			(0.04757)	(0.02565)***
Junior secondary school			-0.05602	0.21374			-0.04308	0.20898
			(0.05108)	(0.02752)***			(0.04887)	(0.02634)***
Vocational senior secondary school			0.07366	0.36193			0.07374	0.33698
			(0.05282)	(0.02833)***			(0.04976)	(0.02674)***
General senior secondary school			0.07924	0.36432			0.07732	0.33720
			(0.05045)	(0.02705)***			(0.04724)	(0.02539)***
College			0.07129	0.51473			0.05711	0.46564
			(0.06307)	(0.03375)***			(0.05987)	(0.03211)***
Undergraduate			0.00559	0.62907			-0.01077	0.57856
			(0.05759)	(0.03093)***			(0.05421)	(0.02920)***
Master			0.23895	0.89090			0.22069	0.83316
			(0.14198)*	(0.07623)***			(0.14060)	(0.07563)***
Experience	0.01092	0.01560	0.01206	0.01541				
	(0.00351)***	(0.00189)***	(0.00354)***	(0.00192)***				
Experience^2	-0.00021	-0.00023	-0.00024	-0.00024				
	(0.00008)***	(0.00004)***	(0.00008)***	(0.00004)***				
Ag					0.02518	0.02309	0.02582	0.02091
					(0.00716)***	(0.00387)***	(0.00720)***	(0.00392)***
Age^2					-0.00031	-0.00023	-0.00032	-0.00021
					(0.00009)***	(0.00005)***	(0.00009)***	(0.00005)***
AveSchool		0.11224		0.12346		0.11361		0.12412
		(0.02250)***		(0.02283)***		(0.02251)***		(0.02285)***
AveSchool-Ind	-0.00025	0.02983	0.001176	0.02888	-0.00017	0.02974	0.00171	0.02903
	(0.00830)	(0.00444)***	(0.00834)	(0.00449)***	(0.00830)	(0.00445)***	(0.00835)	(0.00450)***
SSS-Population	7.19665		7.14797		7.20308		7.15042	
	(0.30240)***		(0.30374)***		(0.30227)***		(0.30361)***	
R^2	0.1267		0.1302		0.1273		0.1306	
Adjusted R^2	0.1257		0.1281		0.1263		0.1285	

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
						age proxying experience		
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Observations	4528	4528	4528	4528	4528	4528	4528	4528
Test Results								
Quality								
F		566.349		553.816		567.853		554.659
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		6.9722		7.23381		7.23381		9.24936
P-Value		0.0083***		0.0024***		0.0072***		0.0024***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.12: Instrumenting Average Years of Schooling with the Ratio of the Number of Senior Secondary School to Population (Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	7.98919	4.15385	8.05422	4.30373	7.68630	3.99360	7.72033	4.16615
	(0.08230)***	(0.18061)***	(0.09096)***	(0.18364)***	(0.15227)***	(0.18585)***	(0.16183)***	(0.18884)***
Years of schooling	0.00684	0.04399			0.00381	0.04201		
	(0.00360)*	(0.00184)***			(0.00325)	(0.00166)***		
Primary school			-0.04264	0.06083			-0.03240	0.07188
			(0.04871)	(0.02504)**			(0.04745)	(0.02440)***
Junior secondary school			-0.07478	0.16138			-0.06840	0.17205
			(0.05140)	(0.02647)***			(0.04888)	(0.02518)***
Vocational senior secondary school			0.03262	0.27061			0.02561	0.27550
			(0.05385)	(0.02757)***			(0.05028)	(0.02578)***
General senior secondary school			0.04518	0.27775			0.03620	0.28229
			(0.05136)	(0.02629)***			(0.04762)	(0.02440)***
College			0.04042	0.44711			0.01846	0.44499
			(0.06398)	(0.03272)***			(0.05992)	(0.03071)***
Undergraduate			-0.02793	0.54404			-0.05219	0.54331
			(0.05862)	(0.03013)***			(0.05436)	(0.02805)***
Master			0.17662	0.79169			0.14934	0.79074
			(0.14227)	(0.07287)***			(0.14038)	(0.07198)***
Experience	0.01023	0.00693	0.01129	0.00687				
	(0.00401)**	(0.00207)***	(0.00405)***	(0.00209)***				
$Experience^2$	-0.00009	-0.00012	-0.00021	-0.00015				
	(0.00013)**	(0.00004)***	(0.00009)	(0.00005)***				
Age					-0.02295	0.01245	0.02317	0.00930
					(0.00815)***	(0.00421)***	(0.00820)***	(0.00425)**
Age^2					-0.00027	-0.00014	-0.00027	-0.00011
					(0.00011)***	(0.00005)***	(0.00011)***	(0.00005)**
Tenure	-0.00002	0.01624	-0.00040	0.01591	-0.00055	0.01632	-0.00060	(0.01656
	(0.00386)	(0.00198)***	(0.00386)	(0.00198)***	(0.00386)	(0.00198)***	(0.00386)	(0.00198)***
$Tenure^2$	-0.00009	-0.00028	-0.00007	-0.00026	-0.00005	-0.00028	-0.00005	-0.00028
	(0.00013)	(0.00006)***	(0.00013)	(0.00006)	(0.00013)	(0.00006)	(0.00005)	(0.00007)***
Marital status	0.05331	-0.00338	0.05372	-0.00490	0.04734	-0.00357	0.04978	-0.00071
	(0.03453)	(0.01773)	(0.03451)	(0.01771)***	(0.03473)	(0.01784)	(0.03472)	(0.01783)
Urban	0.16829	0.06784	0.16352	0.07303	0.16848	0.06776	0.16331	0.07248
	(0.02446)***	(0.01323)***	(0.02464)***	(0.01326)***	(0.02445)***	(0.01323)***	(0.02463)***	(0.01327)***
Female	0.00264	-0.19940	0.00602	-0.20833	0.00130	-0.20040	0.00512	-0.20929
	(0.02303)	(0.01181)***	(0.02316)	(0.01187)***	(0.02300)	(0.01180)***	(0.02315)	(0.01187)***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
						age proxying experience		
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
AveSchool		0.09461		0.10710		0.09514		0.10792
		(0.02180)***		(0.02196)***		(0.02179)***		(0.02198)***
AveSchool-Ind	-0.00945	0.03391	-0.00831	0.03175	-0.00943	0.03393	-0.00791	0.03199
	(0.00844)	(0.00427)***	(0.00849)	(0.00430)***	(0.00844)	(0.00427)***	(0.00849)	(0.00431)***
SSS-Population	7.10672		7.07910		7.11077		7.08011	
	(0.30205)***		(0.30327)***		(0.30194)***		(0.30318)***	
R^2	0.1365		0.1394		0.1369		0.1395	
Adjusted R^2	0.1346		0.1363		0.1350		0.1365	
Observations	4258	4258	4258	4258	4258	4258	4258	4258
Test Results								
Quality								
F		553.566		544.872		554.621		545.355
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		4.24192		6.43835		4.3586		6.56637
P-Value		0.0395**		0.0112**		0.0369**		0.0104**

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.13: Instrumenting Percentage of Workers with Higher Education with the Ratio of the Number of Senior Secondary School to Population (Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	5.13662	4.74228	5.49965	4.95074	4.09868	4.49994	4.25825	4.71373
	(0.24323)***	(0.06525)***	(0.25931)***	(0.07104)***	(0.56847)***	(0.09057)***	(0.59454)***	(0.09605)***
Years of schooling	0.08011	0.05773			0.07119	0.04360		
	(0.01453)***	(0.00881)***			(0.01329)***	(0.00190)***		
Primary school			-0.08041	0.09600			-0.03804	0.10174
			(0.20497)	(0.02822)***			(0.20061)	(0.02764)***
Junior secondary school			0.08781	0.21088			0.11467	0.20570
			(0.21504)	(0.02956)***			(0.20576)	(0.02834)***
Vocational senior secondary school			0.99552	0.32708			0.97218	0.30322
			(0.22137)***	(0.03153)***			(0.20841)***	(0.02990)***
General senior secondary school			0.64534	0.35273			0.61519	0.32693
			(0.21138)***	(0.02951)***			(0.19774)***	(0.02774)***
College			0.73519	0.50543			0.65508	0.45914
			(0.26497)***	(0.03662)***			(0.25123)***	(0.03479)***
Undergraduate			0.39851	0.63406			0.31191	0.58648
			(0.24240)	(0.03330)***			(0.22789)	(0.03137)***
Master			1.76684	0.84092			1.67188	0.78621
			(0.59843)***	(0.08349)***			(0.59262)***	(0.08278)***
Experience	0.03753	0.01443	0.04408	0.01397				
	(0.01483)**	(0.00203)***	(0.01495)***	(0.00209)***				
Experience^2	-0.00071	-0.00020	-0.00084	-0.00021				
	(0.00033)**	(0.00004)***	(0.00033)**	(0.00005)***				
Age					0.07881	0.02102	0.08732	0.01821
					(0.03024)***	(0.00414)***	(0.03038)***	(0.00425)***
Age^2					-0.00096	-0.00020	-0.00105	-0.00017
					(0.00039)**	(0.00005)***	(0.00039)***	(0.00005)***
PerHE		0.08011		0.06260		0.05813		0.06285
		(0.01453)***		(0.00908)***		(0.00882)***		(0.00908)***
PerHE-Ind	0.00184	0.00144	0.00413	0.00146	0.00156	0.00185	0.00446	0.00149
	(0.00054)***	(0.00400)*	(0.00405)	(0.00056)***	(0.00400)	(0.00054)***	(0.00405)	(0.00056)***
SSS-Population	18.76461		18.51046		18.77488		18.51670	
	(1.22072)***		(1.22197)***		(1.22066)***		(1.22168)***	
R^2	0.0611		0.0685		0.0613		0.0685	
Adjusted R^2	0.0601		0.0662		0.0602		0.0663	

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
						age proxying experience		
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Observations	4528	4528	4528	4528	4528	4528	4528	4528
Test Results								
Quality								
F		236.291		229.465		236.573		229.729
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		32.9254		38.0705		33.3415		38.2182
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.14: Instrumenting Percentage of Workers with Higher Education with the Ratio of the Number of Senior Secondary School to Population (Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	4.66068	4.88228	4.85728	5.09730	3.76783	4.74567	3.78874	4.99615
	(0.25581)***	(0.06306)***	(0.27560)***	(0.06727)***	(0.59375)***	(0.09021)***	(0.62103)***	(0.09473)***
Years of schooling	0.03689	0.04474			0.02814	0.04288		
	(0.01503)**	(0.00200)***			(0.01353)**	(0.00180)***		
Primary school			-0.07579	0.06561			-0.04041	0.07570
			(0.20313)	(0.02718)**			(0.19791)	(0.02650)***
Junior secondary school			-0.12264	0.16936			-0.10217	0.17948
			(0.21419)	(0.02718)***			(0.20368)	(0.02729)***
Vocational senior secondary school			0.58455	0.25561			0.55879	0.26105
			(0.22370)***	(0.03018)***			(0.20879)***	(0.02827)***
General senior secondary school			0.28201	0.28361			0.25063	0.28891
			(0.21329)	(0.02853)***			(0.19766)	(0.02649)***
College			0.34830	0.45779			0.27023	0.45759
			(0.26632)	(0.03551)***			(0.24946)	(0.03332)***
Undergraduate			-0.00773	0.57086			-0.08974	0.57208
			(0.24448)	(0.03267)***			(0.22691)	(0.03042)***
Master			1.13122	0.77133			1.04097	0.77219
			(0.59354)*	(0.07973)***			(0.58583)*	(0.07879)***
Experience	0.03470	0.00600	0.04024	0.00572				
	(0.01676)**	(0.00224)***	(0.01691)**	(0.00229)**				
Experience^2	-0.00064	-0.00010	-0.00076	-0.00012				
	(0.00036)*	(0.00005)**	(0.00037)**	(0.00005)**				
Age					0.06966	0.01083	0.07643	0.00711
					(0.03405)**	(0.00455)**	(0.03423)**	(0.00464)
Age^2					-0.00084	-0.00012	-0.00092	-0.00009
					(0.00044)*	(0.00006)**	(0.00044)**	(0.00007)
Tenure	0.00678	0.01584	0.00556	0.01552	0.00673	0.01586	0.00608	0.01613
	(0.01611)	(0.00213)***	(0.01612)	(0.00215)***	(0.01612)	(0.00213)***	(0.01610)	(0.00215)***
Tenure^2	-0.00040	-0.00027	-0.00035	-0.00024	-0.00034	-0.00027	-0.00033	-0.00027
	(0.00052)	(0.00007)***	(0.00053)	(0.00007)***	(0.00053)	(0.00007)***	(0.00053)	(0.00007)***
Marital status	0.26144	-0.01477	0.26184	-0.01704	0.25643	-0.01536	0.25893	-0.01297
	(0.14423)*	(0.01913)	(0.14396)*	(0.01933)	(0.14507)*	(0.01926)	(0.14488)*	(0.01948)
Urban	1.26347	0.02643	1.22154	0.02918	1.26405	0.02619	1.22147	0.02830
	(0.10098)***	(0.01845)	(0.10154)***	(0.01848)	(0.10096)***	(0.01846)	(0.10153)***	(0.01850)
Female	0.01992	-0.19437	0.04673	-0.20475	0.01427	-0.19518	0.04276	-0.20558

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
					age proxying experience			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
	(0.09590)	(0.01266)***	(0.09636)	(0.01287)***	(0.09579)	(0.01265)***	(0.09632)	(0.01288)***
PerHE		0.05532		0.06039		0.05551		0.06078
		(0.00916)***		(0.00935)***		(0.00916)***		(0.00935)***
PerHE-Ind	-0.00129	0.00218	0.00071	0.00161	-0.00123	0.00218	0.00096	0.00165
	(0.00396)	(0.00052)***	(0.00402)	(0.00054)***	(0.00396)	(0.00052)***	(0.00402)	(0.00054)***
SSS-Population	17.40880		17.29611		17.42172		17.30547	
	(1.20811)***		(0.00402)***		(1.20791)***		(1.20958)***	
R^2	0.0932		0.0981		0.0932		0.0981	
Adjusted R^2	0.0911		0.0949		0.0911		0.0949	
Observations	4258	4258	4258	4258	4258	4258	4258	4258
Test Results								
Quality								
F		207.646		204.371		208.022		204.691
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		29.8863		35.5313		30.1608		35.9853
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.14 presents the IV estimates using *SSS-Population* as the sole instrument and *PerHE* and *PerHE-Ind* as the aggregate-level human capital measures for the Mincerian model with the additional individual characteristics. The estimates of the external returns to schooling created by *PerHE* and *PerHE-Ind* are both positive and statistically significant at the 1 percent level. Quantitatively, the estimates of the external returns to schooling based on the *PerHE* variable are comparable with their counterparts report in Table 7.13, except for the estimate based on potential work experience and years of schooling (see column b). When compared to the results obtained from the IV estimatation using *PerPoverty* as an instrument (reported in Tables 7.8 and 7.9), the external returns reported in Table 7.14 are somewhat smaller. The *SSS-Population* variable performs well as an instrument, as shown in the first-stage regression reported in Tables 7.11, 7.12, 7.13, and 7.14. The results consistently show that the coefficient on the *SSS-Population* variable is positive, as it is expected, and significant at the 1 percent level of significance. Moreover, the Hausman test of the endogeneity of *AveSchool* or *PerHE* indicates that the null hypothesis of exogeneity is rejected for all specifications. This result confirms that adopting an IV approach is necessary.

Summing up the patterns of the IV estimates results, there are eight points that need to be highlighted. First, all estimates of the external returns to schooling are positive and statistically significant, both for the overall level of the variable designed to capture them and for the industrial sector levels variant of the same variable. Second, using years of schooling or level of education for the individual’s education, and using potential work experience or age, generates the same results, where the coefficients for the aggregate-level human capital measures are positive and statistically significant. Third, the magnitude of the estimated external return to schooling is comparable across the specifications. Fourth, adding variables for tenure and its square, marital status, urban area of residence, and gender status to the estimating equation leads to a decrease in the coefficients of the variables of *AveSchool* and *PerHE*, but is associated with an increase in the coefficients of the variables of *AveSchool-Ind* and *PerHE-ind*. Fifth, the external return to schooling created by the average years of schooling and the percentage of workers with higher education obtained using the IV approach is much larger than that obtained using OLS. Sixth, the magnitude of the social return to schooling tends to increase with the level of education. Seventh, most of the specifications show that workers with general senior secondary school are associated with a larger social return to school than workers with vocational senior secondary school. Eighth, the *PerPoverty* and *SSS-Population* variables apparently perform well as instruments.

7.4.3 Comparing the Impact of Aggregate-Level Human Capital on Male and Female Workers

The results discussed in sub-sections 7.4.1 and 7.4.2 provide strong evidence of the presence of sizeable human capital externalities in Indonesia. Now, we evaluate the impact of the aggregate-level human capital on the earnings of male and female workers separately. The results from the OLS estimations are presented in Tables 7.15, 7.16, 7.17, and 7.18. Table 7.15 (7.16) reports the OLS estimates separately for males and females based on years of schooling (education levels) without additional individual characteristics. Table 7.17 (7.18) reports the OLS estimates separately for males and females based on years of schooling (education levels) with additional individual characteristics. Note that in these estimations the aggregate-level human capital variable is for all workers, without a gender distinction. This type of measurement is consistent with idea behind the externalities concept.

All variables reported in Table 7.15 are significant and have the expected sign. It can be seen that the private return for females exceeds that for males for all four specifications. The coefficient of *AveSchool* is 0.05422 (0.05753) and 0.05401 (0.05836) for males (females), indicating that an extra year of provincial average years of schooling tends to increase earnings by around 5.42 (5.75) and 5.40 (5.84) percent for males (females). Using the human capital for the industrial sector within each province as the variable to capture the externalities shows that an extra year of schooling based on the industrial sector within each province tends to raise individual earnings by about 3.68 (5.26) and 3.69 (5.26) percent for males (females). To put these figures in perspective, note that the return to own schooling is approximately 4.59 (5.60) and 4.01 (5.02) percent for male and female workers, respectively in these estimation. Thus both the private return and the externality effect for females exceed the comparable magnitudes for males. Consequently, female workers receive a social return to education greater than male workers. The social return to education ranges from 13.10 to 13.69 percent for male workers and from 16.11 percent to 16.59 percent for female workers.

Replacing the variable of *AveSchool* with *PerHE* (see the right-hand side Table 7.15) results in a lower externality effect for all specifications, which is 0.01041 for males and 0.0159 and 0.01613 for females, suggesting that a one percentage point increase in the share of workers with higher education leads to an increase in individual earnings by approximately 1.04 percent for males and about 1.59 and 1.61 percent for females. These results are different from the earlier finding (when *AveSchool* is used as aggregate-level human capital measure), as here the external return to schooling is smaller than the private return to schooling.[42]

Similarly, utilising the *PerHE-Ind* variable instead of *AveSchool-Ind* produces substantially lower figures, where a one percentage point increase in the representation of workers with higher education based on the industrial sector within each province increases an individual's earnings by around 0.20 (0.45) and 0.21 (0.45) percent for male (female) workers.

Supporting the results presented in columns (a), (b), (c), and (d) of Table 7.15 where the years of schooling variable was used, when the percentage of workers with higher education qualifications is used for the aggregate-level variable the social return to education for female workers exceeds for male workers. These social returns to education range from 5.60 to 6.17 percent for male workers and from 7.23 to 7.78 percent for female workers.

The results reported in Table 7.16 which are based on education levels, suggest that the human capitals externalities associated with average years of schooling and average years of schooling based on the industrial sector within each province are slightly larger for female workers than they are for male workers. Analysing the human capital externalities using the *PerHE* and *PerHE-Ind* variables as aggregate-level human capital measures provides a similar result.

Male and female workers have social returns to schooling that increase with the level of education. The magnitude of the social return to schooling for male workers with

[42] Note that this conclusion also holds when the estimated partial effects in this semi-logarithmic earnings equation are multiplied by mean of the respective variable to give an elasticity measure.

primary schooling and master degree qualifications is larger than that of female workers with those education levels, except for the specification based on age where the *AveSchool* and *AveSchol-Ind* variables are used as the aggregate-level human capital measures. The results from this specification show that only male workers with a master degree are associated with a social return to schooling that exceeds that of female workers with master degree.

The results of all the specifications suggest that the social return to schooling for male workers with general senior secondary school is larger than that of male workers with vocational senior secondary school. Female workers are characterised by the opposite pattern, where the social return to schooling is larger for female workers who graduated from vocational senior secondary school than it is for female workers who graduated from general senior secondary school.

Following the approach used in the study of the data pooled across male and female workers in the previous section, the earnings equation was augmented with the additional individual characteristics for tenure, marital status, and area of residence. The results are reported in Tables 7.17 and 7.18. Even after including these additional variables for individual characteristics, all four aggregate-level human capital measures enter the earnings function with a positive and statistically significant coefficient. Moreover, the results in these specifications reveal the same patterns as the earlier results reported in Tables 7.15 and 7.16.

Thus, based on the results reported in Tables 7.15, 7.16, 7.17, and 7.18, the following patterns are established. First, for both males and females, estimating the external return to schooling using the average years of schooling as an aggregate-level human capital measure yields a greater external return than that obtained using the percentage of workers with higher education as an aggregate-level human capital measure, both at the provincial level and when based on the industrial sector within each province. For example, on average the external return to schooling created from the average years of schooling is 4.37 and 4.20 percentage points greater than that associated with the share of workers with higher education for male and female workers, respectively. When the industrial sector within each province is used as the basis for constructing the aggregate-level human capital measure, on average the external return to schooling associated with the average years of schooling based on the industrial sector within each province is 3.48 and 4.81 percentage points greater than that associated with the share of workers with higher education based on the industrial sector for male and female workers, respectively.

Second, the effect of the aggregate-level education on individual earnings associated with the average provincial-level education without a sectoral distinction is greater than that induced by the average human capital with an industrial sector distinction. Thus the external return to schooling from the average years of schooling (the percentage of workers with higher education) is 1.73 (0.84) percentage points higher than that from the average years of schooling based on the province's industrial sector (the percentage of workers with higher education based on the industrial sector within the province) for male workers. Similarly, the external return to schooling from the average years of schooling (the percentage of workers with higher education) is 0.54 (1.15) percentage points higher than that from the average years of schooling based on the province's industrial sector (the percentage of workers with higher education based on the province's industrial sector) for female workers.

Third, similar to the private return, the external return for females also exceeds that for males for all four aggregate-level human capital measures. On average, an extra year of average schooling (average years of schooling based on the industrial sector within the province) increases female workers' earnings by around 0.39 (1.58) percentage points more than the comparable increase for male workers. Likewise, on average, a one percentage point addition to the share of workers with higher education (share of worker with higher education based on the industrial sector within the province) increases female workers' earnings by approximately 0.56 (0.25) percentage points more than the comparable increase for male workers. These three patterns remain when education levels are used in place of years of schooling in the earnings equation (see Tables 7.16 and 7.18).

Fourth, the social return to schooling also has the same pattern as the private and external returns to schooling. Female workers are associated with a higher social return to schooling compared with male workers for the specifications based on years of schooling. For example, the results in Table 7.15 (7.17) suggest that, on average, the social return to schooling for female workers is 2.29 (1.88) percentage points higher than that for male workers. For the specifications based on education levels, most estimations suggests that the social return to schooling for male workers is larger than that of female workers only for workers with primary school or a master degree.

