

**School of Economics and Finance
Curtin Business School**

**Understanding Australia's industry-level productivity dynamics:
from measurement to econometric estimation**

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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 that has been accepted for the award of any other degree or diploma in any university.

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Abstract

This thesis investigates a range of issues related to the industry-level productivity growth in Australia. It approaches the issues from three different, but related angles. First, it derives the estimates of the industry-level multifactor productivity (MFP) index for the 12 market-sector industries in Australia using the non-parametric, growth accounting approach. It then seeks to explain the industry-level productivity changes by estimating the relationship between R&D and MFP growth for several one-digit level industries in Australia. The third major part of the thesis attempts to provide some systematic explanations for the poor productivity performance that has been reflected in measured MFP for the mining industry during the recent mining boom in Australia.

While there have been numerous studies on industry-level productivity dynamics in Australia, the work for this thesis is unique in two respects. First, it takes measurement issues seriously. The emphasis of the study is placed on the understanding of the conceptual basis and statistical limitations of the industry-level MFP measures by exploring the links between production economics and economic measurement. Second, the study decomposes the measured MFP growth into the effects of the 'true' MFP growth, returns to scale, capacity utilisation and natural resource inputs, and then empirically estimates these components for Australia's mining industry. This contributes to the analysis and debate on mining productivity in Australia, which so far seems to have attracted limited attention.

The estimation of the MFP index and the proposed solutions to several econometric specification issues presented in the study are consistent with Australia's System of National Accounts, an economic measurement framework used by the Australian Bureau of Statistics (ABS). Based on the econometric results, the study finds some evidence of a positive relationship between the industry's own R&D capital stock and its productivity growth in several industries in Australia. However, doubts remain about precision and reliability of the estimated returns to industry R&D. Based on the components in the MFP decomposition estimated from a variable cost function of the translog form, the study concludes that the so-called mining

productivity paradox observed recently in Australia is in fact created by the measurement issues, particularly by the omission of the natural resource inputs, that have caused various biases in measured MFP, while the ‘true’ productivity growth in Australian mining has remained positive and stable over the sample period.

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Chapter 1

Introduction

1.1 Background and objectives

This thesis investigates a range of issues related to the industry-level productivity growth in Australia. It approaches the issues from three different, but related angles, with the common theme being to explore the interactions between economic measurement and production economics. First, it derives the estimates of the industry-level multifactor productivity (MFP) index for the 12 market-sector industries in Australia using the non-parametric, growth accounting approach. It then seeks to explain the industry-level productivity changes by estimating the relationship between R&D and MFP growth for several one-digit level industries in Australia. The third major part of the thesis attempts to uncover some underlying causes for the poor productivity performance that has been reflected in measured MFP for the mining industry during the recent mining boom in Australia.

The measurement and analysis of productivity performance at different levels of aggregation continue to attract the attention and interests from both analysts and policy makers. A set of appropriately measured productivity indices is therefore important for the analysis and understanding of the major contributing factors that determine the productivity dynamics of various economic agencies.

The Australian Bureau of Statistics (ABS) publishes a variety of productivity measures in the Australian System of National Accounts (ASNA) (ABS Cat. No. 5204.0). It includes multifactor productivity index for the aggregate market sector and labour productivity index for both the industries and the aggregate market sector. Only recently, has the ABS started publishing the experimental estimates of MFP index for the 12 market-sector industries (ABS 2007a).

The first major part of the thesis investigates several issues associated with the estimation of the industry-level MFP index. The emphasis is placed on the methodological choices, data construction and measurement issues. Estimates of industry-level MFP based on both gross output and value added are derived for the

12 market-sector industries in Australia. The plausibility of these estimates is also assessed. Several related issues, which previously have not attracted much attention in the applied work on MFP, are also investigated. They include the open versus the closed economy MFP measures; the difference between the aggregate and industry-level approaches to the estimation of aggregate MFP; and the assumption underlying the Domar aggregation formula (Domar 1961). These issues are found to be important in our work, since they will influence our assessment of the estimates and will also impact on the magnitudes and interpretations of the results.

The open economy MFP for the aggregate market-sector is also estimated based on the approach suggested by Gollop (1983, 1987). There are several other different approaches dealing with the issues of the MFP measurement under the open economy. They include the methods developed by Diewert and Morrison (1986), Fox and Kohli (1998), Kohli (1990, 2003), Durand (1996) and Cas and Rymes (1991); which are different from each other and also different from the approach proposed by Gollop (1983, 1987). Thus, it appears that a generally accepted solution to the open economy issue has yet to crystallise.

Another important issue related to the industry-level MFP estimates is the aggregation of MFP from the industry-level to the level of the whole economy. Domar (1961) proposes an aggregation rule precisely for this purpose. Aulin-Ahmavaara (2003) and Jorgenson et al. (1987) state that the Domar aggregation formula in its original form (Domar 1961) requires the assumption that all the industries pay the same prices for their capital and labour inputs. Under the framework of production economics, the thesis provides a derivation of the Domar aggregation formula in its original form without relying on the assumption of equal prices for the primary inputs used by the industries. It also derives the Domar aggregation formula in the augmented form as presented in Jorgenson et al. (1987).

There are practical implications from the investigation of the aggregation rules. First, it becomes clearer that the differences in the aggregate MFP estimates from the aggregate approach and the same estimates from the bottom-up (i.e. industry-level) approach are inherent, according to the augmented Domar aggregation formula, and

thus they cannot be attributed entirely to the statistical errors if comparisons are made for the estimates derived from the two approaches. Second, the conditions under which the Domar aggregation rule can be applied seem less restrictive than initially thought.

Apart from the measurement issues, the next important question in relation to the industry-level MFP is about the main drivers for the divergent productivity performance across different industries over time. It has been well accepted that R&D effort and outcomes determine the level of productivity in the long run. However, the empirical evidence supporting this statement is much more difficult to obtain, particularly at the industry level (Griliches 1995). While there is a substantial body of research that quantifies the relationship between R&D and productivity, the number of studies that focus on Australia, particularly at the industry level, is still relatively small. Moreover, given the rapid changes in the Australian economy and the substantial improvement in its productivity growth in recent years, the results from previous Australian studies may require further validation and updating.

The second major part of the thesis focuses on using the recent Australian data at the one-digit (ANZSIC division) level to estimate the returns to R&D in several industries. We also derive and apply an alternative specification for the estimation, which adjusts for the measurement biases that are often encountered in R&D-productivity regressions (Schankerman 1981). The biases in the estimates are the result of using the double-counted R&D expenditure data as well as using the output measures from national accounts in which the expenditure on R&D is treated as a current expense, rather than as an investment.

It is quite likely that the biases in measured MFP are not only originated from the mismeasurement of capital and labour inputs, as in the case of the R&D regressions, they are also closely related to the simplifying assumptions underlying the MFP estimates. Moreover, the biases in measured MFP can also be caused by the problem that some factors are excluded from measured inputs in some industries due to the inherent difficulties in quantifying and measuring them. However, these missing inputs are quite important in the industries' production process. One notable

example is the natural resource inputs in mining. They are excluded from measured inputs, but are crucial in the mining production.

The mining industry in Australia has recently experienced a strong surge in production, investment and employment activities due to commodity price growth stemming from the higher demand for mineral and energy products from China. This mining boom covers roughly from the end of 2001-02 to the beginning of 2008-09. Contrary to the common expectations that the boom would have also boosted mining's productivity performance, Australian mining has in fact suffered from a persistent decline in MFP every year during the entire period of the boom, according to the MFP index published by the ABS (ABS 2008).

While this mining productivity paradox has also been observed in some other advanced commodity-producing countries (Perry 1999) and has also been addressed to some extent in the literature, the number of systematic, comprehensive studies focusing on this issue seems still lacking (Rodriguez and Arias 2008). The number of studies on the productivity in Australian mining appears even more limited, despite the importance of mining in Australian economy. One of the few exceptions includes a recent study by the Productivity Commission (Topp et al. 2008), which focuses on the issues of mining productivity in Australia and attempts to correct for the biases in measured mining MFP by using some alternative measures of inputs.

The last part of the thesis seeks to provide some systematic explanations for the productivity paradox in Australian mining. It extends the work of Topp et al. (2008) by exploring the interactions between economic measurement and production economics, a central theme throughout the thesis. To this end, a cost function and the duality results are used to derive a relationship between the measured and 'true' MFP growth through a decomposition that also separates the effects of returns to scale, market power, capacity utilisation and natural resource inputs on measured MFP. Also incorporated in the derivation of the decomposition equation is the effect of the endogenously derived rental price for capital, a common practice by the national statistical agencies. A translog variable cost function is then estimated that provides the parameter estimates for the components in the decomposition formula.

1.2 Significance

While there have been numerous studies on industry-level productivity dynamics in Australia, the work of this thesis is unique in two respects. First, it takes measurement issues seriously. The emphasis of the study is placed on the understanding of the conceptual basis and statistical limitations of the industry-level MFP measures. One common theme throughout the thesis is to highlight the importance and benefits of exploring the interactions between economic measurement and production economics. The thesis attempts to deal with the measurement issues either directly by using the available data from the ABS that correspond as much to the conceptual and theoretical requirements as possible, or indirectly by adjusting the model specifications used in econometric estimation for the known measurement caveats in those cases where such adjustments are admissible. Consequently, the estimation of the MFP index and the proposed solutions to several econometric specification issues presented in the thesis should be consistent with the requirements of Australia's System of National Accounts, an economic measurement framework used by the ABS to meet the international statistical standards.

Second, the study decomposes the measured MFP growth into the effects of the 'true' MFP growth, returns to scale, capacity utilisation and the natural resource inputs, and then empirically estimates these components for Australia's mining industry. Apart from attempting to seek some systematic answers to the questions raised by the mining productivity paradox, the work of this thesis also contributes to the analysis and debate on mining productivity in Australia, which so far seems to have attracted limited attention.

1.3 Thesis organisation

The thesis has five chapters in total. Chapter 1 is the current chapter, which is the general introduction. Chapter 5, the last chapter, draws the conclusions. Chapters 2 to 4 present the detailed analysis and results from the thesis research. Each of these three chapters deals with one major topic, and it can be read as a separate paper.

Chapter 2 discusses the methodological choices, data construction and measurement issues involved in the estimation of industry-level MFP. It presents the estimates of MFP based on both gross output and value added for the 12 market-sector industries in Australia. Several related issues, which are important for the assessment and interpretation of the industry-level MFP estimates, are also discussed. They include the open versus closed economy MFP measures; the difference between the aggregate and industry-level approaches to the estimation of aggregate MFP; and the assumption underlying the Domar aggregation formula. It is shown that the Domar aggregation formula in its original form can be derived without using the restrictive assumption of equal prices for primary inputs across industries.

Using the data for several one-digit level industries in Australia, Chapter 3 examines the relationship between R&D and productivity at the industry level. It also derives an alternative specification that adjusts for the effects of double counting and expensing biases as a result of using mismeasured data that are often encountered in the R&D-based regressions. Some evidence is found of a positive relationship between the industry's own R&D capital stock and its productivity growth. However, doubts remain about the precision and reliability of the estimated returns to industry R&D.

Chapter 4 seeks to understand the poor productivity performance that has been reflected in measured MFP for the mining industry during the recent mining boom in Australia. It starts with some statistical information about the growth in commodity prices and measured MFP in Australian mining, which puts the scale of the recent mining boom into some perspective. Some intuitive explanations for the puzzling productivity performance during this boom period are also outlined.

The bulk of Chapter 4 focuses on a more formal approach that attempts to uncover some underlying reasons that may explain the mining productivity paradox. It derives a formula that decomposes the measured MFP growth into the growth of 'true' MFP and various other components that are due to the existence of market power, non-constant returns to scale, quasi-fixity of capital and natural resource inputs. A variable cost function of the translog form is then estimated to obtain the

parameter estimates for the various components in the decomposition formula. Here, again, it seeks to explore the links between economic measurement and various concepts in production economics.

As mentioned above, Chapter 5, the last chapter of the thesis, summarises the main findings and draws some major conclusions for the whole thesis.

Chapter 2

Estimating industry-level multifactor productivity in Australia: methods and experimental results

2.1 Introduction

Productivity is one of the driving forces behind economic growth, and in the long run it also determines a country's living standards and economic well being. Productivity statistics are therefore important indicators for our understanding of economic growth and productivity dynamics.

The Australian Bureau of Statistics (ABS) publishes a variety of productivity measures in the Australian System of National Accounts (ABS Cat. No. 5204.0). Before 2007, the most comprehensive productivity measure published by the ABS was the index of multifactor productivity (MFP) for the aggregate market-sector¹. The only available industry-level productivity estimates were based on labour productivity, which is a partial measure and unsatisfactory in a number of ways. To fill the gap, the Australian Productivity Commission (PC) had been estimating the MFP index for the 12 market-sector industries using unpublished ABS data. These estimates were used extensively in their work and by many other analysts. Since 2007, the ABS has been publishing annual index of industry-level MFP, but it emphasizes that the estimates are still experimental due to some measurement issues in the data.

This chapter is based on the author's work at the ABS, which explores various approaches that may be used to produce some early experimental official estimates of the industry-level MFP index as part of ABS' development effort to improve Australia's productivity accounts (Zheng 2005 and Zheng et al. 2002). The emphasis

¹ The market-sector in Australia consists of the following 12 industries: Agriculture, forestry and fishing, Mining, Manufacturing, Electricity gas and water, Construction, Wholesale, Retail, Accommodation, cafes and restaurants, Transport and storage, Communication, Finance and insurance, and Cultural and recreation

is placed on the methodological choices, data construction and measurement issues associated with the estimation. Early experimental estimates of MFP are presented based on both gross output and value added for the 12 market-sector industries in Australia². The plausibility of these estimates is also assessed. Several related issues, which previously have not attracted much attention in the applied work on MFP, are also investigated. They include the open versus the closed economy MFP measures; the difference between the aggregate and industry-level approaches to the estimation of aggregate MFP; and the assumption underlying the Domar aggregation formula (Domar 1961, Hulten 1978). These issues are found to be important, since they influence our assessment of the experimental estimates and alter their magnitude and interpretation.

From the perspective of statistical production, two approaches to estimating industry-level MFP are considered in this chapter: the input-output based approach, which was developed by Statistics Canada (Durand 1996, Cas and Rymes 1991), and the one recently recommended by the OECD (OECD 2001). The latter approach is closely related to the well-known framework developed by Jorgenson et al. (1987), which is also a bottom-up, non-parametric approach based on production economics. After considering the current ABS data environment, the estimation of industry-level MFP presented in this chapter follows the OECD approach and, hence, is able to facilitate international comparison. Using this approach, both gross output and value added based MFP indices are derived.