Fifth, comparing general and vocational senior secondary school, the following conclusion can be drawn. Male workers with general senior secondary school have a larger social return to schooling than male workers with vocational senior secondary school. On the other hand, the social return to schooling for female workers with vocational senior secondary school exceeds that of female workers with general senior secondary school.

The IV approach is also utilised to separately evaluate the impact of aggregate-level human capital on earnings for male and female workers. The results based on the IV approach are presented as appendixes in Tables A7.1 to A7.16. The results from the first-stage regressions provided in Tables A7.1 to A7.8 confirm the endogeneity of *AveSchool* and *PerHE*. Furthermore, it appears that the *PerPoverty* variable is an acceptable instrument for all specifications. The results obtained based on the IV approach using *PerPoverty* as an instrument for males and females separately suggest that the impact of the average years of schooling is greater for male workers than it is for female workers for most specifications, though the specification based on education levels and age with the additional individual characteristics is an exception in this regard (see Tables A7.1 to A7.4). This pattern is contrary to the results obtained using the OLS method, where the average years of schooling was associated with a greater impact for female workers than for male workers. However, the results for the average years of schooling based on the industrial sector within the province have a pattern similar to the OLS results, where that impact is greater for female workers than it is for male workers. In terms of the social return to schooling, the results from Tables A7.1 and A.7.3 suggest that male workers have a slightly smaller social return to schooling. Thus, the social return to schooling for male workers ranges from 27.41 to 28.07 percent, whereas for female workers the social return to schooling ranges from 28.86 to 29.32 percent.

As shown in Tables A7.2 and A7.4 the social return to schooling for male workers exceeds that for female workers only for workers with primary school or a master degree qualification. The size of the social return to schooling for both male and female workers increases with the level of education. The results reported in Table A.7.2 show that male and female workers with general senior secondary schooling are associated with a larger social return to schooling compared to male and female workers with vocational senior secondary schooling. The results presented in Table A7.4 have the same pattern for male workers. However, the opposite pattern occurs for female workers.

In Tables A7.5 to A7.8 it can be seen that the external returns to schooling from the percentage of the workers with higher education for female workers are smaller than those for their male counterparts. This pattern is also different from the results obtained using the OLS approach. However, the results where the aggregate-level variable refers to the percentage of workers with higher education based on the industrial sector within the province are in line with the results presented using the OLS approach. In contrast to the results presented in Tables A7.1 and A7.3, the social return to schooling based on years of schooling for female workers is greater than that for male workers. It ranges from the lowest of 10.76 percent to the highest of 11.29 percent for male workers and from the lowest of 11.74 percent to the highest of 12.31 percent for female workers. The male workers with primary school or master degree education qualification have a greater social return to schooling than comparable female workers. This pattern is also found in the earlier results discussed above. However, for the specification of the IV approach using *PerPover* as an instrument, based on experience and without the additional variables for individual characteristics, the results suggest a different pattern, where in addition to male workers with primary schooling or a master degree, male workers with vocational and general senior secondary schooling have a higher social return to schooling than female workers.

Table 7.15: Impact of Aggregate-Level Human Capital on Male and Female Workers (OLS Estimation based on Years of Schooling - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Variable	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Constant	4.51249	4.00040	4.29647	3.69586	5.19038	4.80864	4.97285	4.51363
	(0.08416)***	(0.13444)***	(0.11350)***	(0.17057)***	(0.03676)***	(0.05352)***	(0.08708)***	(0.11952)***
Years of schooling	0.04590	0.05598	0.04006	0.05016	0.04925	0.05740	0.04351	0.05166
	(0.00215)***	(0.00317)***	(0.00201)***	(0.00287)***	(0.00216)***	(0.00323)***	(0.00200)***	(0.00291)***
Experience	0.01214	0.01601			0.01194	0.01589		
	(0.00227)***	(0.00310)***			(0.00230)***	(0.00311)***		
Experience^2	-0.00015	-0.00024			-0.00015	-0.00024		
	(0.00005)***	(0.00007)***			(0.00005)***	(0.00007)***		
Age			0.01885	0.02512			0.01880	0.02480
			(0.00458)***	(0.00646)***			(0.00463)***	(0.00649)***
Age^2			-0.00017	-0.00026			-0.00018	-0.00025
			(0.00006)***	(0.00009)***			(0.00006)***	(0.00009)***
AveSchool	0.05422	0.05753	0.05401	0.05836				
	(0.00853)***	(0.01349)***	(0.00854)***	(0.05256)***				
AveSchool-Ind	0.03675	0.05256	0.03691	0.05256				
	(0.00476)***	(0.00800)***	(0.00476)***	(0.00801)***				
PerHE					0.01041	0.01590	0.01041	0.01613
					(0.00213)***	(0.00327)***	(0.00214)***	(0.00327)***
PerHE-Ind					0.00203	0.00450	0.00207	0.00449
					(0.00059)***	(0.00089)***	(0.00059)***	(0.00089)***
R^2	0.2224	0.2914	0.2218	0.2897	0.2033	0.2827	0.2028	0.2810
Adjusted R^2	0.2211	0.2891	0.2205	0.2874	0.2020	0.2803	0.2014	0.2786
Observations	3017	1511	3017	1511	3017	1511	3017	1511

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.16: Impact of Aggregate-Level Human Capital on Male and Female Workers (OLS Estimation based on Education Level - Mincerian Model without Additional Individual Characteristics)

Variable	(a) Males	(b) Females	(c) Males	(d) Females	(e) Males	(f) Females	(g) Males	(h) Females
Constant	4.70948	4.34518	4.49121	4.01916	5.42514	5.13137	5.20847	4.82042
	(0.08783)***	(0.13954)***	(0.11832)***	(0.17850)***	(0.03965)***	(0.05730)***	(0.09113)***	(0.12678)***
Primary school	0.09820	0.00186	0.09685	0.01747	0.10093	0.00038	0.10028	0.01620
	(0.03058)***	(0.04419)	(0.03002)***	(0.04318)	(0.03094)***	(0.04450)	(0.03038)***	(0.04347)
Junior secondary school	0.19224	0.19388	0.17830	0.20149	0.20166	0.20390	0.18899	0.21184
	(0.03202)***	(0.04698)***	(0.03088)***	(0.04445)***	(0.03235)***	(0.04726)***	(0.03119)***	(0.04471)***
Vocational senior secondary school	0.31549	0.36488	0.28430	0.35130	0.33584	0.37430	0.30640	0.36081
	(0.03288)***	(0.04945)***	(0.03121)***	(0.04626)***	(0.03310)***	(0.04974)***	(0.03138)***	(0.04652)***
General senior secondary school	0.33033	0.34706	0.29713	0.33078	0.35729	0.36500	0.32586	0.34903
	(0.03155)***	(0.04674)***	(0.02989)***	(0.04303)***	(0.03178)***	(0.04693)***	(0.03005)***	(0.04315)***
College	0.49205	0.53461	0.44011	0.49632	0.52648	0.55127	0.47670	0.51273
	(0.04176)***	(0.05304)***	(0.04013)***	(0.04945)***	(0.04219)***	(0.05367)***	(0.04047)***	(0.05000)***
Undergraduate	0.57333	0.65301	0.51913	0.61254	0.61200	0.67161	0.56007	0.63085
	(0.03642)***	(0.05116)***	(0.03477)***	(0.04723)***	(0.03685)***	(0.05189)***	(0.03510)***	(0.04784)***
Master	0.87066	0.90151	0.80719	0.86119	0.91081	0.91690	0.84989	0.87610
	(0.09250)***	(0.12115)***	(0.09182)***	(0.11983)***	(0.09374)***	(0.12212)***	(0.09300)***	(0.12075)***
Experience	0.01178	0.01711			0.01161	0.01710		
	(0.00229)***	(0.00312)***			(0.00232)***	(0.00313)***		
Experience^2	-0.00016	-0.00029			-0.00016	-0.00029		
	(0.00005)***	(0.00007)***			(0.00005)***	(0.00007)***		
Age			0.01678	0.02337			0.01658	0.02319
			(0.00461)***	(0.00652)***			(0.00467)***	(0.00656)***
Age^2			-0.00015	-0.00026			-0.00015	-0.00024
			(0.00006)***	(0.00009)***			(0.00006)***	(0.00009)***
AveSchool	0.05632	0.05874	0.05623	0.05990				
	(0.00855)***	(0.01353)***	(0.00856)***	(0.01357)***				
AveSchool-Ind	0.03743	0.04756	0.03753	0.04824				
	(0.00477)***	(0.00806)***	(0.00477)***	(0.00810)***				
PerHE					0.01116	0.01559	0.01117	0.01594
					(0.00214)***	(0.00328)***	(0.00214)***	(0.00329)***
PerHE-Ind					0.00192	0.00378	0.00195	0.00388
					(0.00059)***	(0.00092)***	(0.00059)***	(0.00092)***
R^2	0.2226	0.3029	0.2225	0.2990	0.2025	0.2937	0.2024	0.2898
Adjusted R^2	0.2198	0.2978	0.2197	0.2939	0.1996	0.2885	0.1995	0.2846
Observations	3017	1511	3017	1511	3017	1511	3017	1511

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.17: Impact of Aggregate-Level Human Capital on Male and Female Workers (OLS Estimation based on Years of Schooling - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Variable	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Constant	4.56348	4.11880	4.41015	3.91429	5.19346	4.86313	5.02803	4.65826
	(0.08440)***	(0.13248)***	(0.11566)***	(0.17142)***	(0.03792)***	(0.05504)***	(0.09044)***	(0.12499)***
Years of schooling	0.04101	0.04749	0.03867	0.04585	0.04367	0.04917	0.04132	0.04734
	(0.00221)***	(0.00327)***	(0.00204)***	(0.00285)***	(0.00224)***	(0.00332)***	(0.00205)***	(0.00290)***
Experience	0.00697	0.00798			0.00718	0.00849		
	(0.00255)***	(0.00352)**			(0.00258)***	(0.00354)**		
Experience^2	-0.00011	-0.00015			-0.00012	-0.00016		
	(0.00005)**	(0.00008)**			(0.00006)**	(0.00008)**		
Age			0.01245	0.01549			0.01321	0.01596
			(0.00515)**	(0.00725)**			(0.00521)**	(0.00290)**
Age^2			-0.00014	-0.00019			-0.00015	-0.00019
			(0.00007)**	(0.00010)**			(0.00007)**	(0.00010)**
Tenure	0.01163	0.02453	0.01167	0.02461	0.01142	0.02393	0.01143	0.02406
	(0.00233)***	(0.00364)***	(0.00233)***	(0.00365)***	(0.00236)***	(0.00367)***	(0.00235)***	(0.00368)***
Tenure^2	-0.00017	-0.00052	-0.00017	-0.00051	-0.00017	-0.00052	-0.00016	-0.00051
	(0.00008)**	(0.00012)***	(0.00008)**	(0.00012)***	(0.00008)**	(0.00012)***	(0.00008)**	(0.00012)***
Marital Status	0.03293	-0.04520	0.03223	-0.04568	0.02974	-0.04897	0.02861	-0.04908
	(0.23778)	(0.02702)*	(0.02396)	(0.02717)***	(0.02402)	(0.02720)*	(0.02420)	(0.02736)***
Urban	0.06717	0.10325	0.06728	0.10305	0.08412	0.11064	0.08424	0.11040
	(0.01474)***	(0.02369)***	(0.01474)***	(0.02369)***	(0.01484)***	(0.02398)***	(0.01483)***	(0.02398)***
AveSchool	0.05063	0.05577	0.05044	0.05630				
	(0.00848)***	(0.01331)***	(0.00848)***	(0.01329)***				
AveSchool-Ind	0.03308	0.04519	0.03313	0.04528				
	(0.00480)***	(0.00787)***	(0.00480)***	(0.00788)***				
PerHE					0.00807	0.01337	0.00804	0.01352
					(0.00215)***	(0.00326)***	(0.00215)***	(0.00326)***
PerHE-Ind					0.00174	0.00368	0.00175	0.00367
					(0.00058)***	(0.00088)***	(0.00058)***	(0.00088)***
R^2	0.2418	0.3291	0.2417	0.3290	0.2249	0.3198	0.2248	0.3196
Adjusted R^2	0.2396	0.3251	0.2394	0.3249	0.2226	0.3157	0.2225	0.3155
Observations	3017	1511	3017	1511	3017	1511	3017	1511

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.18: Impact of Aggregate-Level Human Capital on Male and Female Workers (OLS Estimation based on Education Levels - Mincerian Model with Additional Individual Characteristics.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Variable	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Constant	4.75623	4.42909	4.62126	4.22430	5.41233	5.16319	5.26957	4.96297
	(0.08790)***	(0.13746)***	(0.12026)***	(0.17862)***	(0.04094)***	(0.05946)***	(0.09431)***	(0.13188)***
Primary school	0.08332	-0.00858	0.09041	0.01207	0.08403	-0.00958	0.09215	0.01147
	(0.03032)***	(0.04353)	(0.02965)***	(0.04224)	(0.03064)***	(0.04387)	(0.02997)***	(0.04256)
Junior secondary school	0.15747	0.14754	0.16210	0.17231	0.16225	0.15640	0.16826	0.18125
	(0.03192)***	(0.04637)***	(0.03063)***	(0.04341)***	(0.03223)***	(0.04671)***	(0.03092)***	(0.04372)***
Vocational senior secondary school	0.26166	0.27970	0.25994	0.29761	0.27420	0.29088	0.27388	0.30798
	(0.03319)***	(0.04945)***	(0.03131)***	(0.04544)***	(0.03343)***	(0.04976)***	(0.03152)***	(0.04573)***
General senior secondary school	0.27826	0.27161	0.27599	0.28889	0.29771	0.28950	0.29681	0.30599
	(0.03177)***	(0.04662)***	(0.02987)***	(0.04219)***	(0.03203)***	(0.04685)***	(0.03010)***	(0.04238)***
College	0.42769	0.44445	0.41796	0.45383	0.45403	0.46482	0.44554	0.47225
	(0.04192)***	(0.05328)***	(0.03994)***	(0.04842)***	(0.04236)***	(0.05382)***	(0.04035)***	(0.04897)***
Undergraduate	0.51196	0.55556	0.50313	0.56623	0.54217	0.57750	0.53468	0.58600
	(0.03665)***	(0.05139)***	(0.03462)***	(0.04630)***	(0.03713)***	(0.05204)***	(0.03507)***	(0.04698)**
Master	0.80130	0.75141	0.78971	0.76702	0.83183	0.7198	0.82167	0.78519
	(0.09176)***	(0.11944)***	(0.09094)***	(0.11711)***	(0.09290)***	(0.12040)***	(0.09206)***	(0.11809)***
Experience	0.00649	0.00933			0.00675	0.00990		
	(0.00258)**	(0.00354)***			(0.00261)***	(0.00356)***		
Experience^2	-0.00012	-0.00022			-0.00013	-0.00023		
	(0.00006)**	(0.00008)***			(0.00008)**	(0.00008)***		
Age			0.00965	0.01330			0.01024	0.01385
			(0.00519)*	(0.00730)*			(0.00007)*	(0.00734)*
Age^2			-0.00011	-0.00018			-0.00012	-0.00018
			(0.00007)*	(0.00010)*			(0.00007)*	(0.00010)*
Tenure	0.01170	0.02333	0.01207	0.02444	0.01145	0.02283	0.01183	0.02397
	(0.00234)***	(0.00363)***	(0.00233)***	(0.00364)***	(0.00236)***	(0.00366)***	(0.00236)***	(0.00367)***
Tenure^2	-0.00016	-0.00046	-0.00018	-0.00049	-0.00016	-0.00046	-0.00017	-0.00049
	(0.00008)**	(0.00012)***	(0.00008)**	(0.00012)***	(0.00008)**	(0.00012)***	(0.00008)**	(0.00012)***
Marital Status	0.03483	-0.05006	0.03615	-0.04265	0.03170	-0.05394	0.03288	-0.04614
	(0.02379)	(0.02690)*	(0.02399)	(0.02706)	(0.02404)	(0.02709)**	(0.02424)	(0.02725)*
Urban	0.07574	0.09922	0.07525	0.09919	0.09326	0.10559	0.09275	0.10558
	(0.01484)***	(0.02383)***	(0.01484)***	(0.02387)***	(0.01492)***	(0.02417)***	(0.01493)***	(0.02416)***
AveSchool	0.05214	0.05880	0.05219	0.04042				
	(0.00849)***	(0.01332)***	(0.00849)***	(0.00797)***				
AveSchool-Ind	0.03298	0.03973	0.03315	0.05976				
	(0.00481)***	(0.00795)***	(0.00481)***	(0.01333)***				
PerHE					0.00862	0.01363	0.00864	0.01388
					(0.00215)***	(0.00327)***	(0.00215)***	(0.00327)***
PerHE-Ind					0.00153	0.00283	0.00156	0.00292
					(0.00059)***	(0.00090)***	(0.00059)***	(0.00090)***
R^2	0.2444	0.3401	0.2440	0.3381	0.2269	0.3304	0.2265	0.3282
Adjusted R^2	0.2406	0.3334	0.2402	0.3314	0.2231	0.3237	0.2226	0.3215
Observations	3017	1511	3017	1511	3017	1511	3017	1511

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

The IV estimates using *SSS-Population* as an instrument are reported in Tables A7.9 to A7.16. Similar to the results reported in Tables A7.1 to A7.4, the impact of the average years of schooling is greater for male workers than it is for female workers, except for the specification based on education levels and age with additional individual characteristics (see Tables A7.9 to A7.12). However, the Hausman test suggests that there is no difference between the IV and OLS approaches for all estimations for the female sample.

The results reported in Tables A7.13 to A7.16 support the earlier findings presented in Tables A7.5 to A7.8. The impact of the percentage of workers with higher education on the earnings of male workers exceeds the impact for female workers for all specifications. In contrast, when the industrial sector within the province is used in the construction of the aggregate-level human capital measure, the effect of the percentage of the workers with higher education is stronger for female workers than it is for male workers for all specifications. Again, the results concerning the social return to schooling for both the specification based on years of schooling and that based on levels of education are very consistent with the earlier findings. The Hausman test confirms that adopting an IV approach is necessary for all specifications in Tables A7.13 to A7.16.

Comparing the impact of aggregate-level human capital on male and female workers using the OLS and IV approaches, there are three issues worth noting. Firstly, using the OLS method, the aggregate-level human capital measured by the average years of schooling in each province has a larger impact on female workers' earnings than it has on the earnings of male workers for most specifications. The only specification that shows the opposite pattern is that based on age with additional variables for individual characteristics. Secondly, applying the OLS approach, the results suggest that female workers are associated with a larger impact on their earnings than is the case for males from the aggregate-level human capital measured by the percentage of workers with higher education in each province. Thirdly, adopting the IV approach, all the estimations suggest that aggregate-level human capital measured by the average years of schooling and the percentage of workers with higher education in each province is associated with a bigger effect on male workers' earnings than it has on the earnings of female workers. Fourthly, using either the OLS or IV approach leads to a similar conclusion, that aggregate-level human capital measured either by the average years of schooling based on the industrial sector within each province or the percentage of workers with higher education consistently has a larger effect on female workers' earnings than it has on the earnings of male workers. Fifthly, adopting either the OLS or IV approach for the estimations based on the years of schooling results in a consistent conclusion, that the social return to schooling for female workers exceeds that for male workers. On the other hand, the estimations based on education levels generally are characterised by a pattern where male workers with primary schooling or a master degree have a higher social return to schooling than their female counterparts, whereas female workers with junior secondary school, vocational senior secondary school, general senior secondary school, college, or undergraduate qualifications are associated with a greater social return to schooling than male workers with these education levels. Sixthly, comparing vocational and general senior secondary school, in general the results indicate that male workers with general senior secondary school tend to have a larger social return to schooling, while female workers with vocational senior secondary school tend to have a greater social return to schooling.

7.4.4 Human Capital Spillovers vs. Substitutability of Workers with Different Levels of Education

Moretti (2003, 2004) stressed that the correlation between aggregate-level human capital and earnings is not always associated with human capital externalities. In this last sub-section, we attempt to verify whether the external effect of education rather than imperfect substitution between low-skilled and high-skilled workers explains the correlation of average-level education and an individual's earnings. To do this we follow Moretti (2003, 2004) and Muravyev (2008), and estimate the education spillover effect in each province separately by the two main education levels represented by low-skilled and high-skilled workers.[43]

Moretti (2003) and Muravyev (2008) explained that an increase in the aggregate level of human capital may have two different effects on an individual's earnings. First, a conventional demand and supply model with imperfect substitution between high-skilled and low-skilled workers suggest that an increase in the number of high-skilled

[43] Low-skilled workers are defined as workers with education lower than higher education. High-skilled workers are defined as workers with higher education.

workers tends to decrease the earnings of the high-skilled workers and, at the same time, the earnings of low-skilled workers will tend to increase in this situation. In other words, although there are no human capital externalities, low-skilled workers receive benefit from an increase in the number of high-skilled workers under imperfect substitution between high- and low-skilled workers. Second, human capital externalities may increase the earnings of both low- and high-skilled workers. In other words, the externalities will be present as long as an increase in the average-level of education translates into an increase in the earnings of high-skilled workers.

Moretti (2004) emphasised that the external return to schooling associated with an increase in the ratio of workers with higher education should be positive for low-skilled workers. The coefficient for high-skilled workers should also be positive as long as the spillover is sufficient to offset the supply effect. Thus the coefficient for high-skilled workers should be negative if the spillover effect is weaker than the supply effect. In order to differentiate these spillover and imperfect substitution channels, we need to evaluate the effect of an increase in the supply of workers with higher education on their own earnings. Based on this rationale, this study estimates the external return to schooling separately for workers with an education level lower than higher education and for workers with higher education.