As the aggregate market-sector MFP indices can also be derived from the industry-level estimates, aggregation provides a way of assessing the plausibility of the industry-level MFP estimates. This is undertaken based on the results from a comparison between the MFP estimates aggregated from the industry-level results and those currently published by the ABS. It is noted, however, that the aggregate MFP estimates derived from the two approaches will not be identical, according to an aggregation formula derived by Jorgenson et al. (1987), which augments the Domar aggregation formula (Domar 1961, Hulten 1978).

² The estimates presented here are not identical to those published by the ABS since 2007.

A directly related issue is the assumption underlying the Domar aggregation formula. Aulin-Ahmavaara (2003) and Jorgenson et al. (1987) state that the Domar aggregation formula in its original form requires the assumption that all the industries pay the same prices for their capital and labour inputs. However, this chapter shows that the original Domar aggregation formula can be derived without using this assumption.

Open economy MFP estimates for the aggregate market-sector are also presented using an approach suggested by Gollop (1983, 1987). There are several other approaches dealing with the issues of MFP measurement under the open economy. They include the methods developed by Diewert and Morrison (1986), Fox and Kohli (1998), Kohli (1990, 2003), Durand (1996) and Cas and Rymes (1991); which are different from each other and also different from the approach proposed by Gollop (1983, 1987). Thus, it appears that a generally accepted solution to the open economy issue has yet to crystallise. This may be the topic for future work.

The chapter is organised as follows. The next section introduces the concepts and methods commonly used in MFP estimation and discusses both aggregate and industry level approaches based on production economics. Some issues related to the choice of the index number formula are also discussed. As an extension, MFP estimation based on the input-output system is also briefly discussed. After introducing the industry-level MFP measures in Section 2.2.5, the analysis of the links between aggregate and industry-level MFP measures is provided in Section 2.2.6.

Section 2.3 focuses on the data and measurement issues. It discusses the issues of data treatment and construction for the estimation of industry-level MFP in the ABS data environment. Each of the components used for deriving the MFP index is considered in detail. The MFP estimates for the 12 market-sector industries are presented in Section 2.4.

By applying the appropriate aggregation rule, the industry-level MFP estimates are aggregated to the market-sector level. The latter are then compared with the market-sector level MFP estimates currently published by the ABS, which are derived using

the aggregate approach. This is the way the plausibility of the experimental industry-level MFP results is assessed. It also raises several issues of consistency in aggregation, which is a topic for Section 2.5.

Section 2.5 presents a derivation of the augmented Domar aggregation formula that was first derived by Jorgenson et al. (1987). Here it is demonstrated that the Domar aggregation formula in its original form does not require the assumption that all the industries pay the same prices for their capital and labour inputs. This section also discusses the implications of the augmented Domar aggregation formula for understanding of the difference between aggregate and industry-level approaches to the estimation of aggregate MFP.

Section 2.6 presents the open economy MFP growth estimates for the aggregate market-sector based on the approach developed by Gollop (1983, 1987). The last section summarises the findings and concludes.

2.2 Concepts and methods

Productivity is generally defined as the ratio of a volume measure of output to a volume measure of input. The single-factor (or partial) measure of productivity includes only one type of input — for example, the labour or capital input corresponds to the labour or capital productivity measures. When it includes all types of inputs used in the production, the corresponding productivity measure is called multifactor productivity (MFP) (also known as total factor productivity, TFP).

This definition of productivity is quite simple. However, the measurement of productivity is not straightforward. There are various complex issues involved in the measurement of output, input and other components used for deriving the MFP estimates. For example, the reliability of an aggregate MFP measure for the whole economy is determined by how well the aggregate output, capital and labour, and factor incomes are measured; these aggregates in turn depend on almost every component of the national accounts in terms of the data quality.

Moreover, there are various frameworks under which the MFP measure can be obtained. The same productivity measure under different approaches often uses different assumptions, and thus will give rise to different interpretations. Therefore, there are two closely related issues involved in MFP estimation - the measurement issue and the issue of applying the appropriate method. Oulton and O'Mahony (1994) express the same view in their work on measuring MFP for the UK:

“...that measurement matters: at every stage of an MFP calculation, empirical and conceptual issues must be faced. Alternative decisions by the researcher can have profound effects on the resulting estimates. That is why it is important to follow a consistent methodology.”

Oulton and O'Mahony (1994, p. 3)

This section focuses on the methodological issues. Before embarking on this task, a few words on the interpretation of MFP estimates are worth mentioning. In general, the MFP measure is intended to capture the change in overall efficiency in production. Under a production function framework, MFP growth can be solely attributable to technological progress. This may be one of the reasons why in many applied work involving MFP, the terms ‘technological progress’ and ‘MFP change’ have been used interchangeably without making explicit distinctions between the two concepts. It can be shown, however, that the estimated MFP growth could reflect the combined effects of technological change, economies of scale, efficiency change, variations in capacity utilisation and measurement errors³.

2.2.1 Growth accounting and the aggregate MFP index

Under some assumptions, there is a close relationship between the MFP measure and economic theory of production. The growth accounting framework set out by Solow

³ For a detailed discussion on the interpretation of MFP and other productivity measures at aggregate and industry levels, see OECD (2001). See also Balk (2003b) for the link between the MFP/TFP measure and profitability, and particularly, for the meaning of productivity change at the individual firm level, as well as the potential uses of the MFP/TFP measure as instruments for monitoring and benchmarking firm performance. See Hulten (2001) for a short biographical account of the development of the MFP/TFP measure. For a critical review of this measure and its relationship with technological progress, see Lipsey and Carlaw (2004).

(1957) provides a derivation of the MFP measure based on an aggregate production function. This production function includes only one aggregate output and two types of aggregate input (capital and labour), with technology as an additional variable shifting over time. More specifically, the aggregate value added production function with the Hicks neutral technological change can be represented as

$$V = F(K, L, t) = A(t)f(K, L) \quad (2.1)$$

where V is the real aggregate value added and K and L are physical capital and labour inputs respectively, t denotes time and $A(t)$ is a technology parameter measuring the factor-neutral shift (also called Hicks-neutral or disembodied technological change) in the production function.

A more general approach based on the existence of an aggregate production possibility frontier can also be used to derive the index of technological progress (e.g. Hulten 1978). However, despite being quite restrictive, the approach using the aggregate production function is the most popular one for deriving the aggregate MFP measure, as the existence of an aggregate production function implies that all industries have the same production function, up to a multiplicative factor (Jorgenson et al. 1987). This also raises an issue of consistency in industry-level MFP aggregation, which will be discussed in detail in Section 2.5. Note also that the MFP indices based on the production function could also serve as useful measures of productivity growth when technological change is of a more general nature, and not necessarily Hicks neutral.

Under the growth accounting framework, output growth from equation (2.1) is decomposed into the contributions of the growth in inputs and the growth in MFP by differentiating totally with respect to time. This yields the following expression,

$$\hat{V} = \eta_K \hat{K} + \eta_L \hat{L} + \tau_V \quad (2.2)$$

where $\eta_K = \frac{\partial F}{\partial K} \frac{K}{F}$ and $\eta_L = \frac{\partial F}{\partial L} \frac{L}{F}$ are elasticities of output with respect to capital and labour; $\hat{X} = \frac{d \ln X}{dt}$ denotes the growth rate under continuous-time for any

variables (in equation (2.2) $X = V, K, L$); and $\tau_v = \frac{\partial \ln F}{\partial t} = \hat{A}$ denotes the Hicks neutral (or disembodied) technological change, also representing the index of MFP growth based on the value added measure of output⁴.

The expression in (2.2) indicates that the growth rate of real value added can be attributed to the growth rates of physical capital and labour, both weighted by the respective output elasticities, and also to the growth rate of the Hicks neutral technology index. MFP growth within this theoretical framework is therefore a direct measure of the Hicks-neutral technological progress. Looking at it differently, under the growth accounting framework technological progress or productivity change is captured by a residual, that is, the growth of output which is not due to the growth of inputs.

Note that the output elasticities are not directly observable. However, when the production process is further assumed to have the properties of constant returns to scale and competitive equilibrium in both output and input markets, equation (2.2) can be written as,

$$\tau_v = \hat{V} - s_K \hat{K} - s_L \hat{L} \quad (2.3)$$

where $s_K \equiv \frac{rK}{p_V V} = \eta_K$ and $s_L \equiv \frac{wL}{p_V V} = \eta_L$, r , w and p_V are the aggregate returns to capital, labour and the price of real value added respectively. Thus, the factor income shares are equal to the respective output elasticities. This is the result of the assumption of competitive equilibrium in both output and input markets. It implies that price is equal to marginal cost and each input is paid the value of its marginal product. Also, $s_K + s_L = 1$ is due to the assumption of constant returns to scale.

⁴ The Hicks-neutral technological change occurs if the competitive economy maintains the existing *capital-labour ratio* for a given factor prices in response to the arrival of new production technologies. Given the real factor price for capital, the technological change is Harrod-neutral if the *capital-output ratio* remains constant in response to the innovation (Gomulka, 1990). MFP growth is often interpreted as the Hicks neutral technological change, while the concept of Harrod-neutral technological progress is more frequently used in theoretical models of economic growth (see, e.g. Barro and Sala-i-Martin 2003).

The last two terms on the right hand side of equation (2.3) form a Divisia index of total input growth. Considering any two discrete points of time, $t, t-1$, equation (2.3) under a discrete approximation then becomes

$$\bar{\tau}_v = [\ln V(t) - \ln V(t-1)] - \bar{s}_k [\ln K(t) - \ln K(t-1)] - \bar{s}_L [\ln L(t) - \ln L(t-1)] \quad (2.4)$$

where $\bar{s}_k \equiv \frac{1}{2}[s_k(t) + s_k(t-1)]$, $\bar{s}_L \equiv \frac{1}{2}[s_L(t) + s_L(t-1)]$.

The combination of capital and labour in the above equation is in the form a Tornqvist index, which is a discrete approximation to the Divisia index in (2.3). With the available data on volume measures of value added and inputs as well as the data on factor income shares at any two points of time, the rate growth in MFP can be readily estimated using (2.4). This method of estimating MFP is often known as the non-parametric, the growth accounting approach.

An alternative aggregate MFP index

The aggregate MFP index of equation (2.3) uses real value added as the measure of output. It has been suggested in the literature (for example, Hulten 1978, Domar 1961, Gollop 1987) that the aggregate deliveries to final demand is an equally valid measure of aggregate output. The aggregate deliveries to final demand measure the goods destined for final demand, which is the ultimate objective of economic production. The value of aggregate deliveries to final demand exceeds the value of aggregate value added by an amount equal to the value of imported intermediate inputs⁵. Thus, the aggregate MFP can be derived in a similar way as that based on value added using the volume measure of aggregate deliveries to final demand and the corresponding measures of inputs. This yields the following aggregate MFP index based on deliveries to final demand,

⁵ The aggregate measure of deliveries to final demand is not to be confused with the concept of final demand which relates to the expenditure side of GDP; i.e. $GDP(E) \equiv \text{Final Demand} - \text{Total imports}$ (including both imported intermediate inputs and imported final products). For the measure of deliveries to final demand, it is defined by the following accounting identity: $\text{Deliveries to Final Demand} \equiv \text{GVA (gross value added)} + \text{Imported intermediate inputs}$.

$$\tau_{FD} = \widehat{FD} - \left(\frac{rK}{P_{FD}FD} \right) \hat{K} - \left(\frac{wL}{P_{FD}FD} \right) \hat{L} - \left(\frac{P_{im}IM}{P_{FD}FD} \right) \widehat{IM} \quad (2.5)$$

where FD stands for aggregate deliveries to final demand; IM is the aggregate imported intermediate inputs; P_{FD} and P_{im} are the aggregate prices for deliveries to final demand and imported intermediate inputs respectively; $\widehat{FD} = d \ln FD / dt$ and $\widehat{IM} = d \ln IM / dt$.

As can be seen from (2.5), the imported intermediate inputs are treated as the additional primary inputs, symmetric to both capital and labour in the above MFP index. Clearly, this formulation of MFP will result in different estimates from those derived from (2.3) in terms of the magnitude. More importantly, it also has its own unique interpretations. According to Gollop (1983, 1987), this MFP index adjusts for the productivity growth under the open economy, while the conventional MFP index as that in equation (2.3) makes no such distinctions, thus the latter is only appropriate for a closed economy. In a closed economy, deliveries to final demand is equal to value added, and $IM = 0$, as all intermediate inputs are produced domestically and there are no imports. Thus, the index in (2.5) will be identical to that in (2.3), the aggregate MFP index based on value added. The distinction between the open and closed economy MFP indices will be further discussed in Section 2.7.

2.2.2 Issues of index numbers

As mentioned at the beginning, MFP is defined as a ratio of the volume measure of output to the volume measure of input. At some level of aggregation, these volume measures have to be derived from the index numbers. Thus, without using the production function and the associated assumptions, the MFP estimates can also be derived solely based on the index numbers. However, there are numerous different index number formulae available when constructing the volume output and input measures.

The early index number literature tends to focus on the axiomatic (or test) approach to the choice of the index number formula. Since the 1970s, the emphasis of the index number literature has shifted to the use of economic theory as a basis for the choice of index numbers. In a path-breaking paper, Diewert (1976) shows how economic theory, in particular, production functions, can also be used to provide a basis for determining which index number formulae are most appropriate and least restrictive. This is the economic-theoretic approach to index numbers.

Clearly, the measurement of the ratio of output to input does not require any parametric estimation. Thus, the index number approach to MFP estimation is also called the ‘non-parametric approach’. This name, however, has been used to describe the technique of MFP estimation based on equations (2.1) to (2.4), which is also called the index number approach by some researchers, presumably since the volume measures of output and inputs have to be derived with the use of index numbers. Adding to this confusion is the fact that other non-parametric methods — for example, the data envelopment analysis (DEA) — can also be used to derive productivity indices. To clarify this terminological confusion, this thesis uses the term ‘the non-parametric, growth accounting approach’ to refer to the MFP index derived from equations (2.1) to (2.4). Indeed, this is our preferred approach to the MFP estimation because of its non-parametric nature as well as the economic interpretations.

As mentioned before, many different index number formulae can be used to derive the volume measures of inputs and output. The Tornqvist index is considered to be exact for the translog function, and to be ‘superlative’, since the translog function is a flexible functional form, that is, it provides a second-order approximation to any arbitrary function. The Fisher index is exact for a quadratic function and thus is also superlative (Diewert 1976). Empirically, when a chained index is employed, the spread between the estimates constructed using the different index formulae is reduced. Nonetheless, Diewert (1992) concludes that there are strong economic justifications for using the Tornqvist or Fisher indices in productivity analysis.