Table 7.19: Test for Imperfect Substitutability of Workers with and without Higher Education (OLS Estimation - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Variable	**Workers without Higher Education**				**Workers with Higher Education**			
Constant	4.51291	4.27871	5.15703	4.92244	3.26900	2.58096	4.05283	3.39352
	(0.08303)***	(0.10681)***	(0.03667)***	(0.07858)***	(0.32272)***	(0.35334)***	(0.28960)***	(0.32161)***
Years of schooling	0.04345	0.03892	0.04608	0.04159	0.10659	0.09640	0.10782	0.09768
	(0.00237)***	(0.00217)***	(0.00237)***	(0.00216)***	(0.01876)***	(0.01906)***	(0.01881)***	(0.01909)***
Experience	0.01269		0.01264		0.03047		0.02937	
	(0.00213)***		(0.00215)***		(0.00521)***		(0.00522)***	
Experience^2	-0.00018		-0.00018		-0.00058		-0.00055	
	(0.00005)***		(0.00005)***		(0.00015)***		(0.00015)***	
Age		0.01985		0.01996		0.05096		0.04871
		(0.00408)***		(0.00411)***		(0.01150)***		(0.01151)***
Age^2		-0.00020		-0.00021		-0.00052		-0.00049
		(0.00005)***		(0.00005)***		(0.00015)***		(0.00015)***
AveSchool	0.05031	0.05048			0.09072	0.09018		
	(0.00847)***	(0.00848)***			(0.01548)***	(0.01552)***		
AveSchool-Ind	0.03527	0.03541			0.01918	0.01908		
	(0.00478)***	(0.00478)***			(0.00896)**	(0.00898)**		
PerHE			0.00915	0.00922			0.02249	0.02247
			(0.00212)***	(0.00212)***			(0.00367)***	(0.00368)***
PerHE-Ind			0.00234	0.00238			0.00091	-0.00089
			(0.00059)***	(0.00060)***			(0.00098)	(0.00098)
R^2	0.1425	0.1421	0.1271	0.1266	0.1667	0.1626	0.1653	0.1615
Adjusted R^2	0.1413	0.1409	0.1259	0.1255	0.1618	0.1576	0.1603	0.1565
Observations	3680	3680	3680	3680	848	848	848	848

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table 7.20: Test for Imperfect Substitutability of Workers with and without Higher Education (OLS Estimation - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Variable	**Workers without Higher Education**				**Workers with Higher Education**			
Constant	4.61950	4.50818	5.28434	5.16038	3.55946	3.06158	4.22160	3.71519
	(0.08031)***	(0.10438)***	(0.03662)***	(0.07906)***	(0.31486)***	(0.36149)***	(0.28318)***	(0.33262)***
Years of schooling	0.03381	0.03319	0.03646	0.03567	0.09673	0.09137	0.09828	0.09314
	(0.00235)***	(0.00212)***	(0.00237)***	(0.00213)***	(0.01827)***	(0.01860)***	(0.01837)***	(0.01869)***
Experience	0.00429		0.00488		0.02097		0.02063	
	(0.00233)*		(0.00235)**		(0.00610)***		(0.00612)***	
Experience^2	-0.00009		-0.00010		-0.00044		-0.00044	
	(0.00005)*		(0.00005)*		(0.00018)**		(0.00018)**	
Age		0.00857		0.00963		0.03603		0.03596
		(0.00443)*		(0.00448)**		(0.01345)***		(0.01349)***
Age^2		-0.00011		-0.00012		-0.00039		-0.00040
		(0.00006)*		(0.00006)**		(0.00017)**		(0.00017)**
Tenure	0.01595	0.01587	0.01551	0.01543	0.01481	0.01554	0.01366	0.01436
	(0.00214)***	(0.00214)***	(0.00216)***	(0.00217)***	(0.00539)***	(0.00540)***	(0.00542)**	(0.00543)***
Tenure^2	-0.00028	-0.00027	-0.00028	-0.00027	-0.00027	-0.00028	-0.00021	-0.00022
	(0.00007)***	(0.00007)***	(0.00007)***	(0.00007)***	(0.00020)	(0.00020)	(0.00020)	(0.00020)
Marital Status	0.00562	0.00523	0.00013	-0.00027	-0.03427	-0.03300	-0.03205	-0.03094
	(0.01990)	(0.01990)	(0.02012)	(0.02012)	(0.03786)	(0.03804)	(0.03795)	(0.03813)
Urban	0.07027	0.07019	0.08984	0.08974	0.14397	0.14499	0.13747	0.01384
	(0.01382)***	(0.01381)***	(0.01386)***	(0.01386)***	(0.03110)***	(0.03116)***	(0.03153)***	(0.03158)***
Female	-0.22461	-0.22507	-0.21849	-0.21899	-0.13431	-0.13469	-0.13233	-0.13266
	(0.01337)***	(0.01337)***	(0.01350)***	(0.01349)***	(0.02463)***	(0.02472)***	(0.02479)***	(0.02488)***
AveSchool	0.05004	0.05004			0.07353	0.07288		
	(0.00809)***	(0.00808)***			(0.01527)***	(0.01530)***		
AveSchool-Ind	0.03854	0.03863			0.01854	0.01816		
	(0.00469)***	(0.00469)***			(0.00888)**	(0.00890)**		
PerHE			0.00830	0.00831			0.01737	0.01724
			(0.00205)***	(0.00205)***			(0.00366)***	(0.00367)***
PerHE-Ind			0.00222	0.00224			0.00101	0.00097
			(0.03662)***	(0.00057)***			(0.00098)	(0.00098)
R^2	0.2274	0.2275	0.2095	0.2096	0.2240	0.2214	0.2195	0.2171
Adjusted R^2	0.2253	0.2254	0.2074	0.2075	0.2147	0.2121	0.2101	0.2078
Observations	3680	3680	3680	3680	848	848	848	848

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Tables 7.19 and 7.20 show the results for the OLS estimations, with and without the tenure, marital status, urban area of residence and gender variables, separately for workers who obtained higher education and for all other (less-skilled) workers. These equations were also estimated using an IV approach. The IV results are presented in the appendix (Tables A7.17 to A7.24).

The results reported in Table 7.19 show that the coefficient of the *AveSchool* (*AveSchool-Ind*) variable for workers without higher education is 0.05031 (0.03527) and 0.05048 (0.03541) for the specifications based on potential work experience and age, respectively. The coefficient of the *AveSchool* (*AveSchool-Ind*) variable for workers with higher education is 0.09072 (0.01918) and 0.09018 (0.01908) for the specifications based on potential work experience and age, respectively. All these four coefficients are statistically significant. These results show that the average years of schooling in each province has a larger effect on the earnings of high-skilled workers than it has on the earnings of low-skilled workers. More importantly, these results confirm the presence of human capital externalities since the average-level of schooling in each province increases the earnings of both low-skilled and high-skilled workers.

In terms of the *AveSchool-Ind* variable, the results show that the average years of schooling based on the industrial sector within each province has a larger effect on earnings for low-skilled workers. However, the coefficients of *AveSchool-Ind* for the high-skilled workers remain positive. Based on Moretti's (2003) and Muravyev's (2008) argument, this implies that the positive effect of human capital externalities is larger than, and so offsets, the negative effect of the increase in their relative supply. This result is similar to Moretti (2004), who found evidence of a human capital spillover in the US, where an increase in the proportion of high-skilled workers had a larger positive effect on the wages of low-skilled workers, and a smaller, though still positive, effect on the wages of the high-skilled workers.

The coefficient of the *PerHE* (*PerHE-Ind*) variable for workers without higher education is 0.00915 (0.00234) and 0.00922 (0.00238) for the specifications based on potential work experience and age, respectively. The coefficient of the *PerHE* (*PerHE-Ind*) variable for workers with higher education is 0.02249 (0.00091) and 0.02247 (-0.00089) for the specifications based on potential work experience and age, respectively. These estimates for the *PerHE* variable indicate that a one percentage point increase in the percentage of workers with higher education in each province increases the earnings of low-skilled workers by 0.92 and 0.23 percent, and increases the earnings of high-skilled workers by 2.25 percent. This result supports the finding discussed earlier in this sub-section. The coefficients of the *PerHE-Ind* variable imply that a one percentage point increase in the percentage of workers with higher education based on the industrial sector within each province increases the earnings of low-skilled workers by 0.23 and 0.24 percent. However, the coefficients of the *PerHE-Ind* variable for workers with higher education are not statistically significant. This suggests that the supply effect approximately off-sets the human capital spillovers.

The results from the specifications with the additional individual characteristics reported in Table 7.20 reveal similar patterns to those discussed in relation to Table 7.19, and as such give further assurance in relation to the existence of human capital externalities.

Repeating the above estimations for separate samples (workers with and without higher education) with the IV approach confirms the conclusion drawn based on the OLS estimates, namely that human capital spillover exists in Indonesia. The results from the IV estimates using the *PerPoverty* variable as the sole instrument are presented in the appendix (see Tables A7.17 to A7.20), and these again reveal a positive relationship between the aggregate-level human capital measures and an individual's earnings. The results from the first-stage regressions provided in these tables suggest that the *PerPoverty* variable is an acceptable instrument. The statistical tests conducted indicate that the *AveSchool* and *PerHE* variables are endogenous.

Utilising *SSS-population* as an instrument (see Tables A7.21 and A7.22) leads to the same conclusion, that there is a major human capital spillover in Indonesia. However, the Hausman test for workers with higher education presented in these sets of analyses cannot reject the null hypothesis of equality of the OLS and IV estimates.

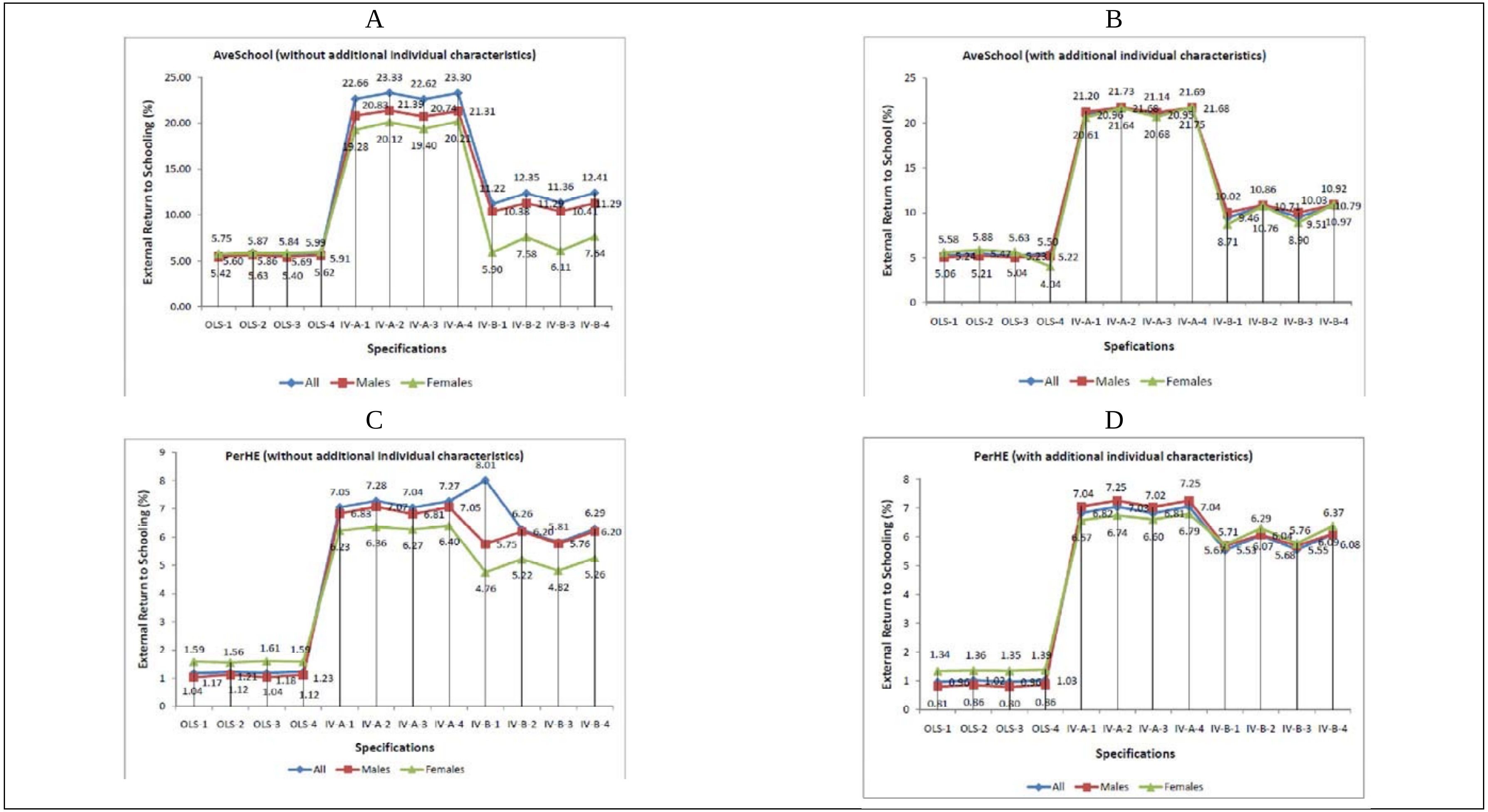
7.4.5 All Estimates Compared

Figures 7.1 and 7.2 provide an overview of the estimated external return to schooling obtained using the OLS and IV approaches. Figure 7.1 presents a comparison of the external return to schooling generated by the aggregate-level human capital in the province obtained using the OLS and IV approaches. The comparison of the human capital externalities estimated using the average years of schooling with the Mincerian model without (with) additional individual characteristics is presented in Panel A (B). The comparison of the human capital externalities estimated using the percentage of workers with higher education with the Mincerian model without (with) additional individual characteristics is presented in Panel C (D).

Using Figure 7.1, six features of the estimated external return to schooling in Indonesia can be readily identified. First, the external return to schooling obtained using the IV approach is greater than that obtained using OLS. Second, when the years of schooling variable is replaced by education levels there is a slightly higher estimate of the external return to schooling. Third, estimating the model with additional individual characteristics leads to a lower estimate of the external return to schooling. Fourth, the external return to schooling obtained using *AveSchool* as an aggregate-level human capital measure is substantially higher than that obtained using *PerHE*. Fifth, using OLS, the external return to schooling for female workers exceeds the external return for male workers. However, when the IV approach is adopted the results exhibit the opposite pattern, where male workers' external return to schooling exceeds that of female workers. Sixth, utilising *PerPoverty* as an instrument is associated with greater external returns to schooling compared to the results obtained using *SSS-Population* as an instrument.

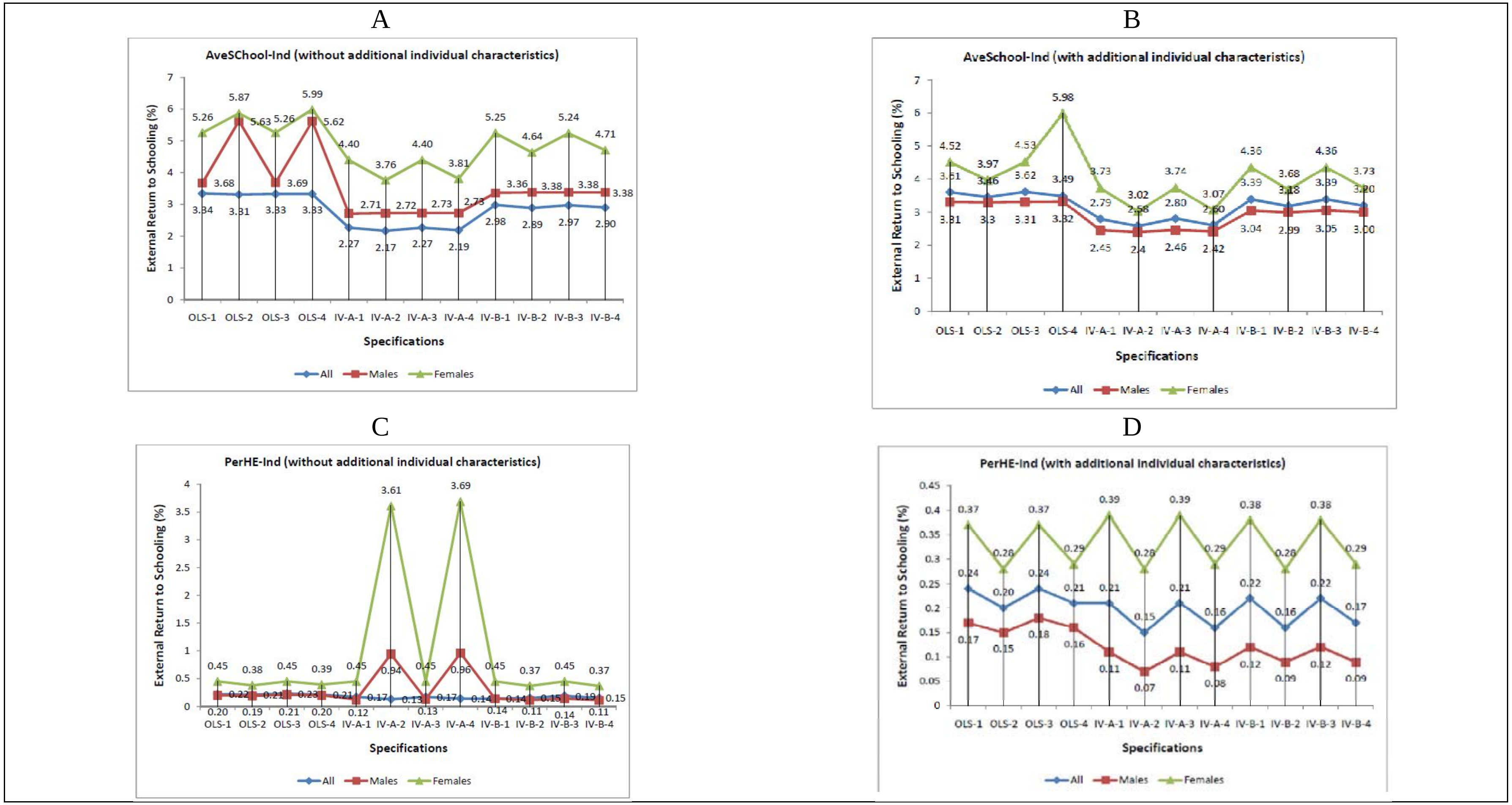
Figure 7.2 presents the comparison of the external return to schooling generated by the measure of the aggregate-level human capital based on the industrial sector within the province obtained using the OLS and IV approaches. The comparison of the human capital externalities estimated using the average years of schooling based on the industrial sector for the Mincerian model without (with) additional individual characteristics is presented in Panel A (B). The comparison of the human capital externalities estimated using the percentage of workers with higher education based on the industrial sector for the Mincerian model without (with) additional individual characteristics is presented in Panel C (D).

Figure 7.1: External Return to Schooling (Provincial Level)



Notes: OLS-1: OLS based on years of schooling and experience; OLS-2: OLS based on education levels and experience; OLS-3: OLS based on years of schooling and age; OLS-2: OLS based on education levels and age; IV-A-1: IV using *PerPoverty* as an instrument and based on years of schooling and experience; IV-A-2: IV using *PerPoverty* as an instrument and based on education levels and experience; IV-A-3: IV using *PerPoverty* as an instrument and based on years of schooling and age; IV-A-4: IV using *PerPoverty* as an instrument and based on education levels and age; IV-B-1: IV using *SSS-Population* as an instrument and based on years of schooling and experience; IV-B-2: IV using *SSS-Population* as an instrument and based on education levels and experience; IV-B-3: IV using *SSS-Population* as an instrument and based on years of schooling and age; IV-B-4: IV using *SSS-Population* as an instrument and based on education levels and age.
Sources: Tables 7.3 to 7.18 and Tables A.7.1 to A7.16.

Figure 7.2: External Return to Schooling (Industrial Sector within Province)



Notes: OLS-1: OLS based on years of schooling and experience; OLS-2: OLS based on education levels and experience; OLS-3: OLS based on years of schooling and age; OLS-2: OLS based on education levels and age; IV-A-1: IV using *PerPoverty* as an instrument and based on years of schooling and experience; IV-A-2: IV using *PerPoverty* as an instrument and based on education levels and experience; IV-A-3: IV using *PerPoverty* as an instrument and based on years of schooling and age; IV-A-4: IV using *PerPoverty* as an instrument and based on education levels and age; IV-B-1: IV using *SSS-Population* as an instrument and based on years of schooling and experience; IV-B-2: IV using *SSS-Population* as an instrument and based on education levels and experience; IV-B-3: IV using *SSS-Population* as an instrument and based on years of schooling and age; IV-B-4: IV using *SSS-Population* as an instrument and based on education levels and age.
Sources: Tables 7.3 to 7.18 and Tables A.7.1 to A7.16.

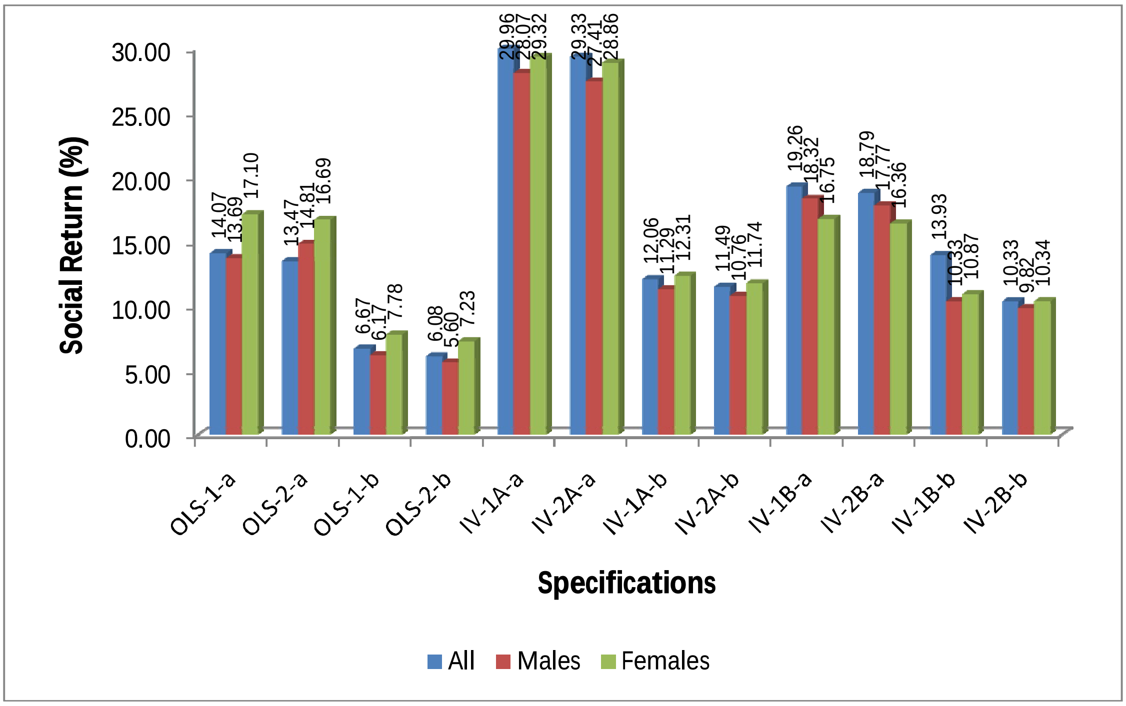
Based on Figure 7.2, there are four features worth noting. First, the external returns to schooling associated with the aggregate-level human capital based on the industrial sector within the province are significantly smaller than those associated with the aggregate-level human capital in the province (displayed in Figure 7.1). In other words, the overall effect is substantially greater than the industrial sector level effect. Second, including additional individual characteristics in the estimating equation is associated with smaller external returns to schooling. Third, the external return to schooling for female workers is consistently higher than that for male workers. Fourth, utilising *AveSchool-Ind* as an aggregate-level human capital measure results in a much higher external return to schooling than using *PerHE-Ind*. This pattern is similar to the pattern in the external returns that was established when comparing the *AveSchool* and *PerHE* variables.

Figures 7.1 and 7.2 show that the strongest effect on the productivity of workers is produced by an increase in the average years of schooling. This is followed by an increase in the share of workers with higher education, then by an increase in the average years of schooling based on the industrial sector, and finally by an increase in the share of workers with higher education based on the industrial sector in each province.

Figures 7.3 and 7.4 present an overview of the estimated social return to schooling obtained using the OLS and IV approaches for the estimations based on years of schooling. Figure 7.3 provide a comparison of the social return to schooling generated by the aggregate-level human capital in the province and the aggregate-level human capital based on the industrial sector within each province obtained using the OLS and IV approaches, without the tenure, marital status, urban area of residence and gender status (where relevant) variables.

The estimates of the social return to schooling using average years of schooling and average years of schooling based on the industrial sector within each province cluster between 14.47 percent and 19.96 percent for the combined sample, between 13.47 percent and 27.41 percent for the male sample, and between 16.36 percent and 29.32 percent for the female sample. The estimates of the social return to schooling using the percentage of workers with higher education and the percentage of workers with higher education based on the industrial sector within each province are typically smaller. Hence, the estimates of the social return to schooling cluster between 6.08 percent and 13.93 percent, 5.60 percent and 11.29 percent, and 7.23 percent and 12.31 percent for the full, male, and female samples, respectively. Most of these estimates suggest that schooling is a very attractive investment opportunity in Indonesia. Figure 7.3 shows an interesting result where most estimations indicate a larger social return to schooling for female workers than for male workers.

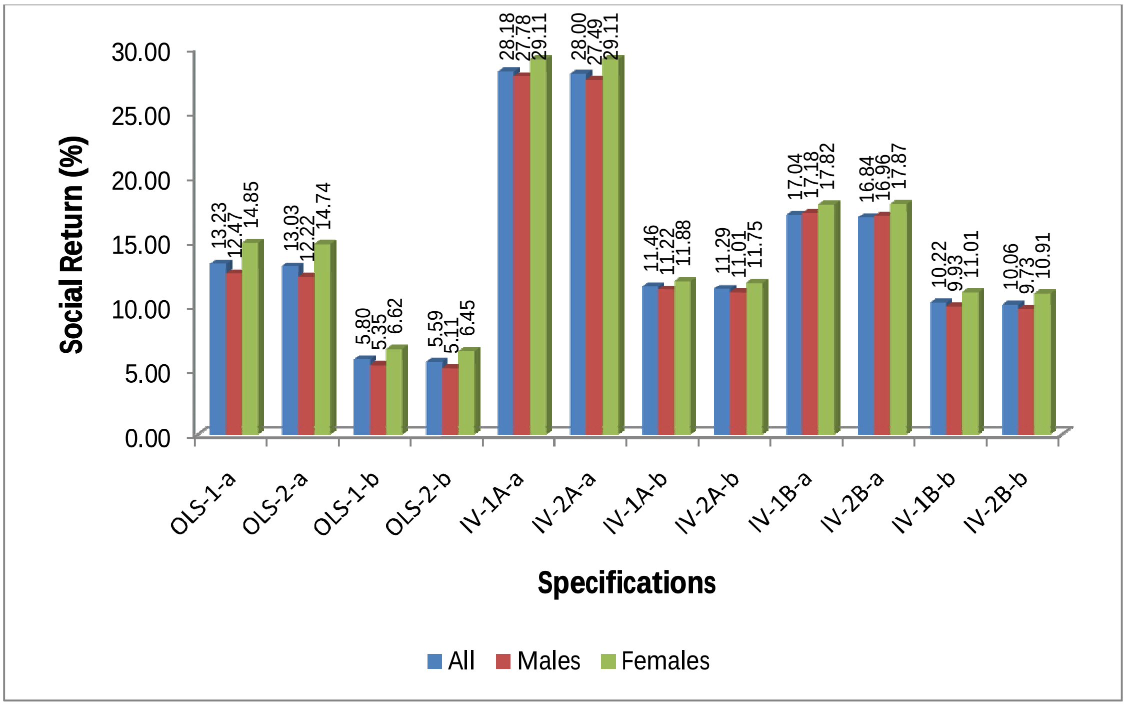
Figure 7.3: Social Return to Schooling (Models based on Years of Schooling without Additional Variables for Individual Characteristics)



OLS-1-a: OLS based on experience and average years of schooling; OLS-2-a: OLS based on age and average years of schooling; OLS-1-b: OLS based on experience and percentage of workers with higher education; OLS-2-b: OLS based on age and percentage of workers with higher education; IV-1A-a: IV using *PerPoverty* as an instrument and based on experience and average years of schooling; IV-2A-a: IV using *PerPoverty* as an instrument and based on age and average years of schooling; IV-1A-b: IV using *PerPoverty* as an instrument and based on experience and percentage of workers with higher education; IV-2A-b: IV using *PerPoverty* as an instrument and based on age and percentage of workers with higher education; IV-1B-a: IV using *SSS-Population* as an instrument and based on experience and average years of schooling ; IV-2B-a: IV using *SSS-Population* as an instrument and based on age and average years of schooling; IV-1B-b: IV using *SSS-Population* as an instrument and based on experience and percentage of workers with higher education; IV-2B-b: IV using *SSS-Population* as an instrument and based on experience and percentage of workers with higher education.

Sources: Tables 7.3, 7.5, 7.9, 7.11, 7.13, 7.15, A7.1, A7.5, A7.13.

Figure 7.4: Social Return to Schooling (Models based on Years of Schooling with Additional Variables for Individual Characteristics)



OLS-1-a: OLS based on experience and average years of schooling; OLS-2-a: OLS based on age and average years of schooling; OLS-1-b: OLS based on experience and percentage of workers with higher education; OLS-2-b: OLS based on age and percentage of workers with higher education; IV-1A-a: IV using *PerPoverty* as an instrument and based on experience and average years of schooling; IV-2A-a: IV using *PerPoverty* as an instrument and based on age and average years of schooling; IV-1A-b: IV using *PerPoverty* as an instrument and based on experience and percentage of workers with higher education; IV-2A-b: IV using *PerPoverty* as an instrument and based on age and percentage of workers with higher education; IV-1B-a: IV using *SSS-Population* as an instrument and based on experience and average years of schooling; IV-2B-a: IV using *SSS-Population* as an instrument and based on age and average years of schooling; IV-1B-b: IV using *SSS-Population* as an instrument and based on experience and percentage of workers with higher education; IV-2B-b: IV using *SSS-Population* as an instrument and based on experience and percentage of workers with higher education.

Sources: Tables 7.4, 7.6, 7.8, 7.10, 7.12, 7.14, 7.17, A7.3, A7.7, A7.9, A7.11, A7.15.

Figure 7.4 provides a comparison of the social return to schooling generated by the aggregate-level human capital in the province and the aggregate-level human capital based on the industrial sector within each province obtained using the OLS and IV approaches following the inclusion in the estimating equation of the variables for tenure, marital status, urban area of residence and gender status (where appropriate). The range of the estimates of the social return to human capital extends from 13.03 percent to 28.18 percent (combined sample), from 11.01 percent to 27.78 percent (male sample), and from 14.74 percent to 29.11 percent (female sample) for the estimations using average years of schooling and average years of schooling based on the industrial sector within each province. Adopting the percentage of workers with higher education in each province and the percentage of workers with higher education based on the industrial sector within each province lowers the span of the social return to schooling for the combined, male, female samples, respectively from 5.59 percent to 11.49 percent, 5.11 percent to 11.22 percent, and 6.45 percent to 11.88 percent. Most estimations imply a larger social return to schooling for female workers than for male workers.

The estimates of the social return to schooling based on education levels are reported in Tables A7.25 and A7.26. The former presents the social return to schooling obtained using the OLS and IV methods without additional variables for individual characteristics. The later reports the social return to schooling obtained using the OLS and IV methods with tenure, marital status, urban area of residence, and gender status variables. When average years of schooling and average years of schooling based on the industrial sector within each province are used as aggregate-level human capital measures, the estimates of the social return obtained using the OLS approach for the workers with primary schooling cluster from 9.85 to 10.80 percent for the full sample, from 10.76 to 11.01 percent for the male sample, and from 10.49 to 11.11 percent for the female sample. These results are substantialy smaller than the social return to schooling for primary schooling reported by Psacharopoulos (1981) for less developed countries and Psacharopoulos (2004) for non-OECD Asian countries. He found that the social return to schooling for primary schooling in less developed countries was 27.00 percent and 16.20 percent for non-OECD Asian countries.

The estimates of the social return to schooling for workers with junior secondary schooling range from the smallest of 12.26 percent to the largest of 13.23 percent for the combined sample, from the smallest of 11.77 percent to the largest of 12.51 percent for the male sample, and from the smallest of 15.83 percent to the largest of 17.03 percent for the female sample. The range in the social return to schooling for junior secondary schooling is very comparable with McMahon and Boediono's (1992) finding. Using a cost benefit analysis technique, they found the social return to schooling at the junior secondary school level in Indonesia was 22.00, 16.00, 13.00, and 11.00 percent in 1982, 1986, 1988, and 1989, respectively.

The range of the estimated social return to schooling for vocational senior secondary schooling is on par with the previous findings reported by McMahon and Boediono (1992) for 1982 and 1986 - 16.00 and 15.00 percent - but it is higher than their findings for 1988 and 1989 - 10.00 and 6.00 percent. Furthermore, our results are on par with Bennell's (1996) finding. He reported that the social return to schooling for vocational senior secondary school in Indonesia was 14.00 percent, whereas our results for the social return to this level of schooling varies from 12.54 to 14.32 percent for the full sample, from 12.64 to 13.48 percent for the male sample, and from 14.99 to 16.33 percent for the female sample.

The estimated social return to schooling for general senior secondary school ranges from 12.79 to 14.42 percent, from 13.17 to 13.98 percent, and from 14.70 to 15.74 percent for the full, male, and female samples, respectively. These magnitudes are broadly equivalent to the previous findings reported by McMahon and Boediono (1992), which are 16.00, 13.00, and 11.00 percent for the years of 1986, 1988, and 1989.

The estimated social return to schooling for college and undergraduate qualifications is larger than McMahon and Boediono's (1992) finding. McMahon and Boediono (1992) reported that the social returns for college (undergraduate) qualifications were 13.00 (11.00), 10.00 (7.00), 12.00 (6.00), and 5.00 (5.00) percent for the years of 1982, 1986, 1988, and 1989, respectively. Our results imply that the social return to schooling for college (undergraduate) level education varies from 13.29 (15.00) to 16.31 (17.73) percent for the combined sample, from 14.11 (14.93) to 14.77 (15.45) percent for the male sample, and from 16.31 (17.73) to 16.88 (18.28) for the female sample. Compared to the finding reported by Psacharopoulos (2004) for non-OECD Asian countries, our results for the social return to schooling for an undergraduate qualification are greater by about 4.00 to 6.73 percentage points.

Compared to the social return to schooling for the other six education levels (primary school, junior secondary school, vocational senior secondary school, general senior secondary school, college, and undergraduate), the social return to schooling for a master degree is subtantially larger. It ranges from 21.86 to 23.05 percent, from 23.71 to 24.24

percent, and from 20.42 to 23.25 percent for the full, male, and female samples, respectively.

Utilising the percentage of workers with higher education and the percentage of workers with higher education based on the industrial sector within each province as aggregate-level human capital measures lowers the estimates of the social return to schooling for all education levels and for each of the three samples. Adopting the IV approach raises the estimate of the social return to schooling compared to the results obtained using the OLS approach. The complete set of calculations of the social returns to schooling based on the level of education obtained using the OLS and IV approaches is reported in Tables A7.25 and A7.26.

7.5 Conclusion

Using IFLS4 data, this study analyses whether a relationship exists between the aggregate-level of human capital and individual earnings in Indonesian provinces, and also whether this relationship reflects the presence of human capital externalities. The estimation framework in this study is the Mincerian earnings regression augmented with measures of the aggregate-level human capital in each province and in the industrial sector within each province. The existence of human capital externalities is thus evaluated at two different levels: within a province and in the same industrial sector within each province. We control for individual characteristics, address a potential endogeneity problem, compare between male and female workers, and check for the imperfect substitutability between low-skilled and high-skilled workers.

Four alternative measures of aggregate-level human capital are proposed in this study: the average years of schooling, the percentage of workers with higher education, the average years of schooling based on the industrial sector within each province, and the percentage of workers with higher education based on the industrial sector within each province. The estimations of the impact of the aggregate-level human capital at the level of the province and in the industrial sector within each province on the individual worker's earnings over different samples and specifications generate consistent results that indicate the presence of human capital externalities. In particular it is found that an increase of the average years of schooling by one year tends to increase the earnings of workers by from 5.60 (5.23) to 5.91 (5.50) percent for the pooled sample, from 5.40 (5.04) to 5.63 (5.22) percent for the male sample, and from 5.75 (4.04) to 5.99 (5.88) percent for the female sample if it is estimated using OLS without (with) additional individual characteristics. A one percentage point increase in the percentage of workers with higher education is associated with a 1.17 (0.96) to 1.23 (1.03) percent, 1.04 (0.80) to 1.12 (0.86) percent, and 1.56 (1.34) to 1.61 (1.39) percent increase in individual earnings when using OLS without (with) additional individual characteristics for the combined, male, and female samples, respectively. It appears that the inclusion of additional individual characteristics reduces the size of the externalities slightly.

Using the aggregate-level human capital measure with smaller scope - based on the industrial sector within each province - the following results were established. The external return to schooling associated with a one year increase in the average years of schooling based on the industrial sector within each province estimated using OLS without (with) additional control variables for individual characteristics is 3.31 (3.49) to 3.34 (3.62) percent, 3.68 (3.30) to 5.63 (3.32) percent, and 5.26 (3.97) to 5.99 (5.98) percent for the pooled, male and female samples, respectively. The percentage of the workers with higher education based on the industrial sector within each province is associated with an external return to schooling of 0.21 (0.20) to 0.23 (0.24) percent, 0.19 (0.15) to 0.21 (0.18) percent, and 0.38 (0.28) to 0.45 (0.37) percent for the combined, male and female samples, respectively when it is estimated using OLS without (with) additional control variables for individual characteristics. Therefore, using this smaller scope for the aggregate-level human capital measure does not support the existence of human capital externalities to the same extent as the province-level measure. Nevertheless, these results reveal the presence of human capital externalities of a more moderate magnitude.

This study exploits variation in the percentage of the population below the poverty line and in the number of senior secondary schools per 1000 persons across provinces to identify the causal relationship between earnings and the average levels of education or the share of workers with higher education. The IV estimates of the specifications without (with) additional individual characteristics using the percentage of the population below the poverty line as an instrument indicate that a one year increase in the provincial average schooling is associated with 22.62 (20.95) to 23.33 (21.68) percent, 20.74 (21.14) to 21.39 (21.73) percent, and 19.28 (20.61) to 20.21 (21.75) percent increases in individual earnings for the combined, male and female samples, respectively. Using the number of senior secondary schools per 1000 persons as the instrument, the increase in individual earnings associated with a one percentage point increase in the percentage of workers with higher education changes to 11.22 to 12.41 percent for the pooled sample, 10.38 to 11.29 percent for the male sample, and 5.90 to 7.64 percent for the female sample based on the models without additional control variables for individual characteristics. It seems that adopting an IV approach results in much larger estimates of the external return to schooling. The above results indicate that human capital externalities are huge, and are significantly greater than the private return to schooling.

When the percentage of workers with higher education is used as the aggregate-level human capital measure instead of the average years of schooling within the IV framework the estimates of the external return to schooling are much lower. In particular, for the IV model using the population below the poverty line as an instrument, a one percentage point increase in the percentage of workers with higher education can be expected to increase the earnings of individual workers by approximately 7.04 (6.81) to 7.28 (7.04) percent for the combined sample, 6.81 (7.02) to 7.07 (7.25) percent for the male sample, and 6.23 (6.57) to 6.40 (6.79) percent for the female sample for the specification without (with) additional control variables for individual characteristics. This result holds for the specification using the number of senior secondary schools per 1000 persons as an instrument. The external return to schooling associated with the percentage of workers with higher education is about 5.81 (5.53) to 8.01 (6.08) percent for the combined sample, 5.75 (5.67) to 6.20 (6.09) percent for the male sample, and 4.76 (5.71) to 5.26 (6.37) percent for the female sample for the specification without (with) additional control variables for individual characteristics. These estimates support the earlier result that shows the existence of human capital externalities in Indonesia.

It is important to note that using the aggregate-level human capital measure based on the industrial sector within each province results in much smaller estimates of the external return than those obtained when using an aggregate-level human capital measure based on the province as a whole. This pattern is consistent with the results obtained using the OLS method. It seems that the provincial concentration of human capital is more important than a concentration based on the industrial sector within each province. However, this result should be considered with caution due to the potential measurement error attached to the aggregate-level human capital measures at the industry level within each province.

When using OLS the impact of aggregate-level human capital measured for the province as a whole for female workers is greater than that for male workers. However when the IV approach is adopted it appears that the impact of this aggregate-level human capital measure for male workers exceeds that for female workers. Regardless of whether the OLS or IV approach is used, the impact of the aggregate-level human capital based on the industrial sector within each province for female workers is consistently greater than that for male workers. One possible reason for this finding is that the female workers are more concentrated in a few industrial sectors than male workers.

The estimated social return to schooling obtained from the estimations based on years of schooling for female workers exceeds that of male workers. The estimated social return tends to increase with the level of education. In general, the social return to schooling for male workers with primary schooling or a master degree is larger than that for female workers. Furthermore, using the full sample, most results suggest that the social return to schooling for general senior secondary school is higher than that for vocational senior secondary school. This pattern is also found for the male sample. However, when estimated using the female sample, most results indicate that the social return to schooling for general senior secondary school is smaller than that for vocational senior secondary school. It is also important to mention that this study shows that the estimated social returns to schooling are much higher than the estimated private returns to schooling. According to Liu (2007), that kind of fact indicates that there is underinvestment in human capital.

The results of the study of imperfect substitutability between low-skilled and high-skilled workers strengthen the earlier conclusion in this chapter that human capital spillovers exist in Indonesia. Furthermore, the results of this study support the view that investing in education is even more important for aggregate economic performance than it is for the individuals who do so. This study also provides evidence of the existence of human capital externalities as high as, or even much higher than, the private return to schooling. Thus, there is clear role for the public sector fostering education and human capital development in order to seize the benefit of those externalities.

Chapter 8

Conclusion and Policy Implications

8.1 Introduction

This concluding chapter brings together the major findings of each chapter and the policy implications of the thesis. The chapter is divided into three sections. The next section provides a summary of the major empirical findings of this study. Then policy implications are briefly discussed. The last section of this chapter presents suggestions for future research.

8.2 Findings of the Study

This study provides an empirical analysis of the return to schooling and human capital externalities in Indonesia. There are several findings worth noting from this study. These findings are summarised below.

8.2.1. Private Return to Schooling

In this study we have examined the labour market returns to schooling in Indonesia using recent nationwide household survey data. We allow these returns to schooling to differ by level of education and by gender. We find that using either the OLS or an IV approach there is evidence of a positive relationship between years of schooling and the earnings of workers (Chapters 5 and 6). Using the OLS method we find that an additional year of schooling increases individual's earnings from 4.72 to 5.66 percent for the pooled sample, from 4.36 to 5.28 percent for the male sample, and from 5.26 to 6.46 percent for the female sample. Using an IV approach the return to schooling ranges from 6.24 to 7.96 percent for the combined sample, from 6.04 to 7.86 percent for the male sample, and from 6.57 to 8.91 percent for the female sample.

A notable finding of our study is the substantial non-linearity in the returns to schooling in Indonesia: returns increase with the level of education. The return to schooling for the pooled sample ranges from 0.97 to 1.63 percent, 3.44 to 4.35 percent, 4.23 to 5.96

percent, 4.80 to 6.34 percent, 4.70 to 6.14 percent, 6.19 to 6.87 percent, and from 13.50 to 14.80 percent for primary schooling, junior secondary schooling, vocational senior secondary schooling, general senior secondary schooling, college, undergraduate, and master degree, respectively. The return to schooling for the male (female) sample ranges between 1.40 (-0.18) and 1.80 (0.19) percent, 2.42 (5.22) and 3.35 (6.90) percent, 3.80 (5.18) and 4.98 (6.90) percent, 4.82 (4.81) and 5.92 (6.16) percent, 5.18 (6.49) and 6.02 (7.36) percent, 6.08 (7.50) and 6.59 (8.40) percent, and 14.80 (10.82) and 15.80 (13.52) percent for primary schooling, junior secondary schooling, vocational senior secondary schooling, general senior secondary schooling, college, undergraduate, and master degree, respectively. These magnitudes of return to schooling are lower compared to those for other Asian countries as well as those reported for other developing countries. Additionally, it is clear that the returns to schooling for females are higher than those for males. The other determinants of earnings are in line with the empirical literature from both developed and developing countries. Thus workers who live in urban areas consistently earn more than those in rural areas. Potential work experience and job tenure have positive effects on earnings for both male and female workers over much of the early part of the career path. Marital status has a negative effect on females' earnings.

8.2.2 Human Capital Externalities

In this study we provide empirical evidence on the magnitude and the pattern of the private return to schooling in Indonesia. However, private returns may be only part of the story. If there is a positive human capital externality, then the private return will underestimate the economic value of schooling. Using individual-level data this study presents empirical evidence that supports the existence of externalities. Using the OLS method, the human capital externalities associated with the average years of schooling in each province (the average years of schooling based on the industrial sector within each province) range between 5.23 (3.31) and 5.99 (3.62) percent, between 5.04 (3.30) and 5.63 (5.63) percent, and between 5.75 (3.97) and 5.88 (5.99) percent for the pooled, male, and female samples, respectively. Utilising an IV approach, the human capital externalities associated with the average years of schooling in each province (the average years of schooling based on the industrial sector within each province) range between

9.46 (2.17) and 23.30 (3.39) percent, between 10.03 (2.40) and 21.69 (3.38) percent, and between 5.90 (3.02) and 21.75 (5.25) percent for the combined, male, and female samples, respectively. Furthermore, utilising the OLS approach, the external return to schooling associated with the percentage of workers with higher education in each province (the percentage of workers with higher education based on industrial sector within each province) varies from 0.96 (0.20) to 1.23 (0.24) percent, from 0.80 (0.15) to 1.34 (0.28) percent, and from 1.34 (0.28) to 1.61 (0.45) percent, for the combined, male, and female samples, respectively. Adopting an IV method, the external return to schooling associated with the percentage of workers with higher education in each province (the percentage of workers with higher education based on the industrial sector within each province) varies from 5.53 (0.24) to 7.28 (0.22) percent, from 5.67 (0.07) to 7.25 (0.96) percent, and from 4.76 (0.28) to 6.79 (3.69) percent, for the pooled, male, and female samples, respectively.

In terms of the social return to schooling, the results show the following patterns. Using the OLS (IV) approach, the estimates of the social return to schooling using the average years of schooling and the average years of schooling based on the industrial sector within each province cluster between 13.03 (16.84) percent and 14.07 (29.96) percent for the pooled sample, between 12.22 (16.96) percent and 14.81 (28.07) percent for the male sample, and between 14.74 (16.36) percent and 17.10 (29.32) percent for the female sample. Utilising the OLS (IV) method, the estimates of the social return to schooling using the percentage of workers with higher education and the percentage of workers with higher education based on the industrial sector within each province cluster between 5.59 (10.33) percent and 6.67 (28.80) percent, between 5.11 (9.73) percent and 6.17 (11.22) percent, and between 6.45 (10.34) percent and 7.78 (12.31) percent for the full, male, and female samples, respectively. Comparing between males' and females' social return to schooling, our results suggest that the estimated social return to schooling obtained from the estimations based on years of schooling for female workers exceeds that of male workers.

The results obtained based on the level of education show that the estimated social return tends to increase with the level of education. In general, the social return to schooling for male workers with primary schooling or a master degree is larger than that for female workers. It is also important to mention that this study shows that the estimated social returns to schooling are much higher than that the estimated private returns to schooling. According to Liu (2007), that kind of fact indicates that there is underinvestment in human capital.

The results of the study of imperfect substitutability between low-skilled and high-skilled workers confirm that human capital spillovers exist in Indonesia. Furthermore, the results of this study support the thought that investing in education is even more important for aggregate economic performance than it is for the individuals who do so. This study also provides evidence of the existence of human capital externalities as high as, or even much higher than, the private return to schooling.

8.3 Policy Implications

In concluding this thesis, we need to consider the implications of the results. This is not a simple task due to the fact that establishing a link between research results and policy implications is not always straightforward. However, we believe that the implications of the results warrant some detailed considerations by policy-makers.