Based on these results, both the Tornqvist and Fisher quantity indices are preferred volume measures of output and inputs in the application of equation (2.4). However, when applied to the actual data, there is little difference between the results from using the two index number formulae — they are often identical up to two decimal points. Despite the fact that the Fisher index can also be used, in the empirical literature on productivity measurement the MFP index in equation (2.4) is sometimes referred to as the Tornqvist index of MFP growth. Perhaps, it particularly refers to the Tornqvist index as a discrete approximation to the Divisia index for combining capital and labour in the MFP formulation of (2.4), rather than to the specific index formulae used for deriving the volume measures.

2.2.3 Developments and applications

The empirical methodology using the non-parametric, growth accounting approach to the measurement of MFP has been further developed and refined over the years. The major methodological innovations for this approach include the quality adjustment of labour input and the adjustment for capital utilization, for example, in the work by Jorgenson and Griliches (1967), and extension of the aggregate framework to the industry or sectoral levels by Jorgenson et al. (1987). The industry-level productivity measure proposed by the latter group of authors is also known as the KLEMS MFP (OECD 2001), since it is derived from a production function based on gross output and including all types of inputs which are generally classified into capital (K), labour (L), energy (E), material (M) and services (S). The dataset specially designed for deriving this type of MFP measure is called the KLEMS database, which has been produced and used by several national statistical agencies.

Another strand of development within this approach is to consider the case where the technological progress is not of the Hicks neutral form; rather, it is embodied in capital. Although this is a somewhat theoretical issue (Hercowitz 1998), its potential impact on the MFP estimates derived from the non-parametric, growth accounting approach has been noted and discussed in Jorgenson (1964) and Hulten (1973, 1974).

Recent progress on this issue has been made by Hulten (1992a), Gordon (1990), Greenwood, Hercowitz and Krusell (1997) and Greenwood and Boyan (2001).

In terms of empirical applications, the non-parametric, growth accounting framework has been used extensively to analyse the issues such as productivity slowdown in the 1970s and early 1980s – the ‘productivity paradox’. The results based on this approach have continued to appear in the work on economic growth and productivity till this day, particularly with the rising interest in the assessment of the impact of information and communications technology (ICT) on the productivity surge that occurred in the early 2000s (see e.g. Jorgenson 2003, 2001, Schreyer 2000, Oliner and Sichel 2000).

Since the 1980s, several national statistical agencies in the OECD countries have been using the non-parametric, growth accounting framework to regularly publish the annual MFP estimates for the aggregate economy or at the industry level. Together with the labour and capital productivity estimates, they form the complete set of productivity accounts. As mentioned before, the ABS started publishing the experimental industry-level MFP estimates from 2007 to complement its annual estimates of MFP, labour and capital productivity for the market-sector and the annual labour productivity indexes for each industry division within the market-sector.

As noted before, the MFP index can also be estimated by other methods, some of which do away with the need for imposing the two simplifying assumptions – constant returns to scale and competitive equilibrium which are necessary under the non-parametric, growth accounting approach. For example, econometric techniques can be applied to estimate the parameters of a production function with some specific forms to obtain the direct measures of productivity growth. The specific production functions commonly used in the empirical work are the Cobb-Douglas and the translog forms. Compared with the method based on econometric techniques, the non-parametric method as outlined above can be applied with less data. For example, it requires only two years of annual data to derive the year-to-year movement in productivity. This makes it cost-effective for national statistical

agencies to regularly publish the estimates of MFP. In this chapter, our attention is focussed on the non-parametric method of estimating MFP under the growth accounting framework.

2.2.4 Input-output based approach

Another extension to the non-parametric, growth accounting framework is to use the data directly from the input-output (I/O) tables. The specific types of I/O tables required in this context are the supply-use tables. The supply table records how supplies of different kinds of goods and services originate from domestic industries and imports, while the use table shows how those supplies are allocated to intermediate uses by industry and to various types of final demand, including exports. The supply-use tables form the rectangular input-output accounting system, which is also the basis for deriving the square (or symmetric) I/O tables typically used for various analytical purposes. The major structure of the rectangular input-output accounting system used by the ABS is shown in Figure 2.1.

Figure 2.1: The rectangular Input-Output accounting framework

| | C = type of commodity | I = type of industry | F = type of final demand |
|---------------------------|-----------------------|----------------------|--------------------------|
| C = type of commodity | | $U_{C \times I}$ | $E_{C \times F}$ |
| I = type of industry | $S_{I \times C}$ | | |
| I = type of primary input | | $R_{I \times I}$ | |

In this input-output accounting framework, the supply table contains matrix S' (the transpose of S) while the use table contains matrices U , E and R . These tables have been partially integrated with the Australian national accounts in the ABS system, meaning that to a certain extent, the aggregates of national accounts are benchmarked from the estimates in the supply-use tables while the I/O tables are also calibrated to be consistent with aggregate statistics from the national accounts. For estimating MFP using the I/O based approach, both current and constant prices supply-use tables are required.

The I/O based approach to MFP estimation has been developed and adopted by Statistics Canada for its productivity accounts (Cas and Rymes 1991, and Durand

1993, 1996)⁶. From the perspectives of national statistical offices, this is an important development, since the I/O based approach provides a unified framework under which aggregate as well as various classes of industry-level MFP measures can be derived consistently⁷. These classes of industry-level MFP measure capture the different levels of integration among industries.

The notion of integration is traditionally a useful concept of describing the interconnectedness among different production units in a production system typically depicted by the I/O framework. It is formalised by Pasinetti (1981) in the analysis of the economic system. Under this system, all production processes are considered as vertically integrated in the sense that all their inputs are reduced to inputs of labour and to services from capital stock.

It turns out that this notion of vertical integration is also particularly useful in the interpretation of the relationships between the different classes of industry-level productivity indices under the I/O based approach. In a dynamic I/O system, one class of the industry-level MFP indices is capable of dealing explicitly with one special characteristic of capital, that is, its reproducibility (Durand 1996). The reproducibility of capital is an important theoretical and empirical issue that has triggered many years of debate and research in the economics profession. Indeed, this notion of capital was the initial impetus to the work by Rymes (1972) who developed a ‘new’ MFP measure under the consideration of the economic system in an attempt to refute the traditional MFP concept that is based on the notion of Hicks neutral technological progress. This ‘new’ measure of MFP is dubbed the Harrod-Robinson-Read (HRR) measure of MFP by Rymes (1983).

Hulten (1992b) notes, however, that the Hicksian and the HRR concepts of technological change are complements, not competitors. Indeed, the latter measure has been empirically implemented using the US and Canadian data. Nonetheless,

⁶ For the details of this method, see Durand (1993, 1996). For a summary of this method and the corresponding productivity indices, see Zheng *et al.* (2002).

⁷ The productivity index specific to a particular commodity aggregate can also be derived under this approach. See Durand (1993, 1996) for details.

this notion of capital and the related productivity measure have not caught much attention of mainstream economists.

Despite this, the estimates of various classes of industry-level MFP under the I/O based approach are expected to generate some new interpretations and additional insights to enrich our understanding of productivity dynamics among the industries. In addition, this approach will be particularly useful if a full integration between the I/O system and the national accounts is established. It can ensure consistency among different classes and levels of productivity estimates.

Thus, the I/O based approach is the initial choice of the methodology to be used to estimate industry-level MFP. However, early exploratory work with this method demonstrates that one additional, yet critical requirement for successfully applying this approach is to have *fully* balanced supply and use tables that are available also in constant prices. The constant prices supply-use tables currently compiled by the ABS do not meet this requirement⁸. This causes the compositional distortions at the detailed commodity level and results in some implausible estimates of MFP at both industry and aggregate levels from our early exploratory work. Unfortunately, the fully balanced constant prices supply-uses tables are costly to compile, but they have great impact on the quality of the MFP estimates derived from the I/O based approach. As a result, this approach is abandoned in the estimation of industry-level MFP.