Estimates of the returns to schooling are a useful indicator of the productivity of education and of the incentive for individuals to invest in their own human capital. Public policy needs to heed this evidence in the design of policies and crafting of incentives that promote investment in education.

The educational attainment of the Indonesian population has increased substantially over the past three decades. However, the return to schooling is low compared to other developing countries and Asian countries. To address this it may be important to establish a unified labour market with fair competition. It is also essential to pay attention on the interaction between supply and demand of the educated workers. Especially, the focus should be on which levels and types of education are in high demand and hence should be prioritised in the allocation of public resources.

The fact that primary education has a lower return to schooling compared to the secondary and tertiary education should not be taken to suggest that the overall rationale for investment in primary schooling is weakened. There are several reasons for this. First, primary schooling is a necessary input into further levels of education which have higher economic returns. Second, whatever its economic return, primary education continues to be important for its intrinsic value from a rights-based perspective.

This study found that the higher the level of education, the higher the returns to schooling to individuals. Accordingly, a further increase in post-compulsory education (senior secondary and higher education) is considered desirable. However, there may be individuals who cannot afford to invest in education at these levels. Hence, it is important that any implicit barriers to access to these levels of education, i.e. liquidity constrains, be eliminated. More attention should be given to the various methods of cost recovery. A well designed student loan programme and mean-tested grants may reduce the problem of liquidity constrains and be an efficient way to provide additional resources to increase the quality of post-secondary education.

Our results indicate that, holding other variables constant, females face an earnings disadvantage in the Indonesian labour market. Accordingly, the issue of gender equity needs to be addressed by policy makers.

With the existence of sizeable social returns to human capital, individuals are likely to under-invest in their education. This is because individuals who do invest in their education are not compensated for the productivity or amenity effects that spillover to others. To the extent that education creates beneficial externalities and other human capital effects, the importance of continuous investment in schooling by government is emphasised.

8.4 Limitations and the Focus of Further Research

This study explores the economic return to schooling and human capital externalities in Indonesia. However, the research has some limitations which may need to be taken into account in interpreting the results and in carrying out further empirical research. The limitations and further research directions may be described as follows:

(i) Due to data unavailability, this study cannot take into account the factors of individuals' innate ability and school quality. The IV analyses suggest that the ability as an omitted variable factor is quite important. Therefore further research including these variables is warranted.

(ii) The private returns to schooling and human capital externalities that are the focus of this research are categorised as a market effect of education. However, it is widely perceived that the total effect of education covers not only market effects, but also non-market efects, such as child quality, own health, consumer choice efficiency, labour market search efficiency, marital choice efficiency, and attainment of desired family size. It would be a valuable contribution to estimate these non-market effects of education in further research.

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Returns to Education and Human Capital Externalities: Empirical Evidence from Indonesia

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Appendices

List of Appendices

Page

Appendix for Chapter 5

Appendix A5.1: Heckman Two-step Method

Supposed we have an earnings equation:

$$W_i = \beta X_i + \varepsilon_i \tag{A5.1}$$

where W_i is earnings, X_i are the observed variables related to individual productivity and ε is an error term. W is observed only for workers.

A reduced form employment equation (participation equation) is given by:

$$E_i^* = \gamma Z_i + \mu_i \tag{A5.2}$$

where E_i^* is the difference between the observed earnings and the reservation earnings. The reservation earnings is the minimum earnings at which the individual is willing to accept employment. E_i^* cannot, however, be observed. Rather we observe only an indicator variable for employment, defined as $E_i = 1$ if $E_i^* > 0$ and $E = 0$ otherwise. Variation in this indicator variable can be examined using a probit model.

The Heckman model uses the following assumptions:

1. $(\varepsilon, \mu) \sim N(0, 0, \sigma_\varepsilon^2, \sigma_\mu^2, \rho_{\varepsilon\mu})$

   This first assumption assumes joint normality of the distribution of the error terms in the participation (A5.2) and outcome (A.5.1) equation.
2. (ε, μ) is independent of X and Z

   This second assumption assumes that both error terms are independent of both sets of observables.
3. $var\ (\mu) = \sigma_\mu^2 = 1$

   The last assumption is the normalisation for the probit regression.

Taking expectation of the earnings equation conditional on working yields:

$$E(W_i|E_i = 1, X_i) = E(W_i|X_i, Z_i, \mu_i) = \beta X_i + E(\varepsilon_i|X_i, Z_i, \mu_i) \tag{A5.3}$$

In equation A5.3 there are two equalities. The first equality comes from the fact that variables determining employment in this model are Z and μ. The second equality comes from the fact that the expected value of X given X is just X.

The final term in A5.3 $\{E(\varepsilon_i|X_i, Z_i, \mu_i)\}$ can be simplified by noting that selection into employment depends just on Z_i and μ_i not upon X_i. Specifically

$$E(W_i|E_i = 1, X_i) = \beta X_i + E(\varepsilon_i|E_i = 1) = \beta X_i + E(\varepsilon_i|\mu_i > -Z_i\gamma) \tag{A5.4}$$

Thus, if we estimate the model using only data on workers, the returns to schooling will be estimated on them alone and not the whole of the population. As a result of this term, OLS estimation on a sample of workers generally provides inconsistent estimates of the parameters of the population wage equation.

According to Heckman (1979), this problem can be approached as an omitted variable problem. $(\varepsilon_i|\mu_i > -Z_i\gamma)$ in A5.4 is the variable that is typically ignored in the estimation of earnings equations on selected samples. An estimate of the omitted variable would solve this problem and hence the problem of sample selection bias. Specifically we can solve the omitted variable by:

$$E[(\varepsilon_i|\mu_i > -Z_i\gamma)] = \rho_{\varepsilon\mu}\sigma_\varepsilon\lambda_i(-Z_i\gamma) = \theta\lambda_i(-Z_i\gamma) \tag{A5.5}$$

where $\lambda_i(-Z_i\gamma)$ is just the inverse Mills ratio evaluated at the indicated value and θ is unknown parameter $\rho_{\varepsilon\mu}\sigma_\varepsilon$.

The first method for estimating this bivariate normal selection model is that due to Heckman (1979). It is sometimes called the "Heckman two-step" method.

Under Heckman's (1975) two-step procedure, the first step is to run a probit model of participation (E on Z) using all the observations. The estimates of γ from this probit are then used to construct consistent estimates of the inverse Mills ratio term

$$\hat{\lambda}_i(-Z_i\hat{\gamma}) = \frac{\emptyset(Z_i\hat{\gamma})}{\Phi(Z_i\hat{\gamma})}$$

In the second stage, the outcome equation is estimated by ordinary least squares where the outcome equation includes both the original X whose coefficients are the parameters of the population earnings equation and the constructed value of the inverse Mills ratio, which is

$$W_i = \beta X_i + \theta \hat{\lambda}_i \left(-Z_i \hat{\gamma}\right) + e_i$$

This step is carried out only for the uncensored observation and provides consistent and asymptotically normal estimators for β and θ.

Appendix A5.2

Summary Statistics for the Participation Rate Component of the Selectivity Bias Correction Model

Variables	Females	
	Mean	**Standard Deviation**
Years of schooling	10.502	3.495
Primary School	0.241	0.428
Dummy for Junior Secondary School	0.200	0.428
Dummy for Vocational Senior Secondary School	0.103	0.303
Dummy for General Senior Secondary School	0.164	0.370
Dummy for College	0.043	0.200
Dummy for Undergraduate	0.044	0.205
Dummy for Master	0.002	0.044
Experience	17.970	13.012
Experience squared	492.231	644.978
Age	35.219	11.950
Age squared	1383.193	949.783
Tenure	1.505	4.763
Tenure squared	24.954	120.287
Marital status dummy	0.851	0.356
Dummy for urban area	0.571	0.495
Household size	6.011	3.197
Child under 5	0.531	0.499
Muslim	0.907	0.290
Father/mother lives in the same house	0.158	0.499

Source: Author's calculation based on the IFLS4 data set.

Appendix for Chapter 7

Table A7.1: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *PerPoverty* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.20613	3.26982	9.39706	2.90984	8.75737	3.11024	2.64461	8.96438
	(0.10482)***	(0.18176)***	(0.14898)***	(0.25467)***	(0.18401)***	(0.19350)***	(0.27045)***	(0.23522)***
Years of schooling	0.01624	0.04526	0.01442	0.05635	0.01318	0.03948	0.05066	0.05066
	(0.00421)***	(0.00226)***	(0.00543)***	(0.00327)***	(0.00391)***	(0.00211)***	(0.00296)***	(0.00296)***
Experience	0.01537	0.01096	0.01766	0.01428				
	(0.00442)***	(0.00239)***	(0.00523)***	(0.00321)***				
Experience^2	-0.00030	-0.00012	-0.00032	-0.00020				
	(0.00010)***	(0.00005)**	(0.00012)***	(0.00007)***				
Age					0.03291	0.01543	0.03361	0.02193
					(0.00889)***	(0.00483)***	(0.01091)***	(0.00669)***
Age^2					-0.00040	-0.00013	-0.00040	-0.00022
					(0.00011)***	(0.00006)**	(0.00014)***	(0.00009)**
AveSchool		0.20834		0.19284		0.20740		0.19396
		(0.02163)***		(0.02994)***		(0.02165)***		(0.02994)***
AveSchool-Ind	0.00600	0.02705	-0.00718	0.04401	0.00615	0.02725	-0.00695	0.04397
	(0.00948)	(0.00516)***	(0.01389)	(0.00841)***	(0.00948)	(0.00516)***	(0.01389)	(0.00843)***
PerPoverty	-0.06258		-0.06573		-0.06250		-0.06585	
	(0.00250)***		(0.00323)***		(0.18401)***		(0.00323)***	
R^2	0.1878		0.2279		0.1884		0.2277	
Adjusted R^2	0.1864		0.2253		0.1870		0.2251	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F	625.139		414.279			624.749		415.195
P-Value	0.0000***		0.0000***			0.0000***		0.0000***
Relevance (Hausman test)								
F	69.3273		28.1838			68.5067		28.3231
P-Value	0.0000***		0.0000***			0.0000***		0.0000***

Notes: Sandard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.2: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Level Using *PerPoverty* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.32534	3.42275	9.36463	3.21097	8.84486	3.26745	8.82348	2.94572
	(0.11355)***	(0.18740)***	(0.16611)***	(0.25930)***	(0.19445)***	(0.19933)***	(0.25538)***	(0.02752)***
Primary school	-0.12671	0.11801	-0.00319	0.01586	-0.00667	0.11340	0.01306	0.02871
	(0.05953)	(0.03229)***	(0.07510)	(0.04569)	(0.05844)	(0.03166)***	(0.07317)	(0.04461)
Junior secondary school	-0.02705	0.21357	0.07550	0.19791	-0.01008	0.19582	0.08599	0.20285
	(0.06236)	(0.03382)***	(0.07987)	(0.04849)***	(0.06012)	(0.03258)***	(0.07534)	(0.04587)***
Vocational senior secondary school	0.03561	0.32784	0.28776	0.34085	0.03853	0.29364	0.27312	0.32684
	(0.06405)	(0.03465)***	(0.08403)***	(0.05125)***	(0.06077)	(0.03229)***	(0.07832)***	(0.04796)***
General senior secondary school	0.10487	0.33438	0.14681	0.33853	0.10600	0.29837	0.12612	0.32233
	(0.06155)*	(0.03322)***	(0.07942)*	(0.04827)***	(0.05826)*	(0.03146)***	(0.07285)	(0.04443)***
College	0.08272	0.50303	0.13263	0.54749	0.06775	0.44921	0.9149	0.51114
	(0.08139)	(0.04399)***	(0.09066)	(0.05480)***	(0.07813)	(0.04224)***	(0.08419)	(0.05111)***
Undergraduate	0.10486	0.59557	0.11194	0.67613	0.09793	0.53928	0.06154	0.63821
	(0.07149)	(0.03845)***	(0.08781)	(0.05299)***	(0.06813)	(0.03667)***	(0.08069)	(0.04898)***
Master	0.23652	0.84594	0.26934	0.90236	0.21726	0.78061	0.21744	0.86408
	(0.17980)	(0.09744)***	(0.20602)	(0.12505)***	(0.17840)	(0.09668)***	(0.20306)	(0.12365)***
Experience	0.01556	0.01036	0.01843	0.01511				
	(0.00446)***	(0.00242)	(0.00529)***	(0.00324)***				
Experience^2	-0.00032	-0.00012	-0.00032	-0.00025				
	(0.00010)***	(0.00005)**	(0.00012)***	(0.00007)***				
Age					0.03247	0.01309	0.03700	0.01938
					(0.00895)***	(0.00487)*	(0.01103)***	(0.00677)***
Age^2					-0.00040	-0.00011	-0.00021	-0.00020
					(0.00011)***	(0.00006)***	(0.01406)	(0.00009)**
AveSchool		0.21388		0.20120		0.21311		0.20210
		(0.02190)***		(0.03047)***		(0.02189)***		(0.03050)***
AveSchool-Ind	0.00748	0.02724	-0.00169	0.03758	0.00790	0.02733	-0.00021	0.03809
	(0.00949)	(0.00518)***	(0.01405)	(0.00853)***	(0.00949)	(0.00518)***	(0.01406)***	(0.00857)***
PerPoverty	-0.06227		-0.06475		-0.06223		-0.06488	
	(0.00252)***		(0.00324)***		(0.00252)***		(0.00324)***	
R^2	0.1887		0.2359		0.1890		0.2363	
Adjusted R^2	0.1857		0.2303		0.1860		0.2307	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
<u>Quality</u>								
F		611.99		398.591		611.999		399.945

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		70.6812		30.0531		70.0198		29.876
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.3: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *PerPoverty* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.14376	3.26712	9.30953	2.91971	8.85256	3.15576	8.89899	2.77530
	(0.10754)***	(0.18266)***	(0.15226)***	(0.25520)***	(0.19088)***	(0.19715)***	(0.24875)***	(0.27018)***
Years of Schooling	0.01086	0.04133	0.01326	0.04773	0.00982	0.03893	0.00652	0.04695
	(0.00437)**	(0.00234)***	(0.00569)**	(0.00339)***	(0.00402)**	(0.00215)***	(0.00496)	(0.00296)***
Experience	0.00875	0.00631	0.02005	0.00467				
	(0.00501)*	(0.00270)**	(0.00606)***	(0.00370)				
Experience^2	-0.00019	-0.00009	-0.00032	-0.00010				
	(0.00011)*	(0.00006)	(0.00013)**	(0.00008)				
Age					0.02105	0.00986	0.03405	0.01036
					(0.01010)**	(0.00545)*	(0.01249)***	(0.00758)
Age^2					-0.00027	-0.00010	-0.00038	-0.00013
					(0.00013)**	(0.00007)	(0.00016)**	(0.00010)
Tenure	0.00414	0.01161	-0.00098	0.02607	0.00378	0.01178	-0.00060	0.02597
	(0.00457)	(0.00246)***	(0.00630)	(0.00379)***	(0.00457)	(0.00246)***	(0.00631)	(0.00380)***
Tenure^2	-0.00012	-0.00016	-0.00012	-0.00054	-0.00011	-0.00016	-0.00010	-0.00052
	(0.00015)	(0.00008)**	(0.00020)	(0.00012)***	(0.00015)	(0.00008)**	(0.00021)	(0.00012)***
Marital Status	0.15312	0.01282	-0.00039	-0.03723	0.14720	0.01372	0.00039	-0.03874
	(0.04659)***	(0.02525)	(0.04670)	(0.02809)	(0.04694)***	(0.02541)	(0.04697)	(0.02824)
Urban	0.11639	0.03878	0.17478	0.06841	0.11641	0.03895	0.17445	0.06818
	(0.02885)***	(0.01596)***	(0.04064)***	(0.02538)***	(0.02884)***	(0.01596)**	(0.04066)***	(0.02538)***
AveSchool		0.21200		0.20605		0.21138		0.20677
		(0.02177)***		(0.03028)***		(0.02178)***		(0.03019)***
AveSchool-Ind	0.00098	0.02451	-0.01400	0.03731	0.00097	0.02461	-0.01404	0.03739
	(0.00961)	(0.00518)***	(0.01394)	(0.00829)***	(0.00961)	(0.00518)***	(0.01395)	(0.00830)***
PerPoverty	-0.06206		-0.06434		-0.06201		-0.06451	
	(0.00251)***		(0.00324)***		(0.00251)***		(0.00324)***	
R^2	0.1948		0.2391		0.1951		0.2383	
Adjusted R^2	0.1924		0.2345		0.1927		0.2337	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
<u>Quality</u>								
F		612.934		394.69		612.479		396.677
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Relevance (Hausman test)								
F		75.6942		34.2767		75.171		34.6147
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.4: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Level Using *PerPoverty* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.24895	3.41448	9.25848	3.18885	8.95059	3.32602	8.73587	3.06726
	(0.11632)***	(0.18761)***	(0.16954)***	(0.25877)***	(0.20111)***	(0.20267)***	(0.26831)***	(0.27341)***
Primary school	-0.03561	0.10589	0.03306	-0.00076	-0.01777	0.10995	0.04027	0.01776
	(0.05959)	(0.03221)***	(0.07552)	(0.04530)	(0.05828)	(0.03146)***	(0.07317)	(0.04395)
Junior secondary school	-0.05923	0.18601	0.08025	0.15022	-0.03902	0.18662	0.07455	0.17469
	(0.06274)	(0.03396)***	(0.08048)	(0.04823)***	(0.06020)	(0.03254)***	(0.07524)	(0.04516)***
Vocational senior secondary school	0.02486	0.28662	0.28941	0.25039	-0.00985	0.28097	0.25204	0.27298
	(0.06528)	(0.03526)***	(0.08573)***	(0.05169)***	(0.06157)	(0.03322)***	(0.07869)***	(0.04746)***
General senior secondary school	0.05402	0.29238	0.14776	0.25963	0.06820	0.28630	0.10453	0.28245
	(0.06257	(0.03366)***	(0.08083)*	(0.04854)***	(0.05883)	(0.03163)***	(0.07306)	(0.04390)***
College	0.01642	0.45120	0.15663	0.44989	0.02408	0.43785	0.08579	0.46945
	(0.08247)	(0.04445)***	(0.09283)*	(0.05543)***	(0.07855)	(0.04233)***	(0.08427)	(0.05044)***
Undergraduate	0.05426	0.54549	0.11772	0.57521	0.06335	0.53281	0.03764	0.59724
	(0.07260)	(0.03900)***	(0.08984)	(0.05356)***	(0.06857)	(0.03681)***	(0.08086)	(0.04847)***
Master	0.14931	0.79275	0.26498	0.74681	0.15768	0.77717	0.17824	0.77434
	(0.18010)	(0.09712)***	(0.20728)	(0.012424)***	(0.17842)	(0.09623)***	(0.20293)	(0.12183)***
Experience	0.00861	0.00563	0.02053	0.00574				
	(0.00507)*	(0.00273)**	(0.20728)***	(0.00374)				
Experience^2	-0.00021	-0.00010	-0.00011	-0.00016				
	(0.00011)*	(0.00006)***	(0.00014)**	(0.00012)**				
Age					0.01982	0.00693	0.03748	0.00722
					(0.01017)*	(0.00550)	(0.01259)**	(0.00766)
Age^2					-0.00026	-0.00007	-0.00041	-0.00011
					(0.00013)**	(0.00007)	(0.00017)	(0.00010)
Tenure	0.00390	0.01174	-0.00142	0.02502	0.00374	0.01220	-0.00151	0.02602
	(0.00459)	(0.00247)***	(0.00630)	(0.00379)***	(0.00457)	(0.00247)***	(0.00630)	(0.00379)***
Tenure^2	-0.00011	-0.00016	-0.00011	-0.00048	-0.00011	-0.00018	-0.00009	-0.00051
	(0.00015)	(0.00008)*	(0.00020)	(0.00012)***	(0.00457)	(0.00008)**	(0.00021)	(0.00012)***
Marital Status	0.15906	0.01363	0.00592	-0.04295	0.15341	0.01643	0.00278	-0.03583
	(0.04664)***	(0.02530)***	(0.04667)	(0.02801)	(0.04703)***	(0.02549)	(0.04686)	(0.02817)***
Urban	0.12262	0.04653	0.16348	0.06619	0.12199	0.04621	0.16317	0.06613
	(0.02906)***	(0.01611)***	(0.04107)***	(0.02545)***	(0.02906)***	(0.01610)***	(0.04108)***	(0.02548)***
AveSchool		0.21730		0.21637		0.21689		0.21753
		(0.02197)***		(0.03071)***		(0.02198)***		(0.03067)***
AveSchool-Ind	0.00179	0.02399	-0.00782	0.03018	0.00203	0.02415	-0.00679	0.03065
	(0.00963)	(0.00520)***	(0.01414)	(0.00843)***	(0.00963)	(0.00520)***	(0.01415)	(0.27341)***
PerPoverty	-0.06183		-0.06359		-0.06180		-0.00679	
	(0.00252)***		(0.00325)***		(0.00252)***		(0.00325)***	
R^2	0.1962		0.2459		0.1963		0.2457	