2.2.5 Industry-level MFP measures

At the industry level or other lower levels of aggregation, MFP can be estimated with different measures of outputs and inputs. This is a salient feature of the I/O based

⁸ For a particular commodity in constant price, its total supply may not be equal to its total use in the constant prices supply-uses tables currently compiled by the ABS. This problem is mainly due to the lack of adequate deflators at the detailed commodity level as well as the shortage of accurate information about the flows of various commodities in constant prices among the use and supply industries. However, for many industry-level statistics based on the supply-use tables, e.g. the gross output, intermediate inputs and valued added by industry in constant prices, they are balanced at the industry-level. For the measurement of these statistics and other aggregate estimates, such as GDP, they are without commodity dimensions, thus balancing at the commodity level is not essential.

approach as discussed previously. The estimation of industry-level MFP can also be based on the approach using the production functions without relying on the supply-uses tables that require detailed flows of commodities among industries.

Different measures of outputs and inputs essentially reflect different representations of the same production process in a particular industry. One such representation is the measure of gross output together with intermediate inputs (both imported and domestically produced) and primary inputs (i.e. capital and labour). For the i th industry, the gross output based production function can be represented as

$$G^i = H^i(M^i, K^i, L^i, t) \quad (2.6)$$

where G denotes the volume of gross output, M , the volume of intermediate inputs including both the imported and domestically produced, and the superscript i indicates the industry.

Another representation uses value-added as a measure of output and includes two types of primary input – capital and labour. The production function based on value added for industry i is

$$V^i = F^i(K^i, L^i, t) \quad (2.7)$$

The existence of the industry-level value-added functions V^i implies that industry-level production of gross output is characterised by value-added separability (Jorgenson et al. 1987)⁹.

$$G^i = H^i[M^i, F^i(K^i, L^i, t)] \quad (2.8)$$

The productivity measures corresponding to (2.6) and (2.7) are known as (industry-level) gross output MFP and value-added MFP, denoted by τ_G^i and τ_V^i respectively. As before, these indices can be derived using equations (2.6) and (2.7) under the assumptions of constant returns to scale and competitive equilibrium, and the results are shown in the following,

⁹ Under the framework developed by Balk (2003a and 2003b), this assumption of separability is not necessary for the existence of a value-added function.

$$\tau_G^i = \hat{G}^i - \tilde{s}_M^i \hat{M}^i - \tilde{s}_K^i \hat{K}^i - \tilde{s}_L^i \hat{L}^i \quad (2.9)$$

$$\tau_V^i = \hat{V}^i - s_K^i \hat{K}^i - s_L^i \hat{L}^i \quad (2.10)^{10}$$

where $\tilde{s}_x^i = \frac{p_x^i x^i}{p_G^i G^i}$, $x = K, L, \text{ or } M$. Note that the factor income shares \tilde{s}^i and s^i are different in the above equations due to the different measures of output used in the denominator.

The Tornqvist versions of equations (2.9) and (2.10) are as follows:

$$\begin{aligned} \bar{\tau}_G^i = & \left[\ln G^i(t) - \ln G^i(t-1) \right] - \bar{\tilde{s}}_M^i \left[\ln M^i(t) - \ln M^i(t-1) \right] \\ & - \bar{\tilde{s}}_K^i \left[\ln K^i(t) - \ln K^i(t-1) \right] - \bar{\tilde{s}}_L^i \left[\ln L^i(t) - \ln L^i(t-1) \right] \end{aligned} \quad (2.11)$$

$$\begin{aligned} \bar{\tau}_V^i = & \left[\ln V^i(t) - \ln V^i(t-1) \right] - \bar{s}_K^i \left[\ln K^i(t) - \ln K^i(t-1) \right] \\ & - \bar{s}_L^i \left[\ln L^i(t) - \ln L^i(t-1) \right] \end{aligned} \quad (2.12)$$

where

$$\bar{\tilde{s}}_j^i \equiv \frac{1}{2} \left[\tilde{s}_j^i(t) + \tilde{s}_j^i(t-1) \right], \quad (j = K, L, M)$$

$$\bar{s}_q^i \equiv \frac{1}{2} \left[s_q^i(t) + s_q^i(t-1) \right], \quad (q = K, L)$$

Based on economic theory, the gross output MFP growth index is intended to measure the Hicks neutral technological progress in an industry, whereas the value-added MFP growth index reflects the industry's capacity to translate technological change into income and into the contribution to final demand. Thus, the two productivity indices are not identical measures of technological change, but they complement each other to reflect an industry's productivity performance.

¹⁰ The gross output and value-added MFP measures can also be derived solely from the accounting relationships and the index number theory, without requiring any economic theory. For this derivation under a rigorous approach, see, for example, Balk (2003a). Balk (2003a) also derives the conditions under which the two MFP indices are path-independent. Path-independence implies that the productivity index between two points in time depends only on the realisation of input and output variables at these two points in time, and not on the specific 'path' that links the two observations.

Here the Hicks neutrality is defined as the form of technological change augmenting both intermediate and primary inputs used in production. Balk (2003a) uses the term 'Hicks input neutrality' to refer to this particular form of technological change. The type of technological progress augmenting only the primary inputs is labelled as the 'Hicks value added neutrality', which corresponds to the technological concept associated with the production function of the form in (2.7). In this sense, both gross output and value added based MFP are valid measures of technological change; they reflect different aspects of the same phenomenon, but they are not identical and thus given different interpretations.

There have been debates over whether gross output or value added, or some other measures are more appropriate in measuring output and thus in measuring the corresponding productivity at the sector/industry level. Although ample reasons have been provided by both sides of the arguments, thesis adopts the view that is advocated by the OECD (OECD 2001), namely that both measures, and indeed some other measures of output, are all valid under their particular constructs. Further, the various approaches complement each other to help our understanding of different aspects of an industry's production and productivity performance.

From the perspective of a national statistical agency, a relevant productivity program is expected to provide a variety of productivity measures to meet different analytical needs. These different measures may also be used to ascertain the quality of the data. If for a particular industry, the gross output and value added based MFP measures tell a different story, then one may suspect some quality issues with the underlying data.

It turns out that there is a direct relation between the gross output and valued-added MFP measures (Bruno 1978). For a particular industry, the gross output MFP growth index is equal to the value added MFP growth index multiplied by a factor, which is equal to the ratio of nominal value of the industry's value added to its gross output:

$$\tau_G^i = \left(\frac{p_V^i V^i}{p_G^i G^i} \right) \tau_V^i \quad (2.13)$$

Drawing on Gollop (1979), Appendix A of the thesis presents a derivation of (2.13) using the production functions. See Balk (2003a) for a derivation of this relationship under a framework that does not rely on the production functions.

Since the multiplying factor is smaller than one, the gross output MFP growth index is systematically smaller than its value added counterpart in absolute value. This difference in magnitude between the two productivity indices does not constitute a bias, but reflects the difference in interpretation as mentioned above. This relationship between the two MFP measures can be clearly observed in the experimental estimates of MFP which will be presented in the next section.

It must be noted, however, that at the industry level, the value-added MFP measure is more sensitive to ‘outsourcing’ than its gross output counterpart. Heuristically, this can be illustrated in the following example using the relationship in (2.13). However, for a fuller illustration using the input-output data and some specific, real world examples, see OECD (2001, pp. 26-29).