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Adjusted R^2	0.1922		0.2383		0.1923		0.2381	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		602.475		382.344		602.133		384.448
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		77.9235		36.6314		77.3812		36.8721
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.5: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *PerPoverty* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	8.52748	4.83756	10.11094	4.46644	6.86423	4.69288	8.92931	4.20042
	(0.29740)***	(0.05578)***	(0.37853)***	(0.08049)***	(0.69559)***	(0.10153)***	(0.85468)***	(0.13731)***
Years of schooling	0.12032	0.04339	0.05795	0.05625	0.10105	0.03825	0.05244	0.05020
	(0.01720)***	(0.00249)***	(0.02336)**	(0.00344)***	(0.01590)***	(0.00230)***	(0.02093)**	(0.00310)***
Experience	0.06521	0.00973	0.04933	0.01450				
	(0.01833)***	(0.00257)***	(0.02242)**	(0.00332)***				
Experience^2	-0.00113	-0.00011	-0.00106	-0.00020				
	(0.00040)***	(0.00006)*	(0.00051)**	(0.00008)***				
Age					0.12803	0.01357	0.09151	0.02250
					(0.03692)***	(0.00519)***	(0.04673)**	(0.00691)***
Age^2					-0.00148	-0.00011	-0.00117	-0.00022
					(0.00047)***	(0.00066)*	(0.00062)*	(0.00009)**
PerHE		0.06825		0.06234		0.06805		0.06269
		(0.00665)***		(0.00847)***		(0.00665)***		(0.00848)***
PerHE-Ind	0.00484	0.00123	-0.00827	0.00453	0.00506	0.00126	-0.00823	0.00453
	(0.00470)	(0.00066)*	(0.00644)	(0.00095)***	(0.00470)	(0.00007)*	(0.00645)	(0.00095)***
PerPoverty	-0.21285		-0.23395		-0.21248		-0.23417	
	(0.01013)***		(0.01343)***		(0.01012)***		(0.01344)***	
R^2	0.1460		0.1714		0.1462		0.1709	
Adjusted R^2	0.1446		0.1686		0.1448		0.1681	
Observation	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		441.884		303.614		440.851		303.618
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		111.722		41.9196		110.507		42.069
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.6: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Levels Using *PerPoverty* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	8.94309	5.03333	10.30272	4.76928	7.02541	4.90739	8.83254	4.50082
	(0.31645)***	(0.06098)***	(0.40502)***	(0.08502)***	(0.72642)***	(0.10688)***	(0.90533)***	(0.14475)***
Primary school	0.22400	0.10495	-0.15864	0.02612	0.26553	0.10174	-0.07294	0.03719
	(0.24675)	(0.03462)***	(0.32073)	(0.04757)	(0.24222)	(0.03397)***	(0.31263)	(0.04641)
Junior secondary school	0.42011	0.19316	0.11616	0.21392	0.41906	0.17915	0.20750	0.21586
	(0.25791)	(0.03621)***	(0.34064)	(0.05036)***	(0.24858)*	(0.03489)***	(0.32140)	(0.04761)***
Vocational senior secondary school	1.16067	0.27964	1.29361	0.32735	1.07742	0.25198	1.33111	0.30854
	(0.26328)***	(0.03752)***	(0.35767)***	(0.05352)***	(0.24945)***	(0.03557)***	(0.33325)***	(0.05026)***
General senior secondary school	1.05337	0.31026	0.30872	0.35929	0.95986	0.28101	0.33342	0.33816
	(0.25298)***	(0.03591)***	(0.33790)	(0.04998)***	(0.23908)***	(0.03394)***	(0.30975)	(0.04597)***
College	1.30822	0.46503	0.35280	0.56164	1.12492	0.42073	0.32685	0.51910
	(0.33572)***	(0.04766)***	(0.38763)	(0.05718)***	(0.32184)***	(0.04564)***	(0.35984)	(0.05323)***
Undergraduate	1.08661	0.58349	0.36576	0.68777	0.89603	0.53723	0.32788	0.64251
	(0.29477)***	(0.04134)***	(0.37561)	(0.05532)***	(0.28041)***	(0.03932)***	(0.34497)	(0.05097)***
Master	2.19778	0.78002	1.34177	0.88543	1.97320	0.72617	1.32399	.83809
	(0.74544)***	(0.10581)***	(0.87961)	(0.13014)***	(0.73947)***	(0.10483)***	(0.86715)	(0.12870)***
Experience	0.06983	0.00880	0.05307	0.01536				
	(0.01852)***	(0.00262)***	(0.02257)**	(0.00335)***				
$Experience^2$	-0.00123	-0.00011	-0.00113	-0.00025				
	(0.00041)***	(0.00006)*	(0.00052)**	(0.00008)***				
Age					0.13492	0.01047	0.10290	0.02015
					(0.03713)***	(0.00526)**	(0.04711)**	(0.00700)***
Age^2					-0.00155	-0.00008	-0.00130	-0.00020
					(0.00047)***	(0.00007)	(0.00062)**	(0.00009)**
PerHE		0.07072		0.06360		0.07054		0.06398
		(0.00680)***		(0.00859)***		(0.00680)***		(0.00861)***
PerHE-Ind	0.00673	0.00094	-0.0055	0.00361	0.00708	0.00096	-0.00474	0.00369
	(0.00474)	(0.00067)	(0.01343)***	(0.00098)***	(0.00474)***	(0.00067)	(0.00662)	(0.00098)***
PerPoverty	-0.21044		-0.23125		-0.21022		-0.23162	
	(0.01018)***		(0.01343)***		(0.01017)***		(0.01344)***	
R^2	0.1475		0.1852		0.1478		0.1848	
Adjusted R^2	0.1443		0.1792		0.1447		0.1789	
Observations	3017	3017	1511	1511	3017	3017	1511	1511

Test Results

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
<u>Quality</u>								
F		427.489		296.582		427.067		297.003
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
<u>Relevance (Hausman test)</u>								
F		113.934		43.6111		113.015		43.5247
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.7: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *PerPoverty* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	7.95697	4.84502	9.22505	4.52718	6.76162	4.74654	8.40042	4.36037
	(0.30987)***	(0.05649)***	(0.40576)***	(0.07900)***	(0.72550)***	(0.10639)***	(0.91215)***	(0.14253)***
Years of Schooling	0.07258	0.04076	0.02882	0.04919	0.06318	0.03873	0.01963	0.04766
	(0.01788)***	(0.00255)***	(0.02419)	(0.00358)***	(0.01640)***	(0.00234)***	(0.02109)	(0.00313)***
Experience	0.04237	0.00541	0.04526	0.00584				
	(0.02060)**	(0.00292)*	(0.02567)*	(0.00384)				
Experience^2	-0.00081	-0.00008	-0.00087	-0.00011				
	(0.00044)*	(0.00006)	(0.00056)	(0.00008)				
Age					0.09031	0.00842	0.06927	0.01261
					(0.04155)**	(0.00591)	(0.05291)	(0.00788)
Age^2					-0.00110	-0.00009	-0.00084	-0.00015
					(0.00053)**	(0.00008)	(0.00070)	(0.00010)
Tenure	0.02259	0.01087	0.01461	0.02480	0.02189	0.01102	0.01842	0.02457
	(0.01880)	(0.00266)***	(0.02668)	(0.00396)***	(0.01879)	(0.00266)***	(0.02675)	(0.00397)***
Tenure^2	-0.00055	-0.00015	-0.00073	-0.00051	-0.00048	-0.00015	-0.00077	-0.00050
	(0.00062)	(0.00009)*	(0.00086)	(0.00013)***	(0.00062)	(0.00009)*	(0.00087)	(0.00013)***
Marital Status	0.53882	0.00393	0.17653	-0.04840	0.52444	0.00454	0.19687	-0.05084
	(0.19156)***	(0.02728)	(0.19779)	(0.02935)*	(0.19300)***	(0.02745)	(0.19889)	(0.02953)*
Urban	1.02022	0.00273	1.26793	0.02902	1.02117	0.00294	1.26720	0.02860
	(0.11704)***	(0.01884)	(0.17099)***	(0.02880)	(0.11700)***	(0.01883)	(0.17106)***	(0.02880)
PerHE		0.07039		0.06574		0.07024		0.06601
		(0.00702)***		(0.00885)***		(0.00702)***		(0.00884)***
PerHE-Ind	0.00286	0.00108	-0.01079	0.00387	0.00296	0.00109	-0.01092	0.00387
	(0.00466)	(0.00066)	(0.00637)*	(0.00095)***	(0.00466)	(0.00066)*	(0.00638)*	(0.00095)***
PerPoverty	-0.20375		-0.22405		-0.20346		-0.22448	
	(0.01009)***		(0.01335)***		(0.01009)***		(0.01335)***	
R^2	0.1687		0.2030		0.1688		0.2008	
Adjusted R^2	0.1662		0.1966		0.1664		0.1960	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		407.385		281.836		406.508		282.794
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Relevance (Hausman test)								
F		118.715		49.9735		117.928		50.4376
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.8: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Levels Using *PerPoverty* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	8.25941	5.03246	9.23837	4.81755	6.90157	4.97096	8.16104	4.67084
	(0.33144)***	(0.06121)***	(0.43785)***	(0.08305)***	(0.75645)***	(0.11149)***	(0.96238)***	(0.14933)***
Primary school	0.11924	0.09565	0.03572	0.00545	0.16691	0.10050	0.07986	0.02271
	(0.24501)	(0.03479)***	(0.31920)	(0.04748)	(0.23956)	(0.03401)***	(0.30929)	(0.04607)
Junior secondary school	0.13855	0.17344	0.03520	0.17126	0.17185	0.17635	0.06411	0.19281
	(0.25769)	(0.03659)***	(0.33981)	(0.05054)***	(0.24716)	(0.03509)***	(0.31765)	(0.04732)***
Vocational senior secondary school	0.65136	0.25193	1.11451	0.24623	0.63949	0.25050	1.08453	0.26279
	(0.26722)**	(0.03801)***	(0.36137)***	(0.05422)***	(0.25181)**	(0.03584)***	(0.33152)***	(0.04992)***
General senior secondary school	0.60172	0.28057	0.13578	0.29087	0.58407	0.27887	0.09638	0.30733
	(0.25615)**	(0.03639)***	(0.34054)	(0.05065)***	(0.24059)**	(0.03420)***	(0.30762)	(0.04584)***
College	0.76006	0.42753	0.26863	0.47612	0.69182	0.42047	0.17285	0.48683
	(0.33845)**	(0.04815)***	(0.39204)	(0.05821)***	(0.32221)**	(0.04584)***	(0.35623)	(0.05300)***
Undergraduate	0.57798	0.54710	0.15294	0.60262	0.50997	0.54099	0.04820	0.61441
	(0.29817)*	(0.04214)***	(0.37976)	(0.05639)***	(0.28145)*	(0.03978)***	(0.34238)	(0.05099)
Master	1.48494	0.74564	0.96943	0.75177	1.40211	0.73748	0.86652	0.76731
	(0.74115)	(0.10580)***	(0.87545)	(0.13019)***	(0.73418)*	(0.10480)***	(0.85746)	(0.12775)***
Experience	0.04552	0.00446	0.04791	0.00693				
	(0.02085)**	(0.00297)	(0.02584)*	(0.00388)*				
Experience^2	-0.00091	-0.00008	-0.00089	-0.00017				
	(0.00062)	(0.00006)	(0.00057)	(0.00009)**				
Age					0.09465	0.00474	0.07952	0.00974
					(0.04183)**	(0.00598)	(0.05323)	(0.00796)
Age^2					-0.00115	-0.00005	-0.00095	-0.00013
					(0.00053)**	(0.00008)	(0.00070)	(0.00010)
Tenure	-0.02235	0.01095	0.01097	0.02398	0.02190	0.01142	0.01380	0.02477
	(0.01887)	(0.00268)***	(0.02664)	(0.00396)***	(0.01882)	(0.00267)***	(0.02666)	(0.00397)***
Tenure^2	-0.00051	-0.00014	-0.00069	-0.00017	-0.00048	-0.00016	-0.00070	-0.00048
	(0.00062)	(0.00009)	(0.00086)	(0.00013)***	(0.00062)	(0.00009)*	(0.00087)	(0.00013)***
Marital Status	0.54088	0.00544	0.20267	-0.05479	0.52214	0.00845	0.21481	-0.04905
	(0.19184)***	(0.02742)	(0.19716)	(0.02929)*	(0.19344)***	(0.02762)	(0.19797)	(0.02948)
Urban	1.01013	0.01150	1.22606	0.02592	1.00930	0.01116	1.22609	0.02554
	(0.11786)***	(0.01899)	(0.17233)***	(0.02875)	(0.11783)***	(0.01898)	(0.17239)***	(0.02880)
PerHE		0.07252		0.06741		0.07245		0.06786
		(0.00714)***		(0.00891)***		(0.00714)***		(0.00891)***
PerHE-Ind	0.00411	0.00073	-0.00810	0.00281	0.00435	0.00076	-0.00777	0.00288
	(0.00470)	(0.00067)	(0.00656)	(0.00097)***	(0.00470)	(0.00067)	(0.00657)	(0.00098)***
PerPoverty	-0.20211		-.022287		-0.20192		-0.22338	
	(0.01014)***		(0.01335)***		(0.01014)***		(0.01335)***	
R^2	0.1695		0.2127		0.1697		0.2122	

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Adjusted R^2	0.1654		0.2048		0.1655		0.2043	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		397.028		278.717		396.486		279.947
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		121.639		52.2238		121.008		52.7707
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.9: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *SSS-Population* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	7.94770	4.11245	8.16281	3.98833	7.56787	3.90916	7.87656	3.67477
	(0.09820)***	(0.21771)***	(0.14163)***	(0.32005)***	(0.18656)***	(0.22357)***	(0.24091)***	(0.32705)***
Years of schooling	0.01260	0.04569	0.00865	0.05599	0.01028	0.03987	0.00626	0.05017
	(0.00437)***	(0.00216)***	(0.00573)	(0.00317)***	(0.00406)**	(0.00202)***	(0.00517)	(0.00286)
Experience	0.01030	0.01176	0.01166	0.01599				
	(0.00458)**	(0.00228)***	(0.00553)**	(0.00317)***				
Experience^2	-0.00020	-0.00014	-0.00023	-0.00024				
	(0.00010)**	(0.00005)***	(0.00013)*	(0.00007)***				
Age					0.02665	0.01773	0.02218	0.02506
					(0.00923)***	(0.00463)***	(0.01153)*	(0.00650)***
Age^2					-0.00033	-0.00016	-0.00027	-0.00026
					(0.00012)***	(0.00006)***	(0.00015)*	(0.00009)***
AveSchool		0.10383		0.05903		0.10409		0.06108
		(0.02632)***		(0.03848)		(0.02630)***		(0.03846)
AveSchol-Ind	0.00543	0.03363	-0.01647	0.05247	0.00546	0.03375	-0.01633	0.05239
	(0.01003)	(0.00503)***	(0.01525)	(0.00830)***	(0.01003)	(0.00504)***	(0.01526)	(0.00831)***
SSS-Population	7.08053		7.48671		7.08780		7.49744	
	(0.37471)***		(0.51668)***		(0.37454)***		(0.51654)***	
R^2	0.1231		0.1359		0.1242		0.1356	
Adjusted R^2	0.1217		0.1330		0.1227		0.1328	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		357.958		209.962		358.125		210.676
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		4.01639		0.00172		4.09877		0.00568
P-Value		0.0451**		0.09669		0.0430**		0.9400

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.10: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Levels Using *SSS-Population* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	8.06637	4.24776	8.16245	4.20917	7.65718	4.04879	7.80907	3.89492
	(0.10751)***	(0.22347)***	(0.15967)***	(0.32477)***	(0.19715)***	(0.22910)***	(0.26209)***	(0.33115)***
Primary school	-0.05547	0.10531	-0.04300	0.00354	-0.04058	0.10283	-0.02946	0.01877
	(0.06177)	(0.03090)***	(0.07930)	(0.04419)	(0.06061)	(0.03030)***	(0.07728)	(0.04313)
Junior secondary school	-0.07443	0.19989	-0.02186	0.19436	-0.06177	0.18463	-0.01194	0.20165
	(0.06465)	(0.03237)***	(0.08422)	(0.04682)***	(0.06231)	(0.03117)***	(0.07949)	(0.04430)***
Vocational senior secondary school	0.01112	0.31993	0.22447	0.36200	0.01342	0.28767	0.21896	0.34847
	(0.06649)	(0.03311)***	(0.08866)**	(0.04967)***	(0.06395)	(0.03141)***	(0.08269)***	(0.04654)***
General senior secondary school	0.06753	0.33178	0.09621	0.34604	0.06807	0.29758	0.08715	0.32980
	(0.06385)	(0.03172)***	(0.08383)	(0.04663)***	(0.06042)	(0.03005)***	(0.07696)	(0.04294)***
College	0.08262	0.49599	0.07749	0.53616	0.07159	0.44340	0.05487	0.49804
	(0.08464)	(0.04202)***	(0.09580)	(0.05296)***	(0.08120)	(0.04036)***	(0.08911)	(0.04943)***
Undergraduate	0.01907	0.58131	-0.00269	0.65578	0.00700	0.52642	-0.02959	0.61551
	(0.07394)	(0.03678)***	(0.09233)	(0.05133)***	(0.07044)	(0.03510)***	(0.08502)	(0.04753)***
Master	0.01141	0.86179	0.20956	0.90161	0.25330	0.79758	0.18491	0.86152
	(0.18671)	(0.09307)***	(0.21774)	(0.12073)**	(0.18519)	(0.09240)***	(0.21479)	(0.11942)***
Experience	0.01141	0.01127	0.01292	0.01687				
	(0.00462)**	(0.00232)***	(0.00558)**	(0.00315)***				
Experience^2	-0.00024	-0.00015	-0.00024	-0.00029				
	(0.00010)**	(0.00005)***	(0.00013)*	(0.00007)***				
Age					0.02700	0.01545	0.02459	0.02291
					(0.00928)***	(0.00467)***	(0.01165)**	(0.00658)***
Age^2					-0.00034	-0.00014	-0.00030	-0.00024
					(0.00012)***	(0.00006)**	(0.00015)*	(0.00009)***
AveSchool		0.11286		0.07583		0.11294		0.07636
		(0.02657)***		(0.03925)*		(0.02654)***		(0.03939)*
AveSchool-Ind	0.00638	0.03377	-0.01226	0.04636	0.00664	0.03384	-0.01107	0.04707
	(0.01005)	(0.00506)***	(0.01548)***	(0.00844)***	(0.01004)***	(0.00506)***	(0.01551)***	(0.00849)***
SSS-Population	7.04929		7.37884		7.05780		7.37284	
	(0.37590)***		(0.52109)***		(0.37568)***		(0.52120)***	
R^2	0.1257		0.1468		0.1264		0.1465	
Adjusted R^2	0.1225		0.1406		0.1233		0.1403	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		351.683		200.517		352.933		200.11

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		5.11833		0.21318		5.16633		0.19633
P-Value		0.0237**		0.6444		0.0231**		0.6578

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.11: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *SSS-Population* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	7.90163	4.16513	8.11892	3.86892	7.63857	4.02126	7.79821	3.66677
	(0.10167)***	(0.21647)***	(0.14481)***	(0.32091)***	(0.19321)***	(0.22523)***	(0.25367)***	(0.32460)***
Years of Schooling	0.00701	0.04110	0.00710	0.04754	0.00559	0.03875	0.00223	0.04609
	(0.00453)	(0.00222)***	(0.00599)	(0.00326)***	(0.00416)	(0.00205)***	(0.00523)	(0.00286)***
Experience	0.00571	0.00677	0.01599	0.00729				
	(0.00519)	(0.00256)***	(0.00642)	(0.00361)**				
$Experience^2$	-0.00011	-0.00017	-0.00027	-0.00014				
	(0.00011)	(0.00005)*	(0.00014)	(0.00012)*				
Age					0.01856	0.01165	0.02658	0.01438
					(0.01048)*	(0.00519)**	(0.01321)**	(0.00735)**
Age^2					-0.00023	-0.00013	-0.00030	-0.00018
					(0.00013)*	(0.00007)*	(0.00017)*	(0.00010)*
Tenure	0.00041	0.01162	-0.00067	0.02485	-0.00057	0.01171	-0.00007	0.02491
	(0.00474)	(0.00234)***	(0.00667)	(0.00365)***	(0.00474)	(0.00234)***	(0.00668)	(0.00366)***
$Tenure^2$	-0.00007	-0.00017	-0.00011	-0.00053	-0.00003	-0.00016	-0.00011	-0.00051
	(0.00016)	(0.00008)**	(0.00021)	(0.00012)***	(0.00016)	(0.00008)**	(0.00022)	(0.00012)***
Marital Status	0.14460	0.02675	0.04205	-0.04354	0.13328	0.02650	-0.03989	-0.04417
	(0.04835)***	(0.02407)	(0.04927)	(0.02705)	(0.04869)***	(0.02422)	(0.04956)	(0.02719)
Urban	0.15251	0.05844	0.20009	0.09599	0.15285	0.05850	0.19980	0.09547
	(0.02986)***	(0.01543)***	(0.04289)***	(0.02513)***	(0.02984)***	(0.01543)***	(0.04291)***	(0.02512)***
AveSchool		0.10022		0.08709		0.10033		0.08900
		(0.02622)***		(0.03898)**		(0.02621)***		(0.03878)**
AveSchool-Ind	-0.00216	0.03044	-0.02412	0.04355	-0.00232	0.03049	-0.02434	0.04357
	(0.01016)	(0.00500)***	(0.01530)	(0.00809)***	(0.01016)***	(0.00450)***	(0.01531)	(0.00809)***
SSS-Population	7.02705		7.27635		7.02968		7.30669	
	(0.37332)***		(0.51792)***		(0.37322)***		(0.51753)***	
R^2	0.1329		0.1507		0.1334		0.1499	
Adjusted R^2	0.1303		0.1457		0.1308		0.1448	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		354.302		197.383		354.774		199.33
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Relevance (Hausman test)								
F		4.03536		0.72816		4.08847		0.80334
P-Value		0.0446		0.3936		0.0433**		(0.3702)

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.12: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Levels Using *SSS-Population* as an Instrument and *AveSchool* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	8.00703	4.29719	8.09655	4.04532	7.73403	4.17328	7.70267	3.85804
	(0.11105)***	(0.22141)***	(0.16332)***	(0.32397)***	(0.20353)***	(0.23059)***	(0.27434)***	(0.32652)***
Primary school	-0.06433	0.09104	-0.00566	-0.00616	-0.05317	0.09717	0.00246	0.01387
	(0.06177)	(0.03065)***	(0.07964)	(0.04353)	(0.06038)	(0.02994)***	(0.07719)	(0.04223)
Junior secondary school	-0.10750	0.16723	-0.02103	0.14837	-0.09582	0.17058	-0.02329	0.17307
	(0.06499)*	(0.03236)***	(0.08477)	(0.04633)***	(0.06231)	(0.03100)***	(0.07930)	(0.04339)***
Vocational senior secondary school	-0.05427	0.27020	0.21959	0.27063	-0.04772	0.26721	0.19307	0.28981
	(0.06768)	(0.03356)***	(0.09034)**	(0.04990)***	(0.06378)	(0.03162)***	(0.08296)**	(0.04578)***
General senior secondary school	0.01442	0.28309	0.09251	0.26790	0.01967	0.27956	0.06200	0.28686
	(0.06485)	(0.03199)***	(0.08522)	(0.04666)***	(0.06091)	(0.03006)***	(0.07708)	(0.04220)***
College	0.01579	0.43573	0.09913	0.44613	0.01528	0.42484	0.04635	0.45877
	(0.08568)	(0.04226)***	(0.09790)	(0.05325)***	(0.08154)	(0.03508)***	(0.08904)	(0.04853)***
Undergraduate	-0.03752	0.52343	0.00162	0.56164	-0.03893	0.51340	-0.05656	0.57604
	(0.07503)	(0.03717)***	(0.09435)	(0.05155)***	(0.07075)	(0.03508)***	(0.08505)	(0.04685)***
Master	0.17317	0.79838	0.19842	0.74999	0.17034	0.78538	0.13726	0.76934
	(0.18684)	(0.09220)***	(0.21872)	(0.11934)***	(0.18504)	(0.09140)***	(0.21433)	(0.11705)***
Experience	0.00656	0.00619	0.01719	0.00822				
	(0.00525)	(0.00260)**	(0.00647)***	(0.00364)**				
Experience^2	-0.00015	-0.00012	-0.00028	-0.00020				
	(0.00011)	(0.00006)**	(0.00014)**	(0.00008)**				
Age					0.01804	0.00871	0.02872	0.01137
					(0.01054)*	(0.00523)*	(0.01332)**	(0.00743)
Age^2					-0.00023	-0.00010	-0.00032	-0.00016
					(0.00013)*	(0.00007)	(0.00017)*	(0.00010)
Tenure	0.00004	0.01171	-0.00159	0.02386	-0.00056	0.01212	-0.00093	0.02494
	(0.00475)	(0.00235)***	(0.00667)	(0.00365)***	(0.00474)	(0.00234)***	(0.00667)	(0.00365)***
Tenure^2	-0.00005	-0.00016	-0.00010	-0.00047	-0.00003	-0.00018	-0.00010	-0.00050
	(0.00016)	(0.00008)**	(0.00021)	(0.00012)***	(0.00016)	(0.00008)**	(0.00022)	(0.00012)***
Marital Status	0.14799	0.02758	-0.03740	-0.04786	0.13884	0.02933	-0.03560	-0.04049
	(0.04836)***	(0.02411)	(0.04918)	(0.02693)*	(0.04876)**	(0.02429)	(0.04942)	(0.02709)
Urban	0.15496	0.06575	0.18818	0.08900	0.15459	0.06521	0.18807	0.88723
	(0.03007)***	(0.01556)***	(0.04330)***	(0.02506)***	(0.03006)***	(0.01555)***	(0.04333)***	(0.02510)***
AveSchool		0.10864		0.10756		0.10915		0.10970
		(0.02641)***		(0.03958)***		(0.02639)***		(0.03959)***
AveSchool-Ind	-0.00170	0.02991	-0.01945	0.03677	-0.00164	0.03004	-0.01864	0.03733
	(0.01019)	(0.00502)***	(0.01557)	(0.00825)***	(0.01019)***	(0.00502)***	(0.01560)	(0.00829)***
SSS-Population	7.00075		7.20736		7.00632		7.21787	
	(0.01019)***		(0.52206)***		(0.37429)***		(0.52232)***	
R^2	0.1356		0.1601		0.1359		0.1591	