Suppose that technological progress in the car manufacturing industry has maintained a constant rate for a certain period of time (i.e. τ_G^i is constant over the period). For some reasons, however, many car manufacturers in the industry now start importing the car parts previously produced by the workers within the industry. Thus, less people are employed in the car industry now. Assuming that the value of the industry’s total number of cars sold (the value of gross output) stays the same as in the previous period, while the total value of the inputs used in the car manufacturing industry is also assumed to be constant — the reductions in payrolls for the workers producing the car parts are now transferred to the increased cost of intermediate inputs (imported car parts). Thus, there is a decrease in value added (in value terms) while the value of gross output remains unchanged in the car manufacturing industry in the current period. In terms of equation (2.13), τ_V^i , the value added based MFP growth for the car manufacturing industry will be greater

than in the previous period as $\left(\frac{P_V^i V^i}{P_G^i G^i}\right)$ is reduced. However, this is not due to a technological breakthrough that occurred in the industry; it is only because the effect of reallocation of inputs — ‘outsourcing’, i.e. the ratio of nominal value of the industry’s gross output to its value added is now greater than in the previous period.

2.2.6 Links between aggregate and industry-level MFP measures

Given the two measures of industry-level MFP indices presented above, the question now is how to obtain a consistent measure of MFP at the aggregate level. This is the issue of aggregation, which establishes a link between different levels of production in the economy. It can be used to answer questions such as the contribution of individual industries to overall productivity growth. As will be discussed in Section 2.5, the aggregation can also be used to validate the consistency of the industry-level and the aggregate MFP estimates.

For the value-added MFP growth index, it seems natural to use each industry’s current price share in total value-added as weights for aggregation, since the current price industry-level value-added sums to aggregate value-added. That is,

$$\tau'_V = \sum_i \left(\frac{p_V^i V^i}{\sum p_V^i V^i} \right) \tau_V^i \quad (2.14)$$

It must be noted, however, that the economy-wide MFP growth estimates τ'_V derived from the industry-level aggregation as shown in the above equation will not generally be equal to the MFP growth estimates τ_V based on the direct aggregate approach as presented in equation (2.3), that is $\tau'_V \neq \tau_V$. This point will be further discussed in Section 2.5. It is worth repeating that the value-added MFP measure can be interpreted as an industry’s capacity to contribute to economy-wide productivity and final demand.

The link between aggregate and industry-level MFP measures based on gross output is not obvious, since the gross output MFP index includes intermediate inputs in both

its output and input measures. Domar (1961) shows that the measure of industry-level MFP growth based on gross output can be correctly aggregated to the economy-wide level using the weights that are equal to the ratio of the nominal values of each industry's gross output to aggregate valued-added. This is shown in the following equation:

$$\tau'_V = \sum_i \left(\frac{p_G^i G^i}{\sum_i p_V^i V^i} \right) \tau_G^i \quad (2.15)^{11}$$

This aggregation rule is known as the Domar aggregation and is formally derived by Hulten (1978). It is argued that this form of the Domar aggregation formula requires the assumption that all the industries pay the same prices for their capital and labour inputs (Aulin-Ahmavaara 2003 and Jorgenson et al. 1987).

Without using this and other restrictive assumptions concerning the outputs and inputs, Jorgenson et al. (1987) derive an *augmented* Domar aggregation formula that includes terms that capture the contributions of reallocations of sectoral value added and the primary factor inputs to aggregate productivity growth. However, Section 2.5 shows that the Domar aggregation in its original form as presented in equation (2.15) can still be derived without the assumption of equal primary input prices across industries.

The augmented Domar aggregation formula of Jorgenson et al. (1987) provides a systematic way to explain the differences between the aggregate MFP estimates derived from the aggregate and industry-level approaches. As is shown in Section 2.5, understanding and explaining these differences form an important part of the exercise of validating the industry-level MFP estimates presented in Section 2.4.

Notice that the weights in equation (2.15) sum to more than one, implying that aggregate MFP growth exceeds the weighted average of the productivity growth of its component industries when the industry-level MFP is based on gross output. The

¹¹ If one accepts that there is a distinction between the MFP formulations under the open and the closed economy settings, and if one also follows the approach to this issue by Gollop (1987), then equation (2.15) should be modified by replacing value added with deliveries to final demand in the weights. This modified version of the Domar aggregation formula is also used in OECD (2001). The issue of the open versus the closed economy MFP is further discussed in Section 2.6.

weights are called the Domar weights because of this property. The intuitive justification for the Domar weights is that an industry contributes not only directly to aggregate MFP growth by efficiently producing its final product, but also indirectly through helping lower costs elsewhere in the economy when other industries purchase its product as intermediate input.

From the input-output based MFP methodology, the industry-level MFP index based on gross output is interpreted as a non-integrated (or integrated at establishment level) measure, whereas the MFP index based on value-added is a fully integrated measure. At the level of aggregate economy, all industries are fully integrated. For the value added industry-level MFP, which is a fully integrated productivity index, performing aggregation alone is sufficient to derive the aggregate MFP index. To aggregate gross output based industry-level MFP measures, however, one has to perform both aggregation and integration. Thus, the Domar weights are also called aggregation-integration weights because they are used to perform these dual functions (Durand 1993, 1996). This interpretation under the I/O based approach may provide further intuitive justifications for our understanding of the uniqueness of the Domar weights.

There are many analytical implications of the Domar aggregation rule. For example, one common perception is that the aggregate MFP growth will be reduced if the shares of the low productivity industries (e.g. the services industries) are increasing in the economy (Baumol 1967). Oulton (2001) shows that this is true only if the industry-level productivity is measured by the value-added MFP index. On the contrary, the aggregate MFP growth will rise if resources are shifting into industries producing intermediate inputs (e.g. the services industries), however low the MFP growth rates are in those industries, provided that they are measured by the gross output MFP index and are positive.

2.3 Data and measurement issues

To estimate the industry-level MFP indices of equations (2.11) and (2.12), data on volume measures of output, primary and intermediate inputs are needed along with

data on industry-level factor incomes. Diewert (2000) highlights the difficulties and various measurement problems associated with industry-level MFP estimation. Some of these issues are addressed in this section. Note that reliance is placed on the data currently available in the ABS to derive the industry-level MFP estimates. Needless to say, any future improvements in the quality and measurement of these data will have a direct impact on the industry-level MFP estimates.

Note also that the MFP index is only estimated for the twelve market-sector industries that are classified at the Division (one digit) level of the Australian and New Zealand Standard Industrial Classification (ANZSIC). They include Agriculture, forestry and fishing, Mining, Manufacturing, Electricity gas and water, Construction, Wholesale, Retail, Accommodation, cafes and restaurants, Transport and storage, Communication, Finance and insurance, and Cultural and recreational. The non-market-sector industries are: Property and business services, Government administration and defence, Education, Health and community services and Personal and other services. These industries are excluded in the MFP estimation owing to the difficulty in estimating volume measures of output for the industries.

2.3.1 Output and intermediate inputs

The gross output for each market-sector industry in both constant and current prices is obtained from the ABS supply-use tables which contain both market and non-market-sector industries and more than one hundred commodity groups¹². Since 1994-95, the ABS has been compiling annual supply-use tables in both current and constant prices. Thus, industry-level gross output MFP growth can be estimated from that period.