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Adjusted R^2	0.1312		0.1516		0.1316		0.1507	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
			0.1516					
Test Results								
Quality								
F		349.562		190.597		350.406		190.961
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		5.16683		1.70853		5.26055		1.79314
P-Value		0.0231**		0.1914		0.0219**		0.1807

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.13: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *SSS-Population* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	4.67214	4.90326	5.96040	4.57532	3.28636	4.74367	5.29790	4.29776
	(0.30931)***	(0.07429)***	(0.39674)***	(0.11671)***	(0.73135)***	(0.10631)***	(0.91370)***	(0.15477)***
Years of schooling	0.10698	0.04448	0.03291	0.05662	0.09178	0.03920	0.03592	0.05065
	(0.01796)***	(0.00255)***	(0.02483)	(0.00334)***	(0.01661)***	(0.00235)***	(0.04973)	(0.00302)***
Experience	0.04570	0.01014	0.02867	0.01494				
	(0.01912)**	(0.00250)***	(0.02387)	(0.00323)***				
Experience^2	-0.00077	-0.00011	-0.00077	-0.00021				
	(0.00041)*	(0.00005)**	(0.00055)	(0.00007)***				
Age					0.10299	0.01452	0.05091	0.02321
					(0.03855)***	(0.00507)***	(0.04973)	(0.00302)***
Age^2					-0.00120	-0.00012	-0.00074	-0.00023
					(0.00049)**	(0.00006)*	(0.00066)	(0.00009)***
PerHE		0.05747		0.04756		0.05759		0.04822
		(0.01056)***		(0.01436)***		(0.01056)***		(0.01436)***
PerHE-Ind	0.00632	0.00138	-0.00802	0.00452	0.00647	0.00141	-0.00800	0.00452
	(0.00493)	(0.00065)**	(0.00690)	(0.00092)***	(0.00493)	(0.00065)**	(0.00690)	(0.00092)***
SSS-Population	18.38104		19.52913		18.39147		19.57032	
	(1.50241)***		(2.09305)***		(1.50219)***		(2.09287)***	
R^2	0.0670		0.0587		0.0676		0.0583	
Adjusted R^2	0.655		0.0555		0.0660		0.0552	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
Quality								
F		149.68		87.0578		149.893		87.4407
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		24.3598		5.45577		24.4833		5.6192
P-Value		0.0000***		0.0196**		0.0000***		0.0179**

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.14: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Levels Using *SSS-Population* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	5.10966	5.09093	6.19769	4.85535	3.47085	4.95074	5.35993	4.57661
	(0.33087)***	(0.08162)***	(0.42272)***	(0.12388)***	(0.76296)***	(0.11255)***	(0.96538)***	(0.16272)***
Primary school	0.08177	0.10436	-0.36318	0.02000	0.11026	0.10153	-0.28071	0.03221
	(0.25737)	(0.03365)***	(0.34139)	(0.04677)	(0.25255)	(0.03303)***	(0.33271)	(0.04550)
Junior secondary school	0.23317	0.19441	-0.22976	0.21154	0.22649	0.18057	-0.13135	0.21490
	(0.26887)	(0.03521)***	(0.36231)	(0.04909)***	(0.25910)	(0.03396)***	(0.34195)	(0.04636)***
Vocational senior secondary school	1.04731	0.28791	1.03575	0.33851	0.97537	0.25982	1.11603	0.32093
	(0.27465)***	(0.03734)***	(0.38056)***	(0.05345)***	(0.26019)***	(0.03546)***	(0.35470)***	(0.05071)***
General senior secondary school	0.89669	0.31718	0.11745	0.36064	0.81532	0.28747	0.19382	0.34074
	(0.26380)***	(0.03554)***	(0.35976)	(0.03868)***	(0.24929)***	(0.03363)***	(0.32993)	(0.04484)***
College	1.24666	0.47407	0.04611	0.55918	1.09538	0.42879	0.09825	0.51759
	(0.35050)***	(0.04714)***	(0.41242)	(0.05572)***	(0.33591)***	(0.04510)***	(0.38311)	(0.05185)***
Undergraduate	0.70711	0.58768	-0.13370	0.68393	0.54539	0.54052	-0.07466	0.63975
	(0.30664)**	(0.04038)***	(0.39837)	(0.05401)***	(0.77155)*	(0.03838)***	(0.36626)	(0.04971)***
Master	2.28512	0.79925	0.98751	0.89291	2.09637	0.74398	1.08233	0.84710
	(0.77792)***	(0.10452)***	(0.93675)	(0.12694)***	(0.77155)***	(0.10347)***	(0.92373)	(0.12568)***
Experience	0.05384	0.00922	0.03431	0.01577				
	(0.01930)***	(0.00257)***	(0.02402)	(0.00329)***				
Experience^2	-0.00094	-0.00011	-0.00088	-0.00026				
	(0.00042)**	(0.00006)**	(0.00055)	(0.00008)***				
Age					0.11328	0.01135	0.06025	0.02087
					(0.03871)***	(0.00519)**	(0.05012)	(0.00686)***
Age^2					-0.00131	-0.00009	-0.00085	-0.00021
					(0.00049)***	(0.00007)	(0.00066)	(0.00009)**
PerHE		0.06197		0.05219		0.06199		0.05259
		(0.01079)***		(0.01481)***		(0.01078)***		(0.01482)***
PerHE-Ind	0.00837	0.00109	-0.00519	0.00365	0.00864	0.00110	-0.00467	0.00374
	(0.00497)*	(0.00067)	(0.00708)	(0.00096)***	(1.50345)***	(0.00067)*	(0.00710)	(0.00096)***
SSS-Population	18.24462		19.15300		18.25801		19.17948	
	(1.50416)***		(2.09766)***		(1.50345)***		(2.09770)***	
R^2	0.0716		0.0754		0.07222		0.0749	
Adjusted R^2	0.0682		0.0686		0.0688		0.0681	
Observations	3017	3017	1511	1511	3017	3017	1511	1511

Test Results

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
<u>Quality</u>								
F		147.123		83.369		147.478		83.5963
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
<u>Relevance (Hausman test)</u>								
F		27.7398		6.95398		27.8153		6.96053
P-Value		0.0000***		0.0084***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.15: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Years of Schooling Using *SSS-Population* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	4.25805	4.92164	5.27627	4.58283	3.16413	4.80763	4.68816	4.40801
	(0.32064)***	(0.07394)***	(0.41507)***	(0.11533)***	(0.75676)***	(0.10969)***	(0.96191)***	(0.15838***
Years of Schooling	0.05633	0.04140	0.00398	0.04919	0.04710	0.03929	0.00040	0.04761
	(0.01862)***	(0.00247)***	(0.02567)	(0.00350)***	(0,01707)***	(0.00227)***	(0.02240)	(0.00306)***
Experience	0.03139	0.00580	0.03690	0.00628				
	(0.02147)	(0.00281)**	(0.02736)	(0.00381)				
Experience^2	-0.00056	-0.00009	-0.00080	-0.00012				
	(0.00046)	(0.00006)	(0.00060)	(0.00008)				
Age					0.08080	0.00946	0.04966	0.01315
					(0.04331)*	(0.00570)*	(0.05631)	(0.00776)*
Age^2					-0.00098	-0.00010	-0.00066	-0.00016
					(0.00055)*	(0.00007)	(0.00074)	(0.00010)
Tenure	0.00998	0.01099	0.00618	0.02466	0.00738	0.01111	0.01156	0.02448
	(0.01960)	(0.00255)***	(0.02845)	(0.00388)***	(0.01958)	(0.00255)***	(0.02851)	(0.00388)***
Tenure^2	-0.00036	-0.00015	-0.00053	-0.00051	-0.00021	-0.00015	-0.00062	-0.00050
	(0.00064)	(0.00008)*	(0.00091)	(0.00012)***	(0.00064)	(0.00008)*	(0.00093)	(0.00013)***
Marital Status	0.48680	0.00960	0.01941	-0.04850	0.45606	0.00977	0.05003	-0.05056
	(0.19974)**	(0.02635)	(0.21016)	(0.02869)*	(0.20119)**	(0.02650)	(0.21138)	(0.02888)*
Urban	1.17818	0.02063	1.40791	0.04254	1.17978	0.02058	1.40681	0.04168
	(0.12165)***	(0.02153)	(0.18186)***	(0.03501)	(0.12158)***	(0.02154)	(0.18193)***	(0.03492)
PerHE		0.05668		0.05707		0.05675		0.05761
		(0.01125)***		(0.01591)***		(0.01126)***		(0.01582)***
PerHE-Ind	0.00407	0.00122	-0.01042	0.00383	0.00411	0.00123	-01060	0.00384
	(0.00488)	(0.00064)*	(0.00681)	(0.00093)***	(0.00487)	(0.00064)*	(0.00681)	(0.00093)***
SSS-Population	17.17021		17.83386		17.16580		17.94501	
	(1.48717)***		(2.07872)***		(1.48690)***		(2.07738)***	
R^2	0.0961		0.0958		0.0965		0.0952	
Adjusted R^2	0.0934		0.0904		0.0938		0.0897	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Results								
<u>Quality</u>								
F		133.3		73.6036		133.281		74.6203
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Relevance (Hausman test)								
F		22.9146		8.84412		22.9841		9.14201
P-Value		0.0000***		0.0030***		0.0000***		0.0025***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.16: Impact of Aggregate-Level Human Capital on Male and Female Workers (IV Estimations Based on Education Levels Using *SSS-Population* as an Instrument and *PerHE* as the Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	4.57618	5.10277	5.30859	4.84663	3.30265	5.02481	4.55522	4.69316
	(0.34464)***	(0.08015)***	(0.44960)***	(0.12009)***	(0.78834)***	(0.11550)***	(1.01380)***	(0.16494)***
Primary school	-0.02793	0.09350	-0.15306	0.00418	0.00423	0.09899	-0.09842	0.02185
	(0.25505)	(0.03348)***	(0.33930)	(0.04704)	(0.24927)	(0.03274)***	(0.32880)	(0.04563)
Junior secondary school	-0.06039	0.17137	0.31106	0.17001	-0.04419	0.17489	-0.26427	0.19193
	(0.26807)	(0.03520)***	(0.36096)	(0.05006)***	(0.25702)	(0.03377)***	(0.33754)	(0.04687)***
Vocational senior secondary school	0.49952	0.25605	0.85099	0.24999	0.47435	0.25472	0.85843	0.26624
	(0.27818)*	(0.03667)***	(0.38401)**	(0.05473)***	(0.26202)*	(0.03465)***	(0.35236)**	(0.05065)***
General senior secondary school	0.41734	0.28374	-0.05599	0.29076	0.38548	0.28211	-0.05269	0.30729
	(0.26653)	(0.03506)***	(0.36214)	(0.05002)***	(0.25022)	(0.03300)***	(0.32720)	(0.04532)***
College	0.66718	0.43244	-0.02464	0.47517	0.59061	0.42499	-0.06447	0.48571
	(0.35273)*	(0.04643)***	(0.41651)	(0.05755)***	(0.33563)*	(0.04425)***	(0.37871)	(0.05253)***
Undergraduate	0.18445	0.54619	-0.32789	0.60051	0.10254	0.53985	-0.36445	0.61224
	(0.30950)	(0.04050)***	(0.40239)	(0.05605)***	(0.29189)	(0.04425)***	(0.36292)	(0.05091)***
Master	1.50524	0.76159	0.61741	0.75347	1.40847	0.75266	0.59571	0.76868
	(0.77201)*	(0.10243)***	(0.93097)	(0.12868)***	(0.76460)*	(0.10154)***	(0.91215)	(0.12637)***
Experience	0.03801	0.00489	0.04190	0.00718				
	(0.02171)*	(0.00288)*	(0.02753)	(0.00390)*				
Experience^2	-0.00072	-0.00009	-0.00087	-0.00017				
	(0.00046)	(0.00006)*	(0.00061)	(0.00009)**				
Age					0.08806	0.00574	0.05718	0.01006
					(0.04356)**	(0.00581)	(0.05668)	(0.00794)
Age^2					-0.00106	-0.00006	-0.00073	-0.00013
					(0.00056)*	(0.00074)	(0.00074)	(0.00010)
Tenure	0.00933	0.01104	0.00107	0.02388	0.00754	0.01149	0.00688	0.02471
	(0.01963)	(0.00258)***	(0.02839)	(0.00392)***	(0.01959)	(0.00257)***	(0.02842)	(0.00393)***
Tenure^2	-0.00030	-0.00014	-0.00046	-0.00046	-0.00021	-0.00017	-0.00056	-0.00048
	(0.00064)	(0.00008)*	(0.00091)	(0.00013)***	(0.00064)	(0.00008)**	(0.00093)	(0.00013)***
Marital Status	0.48181	0.01030	0.04095	-0.05472	0.45227	0.01285	0.07268	-0.04883
	(0.00064)**	(0.02661)	(0.20942)	(0.02892)*	(0.20141)**	(0.02680)	(0.21039)	(0.02915)
Urban	1.15352	0.02664	1.35434	0.03263	1.15307	0.02588	1.35462	0.03165
	(0.12244)***	(0.02168)	(0.18322)***	(0.03486)	(0.12239)***	(0.02169)	(0.18329)***	(0.03488)***
PerHE		0.06070		0.06288		0.06094		0.06374
		(0.01144)***		(0.01624)***		(0.01144)***		(0.01620)***
PerHE-Ind	0.00545	0.00088	-0.00778	0.00281	0.00563	0.00090	-0.00756	0.00288
	(0.00492)	(0.00066)	(0.00703)	(0.00096)***	(0.00491)	(0.00066)	(0.00704)	(0.00097)***
SSS-Population	17.08529		17.71374		17.09004		17.80774	
	(1.48993)***		(2.08274)***		(1.48925)***		(2.08277)***	

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Males		Females		Males		Females	
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
R^2	0.0991		0.1090		0.0995		0.1083	
Adjusted R^2	0.0946		0.1001		0.950		0.0993	
Observations	3017	3017	1511	1511	3017	3017	1511	1511
Test Result								
Quality								
F		131.496		72.3352		131.689		73.103
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		25.9324		11.0664		26.1807		11.4403
P-Value		0.0000***		0.0009***		0.0000***		0.0007***

Notes:Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.17: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *PerPoverty* as an Instrument and *AveSchool* as Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				Workers with higher education			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.06090	3.08394	8.63447	2.91800	9.05765	2.07088	8.62697	1.40640
	(0.20203)***	(0.17655)***	(0.15907)***	(0.18497)***	(0.58752)***	(0.41951)***	(0.64991)***	(0.44343)***
Years of schooling	0.01971	0.04124	0.01574	0.03709	0.05188	0.10085	0.04760	0.09065
	(0.00420)***	(0.00253)***	(0.00384)***	(0.00231)***	(0.03687)	(0.01972)***	(0.03733)	(0.02001)***
Experience	0.01906	0.01006			0.00996	0.03073		
	(0.00377)***	(0.00228)***			(0.01027)	(0.00547)***		
Experience^2	-0.00035	-0.00013			-0.00028	-0.00058		
	(0.00008)***	(0.00005)***			(0.00030)	(0.00016)***		
Age			0.03388	0.01487			0.03016	0.04971
			(0.00721)***	(0.00436)***			(0.02258)	(0.01206)***
Age^2			-0.00040	-0.00014			-0.00038	-0.00050
			(0.00009)***	(0.00006)**			(0.00029)	(0.00016)***
AveSchool		0.23426		0.23394		0.23838		0.23742
		(0.02165)***		(0.02167)***		(0.03459)***		(0.03462)***
AveSchool-Ind	0.01353	0.02063	0.01381	0.02078	-0.02212	0.01835	-0.02176	0.01819
	(0.00871)	(0.00531)***	(0.00871)	(0.00531)***	(0.00442)***	(0.00940)*	(0.01770)	(0.00942)*
PerPoverty	-0.06147		-0.06141		-0.06813		-0.06820	
	(0.00222)***		(0.00222)***		(0.00442)***		(0.00441)***	
R^2	0.1974		0.1971		0.2223		0.2231	
Adjusted R^2	0.1963		0.1961		0.2177		0.2185	
Observation	3680	3680	3680	3680	848	848	848	848
Test Results								
Quality								
F		766.41		764.947		238.052		238.805
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		100.948		100.138		26.5014		26.2884
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.18: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *PerPoverty* as an Instrument and *AveSchool* as Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	9.06170	3.29859	8.68636	3.24863	8.98109	2.40432	8.67869	1.91312
	(0.10280)***	(0.16979)***	(0.16473)***	(0.17854)***	(0.58173)***	(0.41014)***	(0.67945)***	(0.44929)***
Years of schooling	0.01715	0.03236	0.01280	0.03234	0.03604	0.09457	0.03728	0.08864
	(0.00439)***	(0.00249)***	(0.00396)***	(0.00224)***	(0.03660)	(0.01907)***	(0.03717)	(0.01942)***
Experience	0.01804	0.00156			-0.00004	0.02228		
	(0.00432)***	(0.00248)			(0.01223)	(0.00637)***		
Experience^2	-0.00031	-0.00004			-0.00015	-0.00045		
	(0.00009)***	(0.00005)			(0.00035)	(0.00018)**		
Age			0.03039	0.00373			0.01908	0.03595
			(0.00823)***	(0.00471)			(0.02689)	(0.01403)***
Age^2			-0.00035	-0.00005			-0.00032	-0.00038
			(0.00011)***	(0.00006)			(0.00035)	(0.00018)**
Tenure	0.00249	0.01646	0.00262	0.01638	0.00009	0.01500	-0.00217	0.01604
	(0.00398)	(0.00226)***	(0.00399)	(0.00226)***	(0.01079)	(0.00563)***	(0.01079)	(0.00564)***
Tenure^2	-0.00014	-0.00027	-0.00014	-0.00027	0.00023	-0.00030	0.00033	-0.00032
	(0.00013)	(0.00007)***	(0.00013)	(0.00007)***	(0.00039)	(0.00021)	(0.00040)	(0.00021)
Marital Status	0.03353	0.00458	0.03630	0.00400	0.24273	-0.05848	0.23700	-0.05653
	(0.03701)	(0.02102)	(0.03702)	(0.02102)	(0.07575)***	(0.03984)	(0.07596)***	(0.04000)
Urban	0.10198	0.04545	0.10151	0.04546	0.26391	0.09528	0.26283	0.09653
	(0.02565)***	(0.01486)***	(0.02565)**	(0.01485)***	(0.06158)***	(0.03406)***	(0.06157)***	(0.03410)***
Female	0.05403	-0.22437	0.05250	-0.22459	-0.03287	-0.11743	-0.03242	-0.11781
	(0.02494)**	(0.01412)***	(0.02493)**	(0.01412)***	(0.04949)	(0.02595)***	(0.04957)	(0.02604)***
AveSchool		0.21912		0.21901		0.21548		0.21477
		(0.02067)***		(0.02069)***		(0.03412)***		(0.03413)***
AveSchool-Ind	0.00387	0.02723	0.00428	0.02727	-0.06735	0.01730	-0.02431	0.01689
	(0.00896)	(0.00511)***	(0.00896)	(0.00511)***	(0.00441)***	(0.00927)*	(0.01790)	(0.00929)*
PerPoverty	-0.06130		-0.06125		-0.06735		-0.07643	
	(0.00223)***		(0.00223)***		(0.00441)***		(0.00441)***	
R^2	0.2026		0.2023		0.2489		0.1414	
Adjusted R^2	0.2005		0.2001		0.2399			
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
<u>Quality</u>								
F		755.254		753.771		233.52		234.265

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
		Workers without higher education				Workers with higher education		
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		92.24		91.9699		24.7992		24.7656
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.19: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *PerPoverty* as an Instrument and *PerHE* as Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	8.54279	4.76944	7.29440	4.59800	7.49143	3.83006	4.99759	3.23083
	(0.27487)***	(0.05482)**	(0.57531)***	(0.09327)***	(2.49599)***	(0.31716)***	(2.76007)*	(0.34984)***
Years of schooling	0.12282	0.03845	0.10606	0.03461	0.24449	0.09767	0.22685	0.08768
	(0.01717)***	(0.00276)***	(0.01564)***	(0.00251)***	(0.16173)	(0.02050)***	(0.16369)	(0.02077)***
Experience	0.06309	0.00970			0.06779	0.02834		
	(0.01561)***	(0.00242)***			(0.04503)	(0.00566)***		
Experience^2	-0.00107	-0.00013			-0.00190	-0.00051		
	(0.00033)***	(0.00005)**			(0.00131)	(0.00016)***		
Age			0.10444	0.01483			0.17213	0.04483
			(0.02989)***	(0.00464)***			(0.09898)*	(0.01249)***
Age^2			-0.00119	-0.00014			-0.00218	-0.00044
			(0.00039)***	(0.00006)**			(0.00127)*	(0.00016)***
PerHE		0.07480		0.07475		0.06819		0.06793
		(0.00658)***		(0.00658)***		(0.00995)***		(0.00996)***
PerHE-Ind	0.01112	0.00079	0.01139	0.00082	-0.02146	0.00208	-0.02127	0.00205
	(0.00434)**	(0.00068)	(0.00435)***	(0.00068)	(0.00838)**	(0.00109)*	(0.00837)**	(0.00109)*
PerPoverty	-0.20930		-0.20902		-0.24384		-0.24405	
	(0.00892)***		(0.0892)***		(0.01926)***		(0.01926)***	
R^2	0.1523		0.1518		0.1703		0.1711	
Adjusted R^2	0.1511		0.1506		0.1654		0.1661	
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
<u>Quality</u>								
F		550.898		549.19		160.235		160.642
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
<u>Relevance (Hausman test)</u>								
F		150.351		149.248		30.5415		30.1308
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.20: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *PerPoverty* as an Instrument and *PerHE* as Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	7.96594	4.92856	6.85240	4.87557	7.07389	3.99634	6.64020	3.46227
	(0.28573)***	(0.05329)***	(0.60273)***	(0.09321)***	(2.45530)***	(0.30949)***	(2.87374)**	(0.36298)***
Years of schooling	0.08381	0.03187	0.06874	0.03193	0.15682	0.09333	0.16726	0.08716
	(0.01783)***	(0.00271)***	(0.01607)***	(0.00243)***	(0.15919)	(0.01988)***	(0.16170)	(0.02023)***
Experience	0.06061	0.00124			-0.01861	0.02324		
	(0.01771)***	(0.00268)			(0.05313)	(0.00664)***		
Experience^2	-0.00105	-0.00003			-0.00004	-0.00048		
	(0.00037)***	(0.00006)			(0.00154)	(0.00019)**		
Age			0.09423	0.00372			0.02317	0.03834
			(0.03375)**	(0.00509)			(0.11686)	(0.01458)***
Age^2			-0.00108	-0.00005			-0.00058	-0.00041
			(0.00044)**	(0.00007)			(0.00151)	(0.00019)**
Tenure	0.00698	0.01636	0.00877	0.01619	0.09483	0.00929	0.08803	0.01029
	(0.01631)	(0.00244)***	(0.01637)	(0.00245)***	(0.04690)**	(0.00593)	(0.04690)*	(0.00592)*
Tenure^2	-0.00030	0.00028	-0.00033	-0.00028	-0.00231	-0.00010	-0.00197	-0.00013
	(0.00052)	(0.00008)***	(0.00053)	(0.00008)***	(0.00171)	(0.00022)	(0.00172)	(0.00022)
Marital Status	0.23020	-0.00739	0.25320	-0.00897	0.85821	-0.05978	0.84465	-0.05817
	(0.15180)	(0.02272)	(0.15185)***	(0.02272)	(0.32896)***	(0.04141)	(0.32994)**	(0.04156)
Urban	0.97843	0.00871	0.97752	0.00871	1.55657	0.05466	1.55182	0.05609
	(0.10339)***	(0.01742)	(0.10341)***	(0.01742)	(0.26796)***	(0.03797)	(0.26796)***	(0.03797)
Female	0.26877	-0.22652	0.26363	-0.22669	-0.18808	-0.11157	-0.18957	-0.11179
	(0.10194)***	(0.01525)***	(0.10195)***	(0.01524)***	(0.21546)	(0.02713)***	(0.21585)	(0.02721)***
PerHE		0.07374		0.07372		0.06281		0.06257
		(0.00661)***		(0.00661)***		(0.00999)***		(0.00999)***
PerHE-Ind	0.00650	0.00109	0.00678	0.00110	-0.02161	0.00207	-0.02152	0.00202
	(0.00432)	(0.00065)*	(0.00432)	(0.00065)*	(0.00845)**	(0.00108)*	(0.00844)**	(0.00108)*
PerPoverty	-0.20160		-0.20145		-0.23721		-0.23741	
	(0.00890)***		(0.00890)***		(0.01900)***		(0.01900)***	
R^2	0.1753		0.1746		0.2130		0.2134	
Adjusted R^2	0.1730		0.1724		0.2036		0.2040	
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
<u>Quality</u>								
F		513.292		512.11		155.84		156.176
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Relevance (Hausman test)								
F		148.148		147.735		29.6605		29.4765
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.21: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *SSS-Population* as an Instrument and *AveSchool* as Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				Workers with higher education			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	7.76039	4.02250	7.40670	3.80970	8.37884	2.73305	8.23324	2.04730
	(0.09261)***	(0.20116)***	(0.15797)***	(0.20512)***	(0.63299)***	(0.52282)***	(0.70266)***	(0.53840)***
Years of schooling	0.01567	0.04269	0.01340	0.03829	0.03424	0.10402	0.03308	0.09379
	(0.00434)***	(0.00240)***	(0.00397)***	(0.00220)***	(0.03989)	(0.01900)***	(0.04041)	(0.01930)***
Experience	0.01487	0.01179			0.00019	0.03059		
	(0.00389)***	(0.00240)***			(0.01109)	(0.00525)***		
Experience^2	-0.00027	-0.00017			-0.00006	-0.00058		
	(0.00008)***	(0.00005)***			(0.00032)	(0.00015)***		
Age			0.02778	0.01813			0.00981	0.05039
			(0.00745)***	(0.00415)***			(0.02439)	(0.01159)***
Age^2			-0.00033	-0.00018			-0.00015	-0.00051
			(0.00010)***	(0.00005)***			(0.00031)	(0.00015)***
AveSchool		0.11344		0.11371		0.15677		0.15708
		(0.02505)***		(0.02505)***		(0.05282)***		(0.05300)***
AveSchool-Ind	0.01669	0.03025	0.01689	0.03037	-0.06070	0.01881	-0.06037	0.01867
	(0.00912)*	(0.00516)***	(0.00912)*	(0.00517)***	(0.02045)***	(0.00903)**	(0.02045)***	(0.00906)**
SSS-Population	7.26930		7.27128		6.67168	0.01881	6.66933	
	(0.33108)***		(0.33103)***		(0.74424)***	(0.00903)**	(0.74434)***	
R^2	0.1425		0.1426		0.0893		0.0895	
Adjusted R^2	0.1413		0.1414		0.0839		0.0841	
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
Quality								
F		482.074		482.487		80.3606		80.2834
P-Value		0.0000		0.0000***		0.0000***		0.0000***
Relevance (Hausman test)								
F		7.29325		7.31919		1.73892		1.77285
P-Value		0.0070***		0.0069***		0.1876		0.1834

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.22: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *SSS-Population* as an Instrument and *AveSchool* as Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Constant	7.78994	4.21566	7.45043	4.12239	8.34669	3.09337	8.33199	2.58978
	(0.09527)***	(0.19379)***	(0.16373)***	(0.19896)***	(0.62572)***	(0.50912)***	(0.73330)***	(0.53880)***
Years of schooling	0.01276	0.03337	0.00840	0.03293	0.01394	0.09586	0.01808	0.09025
	(0.00453)***	(0.00237)***	(0.00408)**	(0.00213)***	(0.03949)	(0.01832)***	(0.04014)	(0.01867)***
Experience	0.01557	0.00345			-0.00961	0.02150		
	(0.00446)***	(0.00236)			(0.01319)	(0.00613)***		
Experience^2	-0.00026	-0.00007			-0.00002	-0.00045		
	(0.00009)***	(0.00005)			(0.01165)	(0.00018)**		
Age			0.02748	0.00709			-0.00145	0.03600
			(0.00850)***	(0.00449)			(0.02902)	(0.01348)***
Age^2			-0.00031	-0.00009			-0.00008	-0.00039
			(0.00011)***	(0.00006)			(0.00038)	(0.00017)**
Tenure	0.00018	0.01610	0.00006	0.01603	-0.00002	0.01488	-0.00199	0.01575
	(0.00411)	(0.00215)***	(0.00412)	(0.00215)***	(0.01165)	(0.00540)***	(0.01166)	(0.00542)***
Tenure^2	-0.00011	-0.00028	-0.00009	-0.00027	0.00024	-0.00028	0.00032	-0.00030
	(0.00013)	(0.00007)***	(0.00013)	(0.00007)***	(0.00043)	(0.00020)	(0.00043)	(0.00020)
Marital Status	0.00926	0.00530	0.00928	0.00485	0.22982	-0.04404	0.22524	-0.04267
	(0.03823)	(0.01998)	(0.03823)***	(0.01998)	(0.08189)***	(0.03884)	(0.08216)***	(0.03898)
Urban	0.12372	0.06268	0.12347	0.06262	0.32245	0.12433	0.32125	0.12508
	(0.02647)***	(0.01426)***	(0.02646)***	(0.01426)***	(0.06630)***	(0.03542)***	(0.06631)***	(0.03547)***
Female	0.02370	0.22454	0.02259	-0.22492	-0.07053	-0.12433	-0.07050	-0.12775
	(0.02571)	(0.01342)***	(0.02570)	(0.01342)***	(0.05336)	(0.03542)***	(0.05347)	(0.02546)***
AveSchool		0.10173		0.10179		0.13080		0.13117
		(0.02397)***		(0.02396)***		(0.05144)**		(0.05161)**
AveSchool-Ind	0.00584	0.03508	0.00613	0.03515	-0.06159	0.01804	-0.06120	0.01764
	(0.00938)	(0.00494)***	(0.00938)	(0.00495)***	(0.02072)***	(0.00891)**	(0.02072)***	(0.01764)**
SSS-Population	7.21430		7.21609		6.66674		6.65780	
	(0.33090)***		(0.33088)***		(0.73981)***		(0.73983)***	
R^2	0.1488		0.1487		0.1243		0.1243	
Adjusted R^2	0.1465		0.1464		0.1138		0.1138	
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
<u>Quality</u>								
F		475.335		47.623		81.2053		80.9845
P-Value		0.0000****		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings	Reduced-Form Average Schooling	IV-Earnings
Relevance (Hausman test)								
F		5.30074		5.31882		1.36577		1.40563
P-Value		0.0214**		0.0212**		0.2429		0.2361

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.23: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *SSS-Population* as an Instrument and *PerHE* as Aggregate-Level Human Capital Measure - Mincerian Model without Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				Workers with higher education			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	4.63136	4.85317	3.64147	4.66736	4.08869	3.85643	2.67013	3.24886
	(0.27766)***	(0.07065)***	(0.59949)***	(0.09786)***	(2.65695)	(0.32118)***	(2.94676)	(0.34892)***
Years of schooling	0.11037	0.04010	0.09724	0.03610	0.19443	0.06278	0.18805	0.08878
	(0.01795)***	(0.00280)***	(0.01635)***	(0.00256)***	(0.17260)	(0.01872)***	(0.17477)	(0.02074)***
Experience	0.04768	0.01033			0.03087	0.02846		
	(0.01630)***	(0.00235)***			(0.04791)	(0.00557)***		
Experience^2	-0.00081	-0.00014			-0.00105	-0.00051		
	(0.00035)**	(0.00005)***			(0.00139)	(0.00016)***		
Age			0.08230	0.01593			0.09572	0.04526
			(0.03122)***	(0.00449)***			(0.10539)	(0.01236)***
Age^2			-0.00095	-0.00016			-0.00130	-0.00044
			(0.00040)**	(0.00006)***			(0.00136)	(0.00016)***
PerHE		0.06062		0.06074		0.06278		0.06289
		(0.01018)***		(0.01019)***		(0.01872)***		(0.01878)***
PerHE-Ind	0.01608	0.00112	0.01630	0.00116	-0.03500	0.00194	-0.03486	0.00192
	(0.00454)***	(0.00068)*	(0.00454)***	(0.00068)*	(0.00906)***	(0.00114)*	(0.00906)***	(0.00114)*
SSS-Population	18.45270		18.44920		18.83870		18.82352	
	(1.32668)***		(1.32681)***		(3.03951)***		(3.03938)***	
R^2	0.0740		0.0737		0.0555		0.0559	
Adjusted R^2	0.0727		0.0724		0.0499		0.0503	
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
<u>Quality</u>								
F		193.46		193.346		38.4146		38.3558
P-Value		0.0000***		0.0000***		0.0000***		0.0000***
<u>Relevance (Hausman test)</u>								
F		31.4402		31.4789		5.52801		5.52755
P-Value		0.0000***		0.0000***		0.0189**		0.0189**

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.24: Test for Imperfect Substitutability for the Workers with and without Higher Education (IV Estimations Using *SSS-Population* as an Instrument and *PerHE* as Aggregate-Level Human Capital Measure - Mincerian Model with Additional Individual Characteristics)

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				Workers with higher education			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Constant	4.27913	4.99642	3.25650	4.92980	3.97346	4.03725	4.59169	3.50711
	(0.28864)***	(0.06899)***	(0.62417)***	(0.09696)***	(2.61411)	(0.31139)***	(3.06480)	(0.36464)***
Years of schooling	0.06894	0.03275	0.05445	0.03264	0.09053	0.09423	0.11113	0.08822
	(0.01861)***	(0.00267)***	(0.01676)***	(0.00239)***	(0.16955)	(0.01944)***	(0.17230)	(0.01983)***
Experience	0.05324	0.00193			-0.05369	0.02277		
	(0.01849)***	(0.00262)			(0.05650)	(0.00653)***		
Experience^2	-0.00090	-0.00004			0.00077	-0.00047		
	(0.00039)**	(0.00005)			(0.00164)	(0.00019)**		
Age			0.08620	0.00484			-0.05113	0.03792
			(0.03523)**	(0.00495)			(0.12435)	(0.01424)***
Age^2			-0.00098	-0.00006			0.00028	-0.00041
			(0.00045)**	(0.00006)			(0.00161)	(0.00018)**
Tenure	-0.00413	0.01620	-0.00307	0.01605	0.09563	0.01008	0.08967	0.01101
	(0.01701)	(0.00235)***	(0.01707)	(0.00235)***	(0.04996)	(0.00597)*	(0.04997)*	(0.00595)*
Tenure^2	-0.00011	-0.00028	-0.00011	-0.00027	-0.00232	-0.00012	-0.00204	-0.00014
	(0.00055)	(0.00008)***	(0.00055)	(0.00008)***	(0.00183)	(0.00021)	(0.00183)	(0.00021)
Marital Status	0.14173	-0.00595	0.15661	-0.00731	0.77431	-0.05474	0.76469	-0.05334
	(0.15839)	(0.02186)	(0.15840)	(0.02188)	(0.35079)**	(0.04146)	(0.35194)**	(0.04161)
Urban	1.10190	0.02419	1.10138	0.02413	1.75700	0.06970	1.75161	0.07068
	(0.10780)***	(0.01979)	(0.10778)***	(0.01978)	(0.28473)***	(0.04681)	(0.28481)***	(0.04684)
Female	0.15610	-0.22499	0.15204	-0.22522	-0.33856	-0.11534	-0.34137	-0.11549
	(0.10623)	(0.01470)***	(0.10622)	(0.01469)***	(0.00915)***	(0.02738)***	(0.00914)***	(0.02750)***
PerHE		0.06125		0.06126		0.05456		0.05454
		(0.01061)***		(0.01060)***		(0.01851)***		(0.01857)***
PerHE-Ind	0.01102	0.00131	0.01125	0.00131	-0.03356	0.00188	-0.03343	0.00184
	(0.00451)**	(0.00064)**	(0.00451)**	(0.00065)**	(0.00915)***	(0.00111)*	(0.00914)***	(0.00111)*
SSS-Population	17.11282		17.12299		18.39189		18.36727	
	(1.31619)***		(1.31636)***		(2.98533)***		(2.98569)***	
R^2	0.1013		0.1009		0.1069		0.1070	
Adjusted R^2	0.0989		0.0984		0.0963		0.0963	
Observations	3680	3680	3680	3680	848	848	848	848
Test Results								
<u>Quality</u>								
F		169.047		169.205		37.9549		37.8443
P-Value		0.0000***		0.0000***		0.0000***		0.0000***

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	Workers without higher education				**Workers with higher education**			
Variable	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings	Reduced-Form Percentage of Workers with Higher Education	IV-Earnings
Relevance (Hausman test)								
F		30.9713		31.0164		4.69877		4.69634
P-Value		0.0000***		0.0000***		0.0305**		0.0305**

Notes: Standard errors in parentheses. *, ** and *** denote statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Table A7.25: Social Return to Schooling (Models Based on Education Levels without Additional Variables for Individual Characteristics)

		Education Levels						
Specifications	**Samples**	**PS**	**JSS**	**VSSS**	**GSSS**	**COLL**	**UG**	**MASTER**
OLS-1-a	**All**	10.60	13.23	14.32	14.42	13.98	15.53	23.05
	Males	11.01	12.51	13.48	13.98	14.77	15.45	24.24
	Females	10.66	17.03	16.33	15.74	16.88	18.28	23.06
OLS-2-a	**All**	10.80	12.91	13.69	13.71	13.29	15.00	22.75
	Males	10.99	12.09	12.91	13.34	14.14	14.93	23.78
	Females	11.11	16.95	15.81	15.12	16.33	17.86	23.25
OLS-1-b	**All**	2.82	5.69	11.05	7.06	6.36	7.95	15.31
	Males	2.99	4.67	5.78	6.50	6.95	7.68	16.25
	Females	1.94	8.72	7.62	7.31	8.15	9.60	14.20
OLS-2-b	**All**	2.99	5.35	10.01	6.32	5.63	7.37	14.96
	Males	2.98	4.27	5.23	5.87	6.34	7.17	15.80
	Females	2.25	8.50	6.95	6.56	7.44	9.03	14.24
IV-1A-a	**All**	27.26	29.48	30.08	30.14	30.87	32.56	37.27
	Males	26.08	27.30	27.92	28.14	29.73	30.64	36.63
	Females	24.14	29.95	28.64	28.57	30.84	32.32	35.19
IV-2A-a	**All**	27.32	29.07	29.44	29.42	30.16	31.98	36.90
	Males	25.93	26.79	27.30	27.46	29.07	30.07	36.11
	Females	24.50	29.82	28.15	28.00	30.31	31.92	35.31
IV-1A-b	**All**	9.05	11.15	10.99	11.96	12.53	14.55	17.04
	Males	8.82	10.01	9.95	10.98	12.23	13.90	16.90
	Females	6.80	12.62	10.14	11.21	13.11	14.57	16.24
IV-2A-b	**All**	9.14	10.79	10.39	11.29	11.86	14.01	16.71
	Males	8.75	9.63	9.48	10.45	11.71	13.46	16.50
	Females	7.02	12.35	9.50	10.47	12.43	14.01	16.18
IV-1B-a	**All**	16.78	19.26	20.17	20.25	20.25	21.85	28.33
	Males	16.42	17.82	18.66	19.06	20.14	20.90	28.69
	Females	12.28	18.58	17.81	17.28	18.56	19.96	24.51
IV-2B-a	**All**	16.98	18.95	19.58	19.59	19.60	21.35	28.05
	Males	16.39	17.40	18.11	18.44	19.54	20.40	28.24
	Females	12.66	18.44	17.24	16.61	17.95	19.49	24.64
IV-1B-b	**All**	8.01	10.24	10.28	11.13	16.22	13.44	16.75
	Males	8.05	9.31	9.42	10.40	11.54	13.07	16.88
	Females	5.92	11.97	9.82	10.55	12.20	13.67	16.03
IV-2B-b	**All**	8.13	9.90	9.68	10.48	14.88	12.92	16.42
	Males	8.00	8.94	8.95	9.87	11.02	12.64	16.48
	Females	6.17	11.72	9.17	9.83	11.53	13.11	16.00

OLS-1-a: OLS based on experience and average years of schooling; OLS-2-a: OLS based on age and average years of schooling; OLS-1-b: OLS based on experience and percentage of workers with higher education; OLS-2-b: OLS based on age and percentage of workers with higher education; IV-1A-a: IV using PerPoverty as an instrument and based on experience and average years of schooling; IV-2A-a: IV using PerPoverty as an instrument and based on age and average years of schooling; IV-1A-b: IV using PerPoverty as an instrument and based on experience and percentage of workers with higher education; IV-2A-b: IV using PerPoverty as an instrument and based on age and percentage of workers with higher education; IV-1B-a: IV using SSS-Population as an instrument and based on experience and average years of schooling; IV-2B-a: IV using SSS-Population as an instrument and based on age and average years of schooling; IV-1B-b: IV using SSS-Population as an instrument and based on experience and percentage of workers with higher education; IV-2B-b: IV using SSS-Population as an instrument and based on experience and percentage of workers with higher education; PS: primary school, JSS: junior secondary school; VSSS: vocational senior secondary school; GSSS: general senior secondary school; COLL: college; UG: undergraduate; MASTER: master degree.
Sources: Tables 7.3, 7.5, 7.9. 7.11, 7.13, 7.16, A7.2, A7.6, A7.14.

Table A7.26: Social Return to Schooling (Models Based on Education Levels with Additional Variables for Individual Characteristics)

		Education Levels						
Specifications	**Samples**	**PS**	**JSS**	**VSSS**	**GSSS**	**COLL**	**UG**	**MASTER**
OLS-1-a	**All**	9.85	12.26	12.70	12.96	14.43	15.39	21.86
	Males	10.76	11.85	12.85	13.40	14.36	15.22	23.84
	Females	10.49	15.83	15.04	14.77	16.39	17.73	20.42
OLS-2-a	**All**	10.11	12.30	12.54	12.79	14.24	15.30	21.91
	Males	10.88	11.77	12.64	13.17	14.11	15.05	23.71
	Females	11.02	16.16	14.99	14.70	16.31	17.75	20.85
OLS-1-b	**All**	2.13	4.72	8.71	5.66	6.88	7.87	14.13
	Males	2.71	3.92	5.04	5.82	6.52	7.42	15.79
	Females	1.78	7.47	6.42	6.37	7.78	9.14	9.05
OLS-2-b	**All**	2.35	4.72	8.49	5.43	6.64	7.72	14.14
	Males	2.85	3.85	4.83	5.60	6.27	7.26	15.66
	Females	2.17	7.64	6.21	6.14	7.52	8.98	11.94
IV-1A-a	**All**	25.47	27.66	27.64	27.82	30.21	31.33	35.49
	Males	25.89	26.80	27.48	27.67	32.57	30.46	36.49
	Females	24.64	29.69	27.99	28.30	35.17	32.54	33.24
IV-2A-a	**All**	25.65	27.67	27.52	27.69	30.06	31.26	35.52
	Males	25.94	26.66	27.25	27.43	32.32	30.27	36.32
	Females	25.11	30.05	28.09	28.41	35.31	32.69	33.67
IV-1A-b	**All**	8.32	10.64	9.84	10.87	13.02	14.47	16.64
	Males	8.85	9.85	9.87	10.82	12.15	13.92	17.18
	Females	6.83	12.27	9.24	10.73	12.92	14.53	14.20
IV-2A-b	**All**	8.48	10.65	9.72	10.74	12.86	14.39	16.65
	Males	8.92	9.77	9.72	10.66	11.97	13.80	17.07
	Females	7.16	12.46	9.12	10.60	12.77	14.46	14.43
IV-1B-a	**All**	14.90	17.24	17.53	17.76	19.53	20.54	26.27
	Males	15.37	16.39	17.29	17.72	18.94	19.86	27.60
	Females	14.33	19.58	18.51	18.42	20.37	21.78	23.85
IV-2B-a	**All**	15.08	17.22	17.33	17.56	19.31	20.41	26.26
	Males	15.54	16.37	17.14	17.55	18.76	19.77	27.52
	Females	14.93	20.01	18.59	18.50	20.43	21.93	24.37
IV-1B-b	**All**	7.29	9.66	9.08	10.01	15.81	13.38	16.22
	Males	7.72	8.75	8.98	9.90	11.11	12.72	16.93
	Females	6.64	12.10	9.24	10.59	12.72	14.31	14.22
IV-2B-b	**All**	7.50	9.70	8.96	9.89	15.51	13.32	16.25
	Males	7.83	8.71	8.85	9.76	10.95	12.63	16.82
	Females	7.03	12.33	9.14	10.51	12.61	14.29	14.48

OLS-1-a: OLS based on experience and average years of schooling; OLS-2-a: OLS based on age and average years of schooling; OLS-1-b: OLS based on experience and percentage of workers with higher education; OLS-2-b: OLS based on age and percentage of workers with higher education; IV-1A-a: IV using PerPoverty as an instrument and based on experience and average years of schooling; IV-2A-a: IV using PerPoverty as an instrument and based on age and average years of schooling; IV-1A-b: IV using PerPoverty as an instrument and based on experience and percentage of workers with higher education; IV-2A-b: IV using PerPoverty as an instrument and based on age and percentage of workers with higher education; IV-1B-a: IV using SSS-Population as an instrument and based on experience and average years of schooling; IV-2B-a: IV using SSS-Population as an instrument and based on age and average years of schooling; IV-1B-b: IV using SSS-Population as an instrument and based on experience and percentage of workers with higher education; IV-2B-b: IV using SSS-Population as an instrument and based on experience and percentage of workers with higher education; PS: primary school, JSS: junior secondary school; VSSS: vocational senior secondary school; GSSS: general senior secondary school; COLL: college; UG: undergraduate; MASTER: master degree.

Sources: Tables 7.4, 7.6, 7.8, 7.10, 7.12, 7.14, 7.18, A7.4, A7.8, A7.10, A7.12, A7.16.