Gross value-added (GVA) is used as the output measure for the MFP index based on value-added. The series for industry-level gross value-added is much longer than that for the gross output, although for years prior to 1994-95 the estimates are

¹² For many of the industries in the ABS supply-use tables, they are classified at lower than the Division level. The industries and particularly the commodity groups have been further refined in the latest ABS supply-use tables.

derived without using the supply-use framework. Estimates of industry-level MFP index based on value added from 1990-01 to 2000-01 are presented in Section 2.4.

Both gross output and gross value-added in current prices include the cost of depreciation. This ensures a consistent treatment of capital input as a flow of capital services (see the following sub-section), which also includes a depreciation component. In the Australian supply-use framework, the current price gross output and gross value-added are valued at basic prices. They exclude taxes payable and any transport charges paid separately by the producer, but include subsidies receivable, as a consequence of production or sale. This valuation of output is consistent with the recommendation by the System of National Accounts 93 (SNA 93) and the OECD Productivity Manual (OECD 2001, pp 76-80). Because the basic price is intended to measure the amount actually retained by the producer, it is the price most relevant to the decision-making regarding outputs and therefore is most appropriate for valuing output in productivity analysis.

The volume measures of gross output and intermediate inputs in the supply-use tables are derived from the aggregation of supply and use commodities at constant prices. The supply and use commodities at constant prices are estimated by deflating the nominal value of each commodity by the corresponding output and input price indices. Thus, the corresponding volume measure of gross value-added is based on the procedure of double-deflation. The method can be illustrated as follows. Write the current price gross value-added for industry i at time t , as

$$p_{V_i}(t)V_i(t) = p_{G_i}(t)G_i(t) - p_{M_i}(t)M_i(t) \quad (2.16)$$

The notations are as defined before. Note that nominal gross output $p_{G_i}(t)G_i(t)$ and nominal gross value added $p_{V_i}(t)V_i(t)$ are both valued at basic prices, whereas nominal intermediate input $p_{M_i}(t)M_i(t)$ is valued at purchaser prices. Purchaser prices include net taxes on products and transport charges and the trade margin paid by the purchaser. They are the prices relevant for purchasing decisions. Again, this is the valuation recommended by the System of National Accounts 1993 (SNA93)

and the OECD productivity manual (OECD 2001) and also used in the Australian supply-use system.

Now deflate nominal gross output $p_{G_i}(t)G_i(t)$, by the price index of two consecutive periods for gross output $p_{G_i}(t)/p_{G_i}(t-1)$; and the current price intermediate input $p_{M_i}(t)M_i(t)$ by the price index for intermediate input $p_{M_i}(t)/p_{M_i}(t-1)$. The result is double-deflated gross value-added in constant (time, $t-1$) prices:

$$p_{V_i}(t-1)V_i(t) = p_{G_i}(t-1)G_i(t) - p_{M_i}(t-1)M_i(t) \quad (2.17)^{13}$$

Indeed, this relationship is strictly maintained by the volume measures (valued at the previous year's prices) obtained from the Australian annual constant price supply-use tables. The chain volume measures of gross value-added for each of the market-sector industries currently published by the ABS are based on this method of estimation.

2.3.2 Capital input

In productivity analysis, the appropriate measure of capital input is capital services (Hulten 1990). They reflect the amount of 'service' each asset provides during a particular period. The services provided by each asset in a period are directly proportional to the asset's productive capital stock in the period.

Since the flows of capital services are not directly observable, they are derived by aggregating the productive capital stock of each asset type using the Tornqvist index with the user cost or rental price as weights. This method of deriving the estimates of capital services is used by the ABS and the Bureau of Labour Statistics (BLS) of the U.S.. Specifically, the Tornqvist index of capital services for industry i is

¹³ This is the procedure of double-deflation in a more narrow sense, where the volume measure of value-added is obtained by subtracting a constant-price value of intermediate inputs from a constant-price value of gross output. This is only possible with the Laspeyres quantity indices. The volume index of value-added can also be derived from the Tornqvist version of double-deflation, where geometric weights expressed in current prices are used. For details of this Tornqvist index formula, see OECD 2001, pp 103.

$$K_i^{t,t-1} = \prod_k \left(\frac{K_{ki}^t}{K_{ki}^{t-1}} \right)^{\bar{\omega}_{ki}} \quad (2.18)$$

where $\bar{\omega}_{ki} = 0.5(\omega_{ki}^t + \omega_{ki}^{t-1})$ and $\omega_{ki}^t = r_{ki}^t K_{ki}^t / \sum_k r_{ki}^t K_{ki}^t$ is the value share of asset i in total assets; K_{ki} stands for the productive capital stock of asset type k , for industry i , and r_{ki} for the rental price or user cost for the same asset,

The productive capital stock reflects the productive capacity of capital and is thus appropriate for measuring the quantity of capital services in production. Productive capital stock for a particular, homogenous asset is constructed with the perpetual inventory (PIM) method and it consists of past investment flows cumulating over time. Weights are attached to each vintage investment to reflect the decline in productive efficiency and the retirement of investment cohorts:

$$K_{ki}^t = \sum_{\tau} h_{ki}^{\tau} \Gamma_{ki}^{\tau} \left(\frac{I_{ki}^{t-\tau}}{P_{ki}^{t-\tau,0}} \right) \quad (2.19)$$

where h_{ki}^{τ} is an age-efficiency profile taking the value between unity when an asset is new and zero when it has lost its entire productive efficiency. Thus, the age-efficiency profile reflects the loss in productive efficiency as an asset ages. Γ_{ki}^{τ} is a retirement function that traces the share of assets of age τ that are still in service. It also takes the value between unity when an asset is new and zero when it reaches its maximum service life at time T . I_{ki}^t is the nominal investment expenditure on asset type k at time t . $p_{ki}^{t,0}$ is the investment price index for type k asset that is new (age zero) in the i th industry. Thus, $I_{ki}^t / p_{ki}^{t,0}$ is the real investment of asset type k at time t .

The ABS uses the normalised hyperbolic age-efficiency profile and a symmetric retirement function in its estimation of the productive capital stock for each asset (ABS 2000). This approach follows that by the BLS of the U.S.. Another often-used form for the age-efficiency profile is geometric, and it has been used by other

statistical agencies and particularly popular among academic researchers¹⁴. The geometric age-efficiency profile facilitates analytical tractability, because it implies the same shape for the corresponding age-price profile. Also, econometric studies (for example, Hulten and Wykoff 1981) have found some support for the use of geometric economic depreciation. The hyperbolic age-efficiency profile used by both the ABS and BLS implies a slow decline in efficiency in early years of the asset's service life and a faster decline towards the end; while the corresponding age-price profile shows the opposite. Thus, this form of age-efficiency profile makes intuitive sense. In addition, there is no strong evidence against using the hyperbolic assumption.

The ABS distinguishes six types of machinery, other building and structure, three types of intangible assets, livestock, inventories and land. The six major types of machinery include computers and peripherals; electrical and electronic equipment; industrial machinery and equipment; road vehicles; other transport equipment; and other plant and equipment. The three types of intangible assets are mineral exploration, computer software and artistic originals.

Aggregation across asset types in each industry is based on the Tornqvist index formula of (2.18) in which the weights are based on the user cost. The ABS augments the usual user cost formulation to incorporate the effects of corporate income taxes, tax depreciation allowances, investment tax credits and indirect taxes,

$$r_{ki}^t = T_{ki}^t p_{ki}^t (i_i^t + d_{ik}^t - g_{ik}^t) + p_{ki}^t x_i^t \quad (2.20)$$

where T_{ki}^t is the income tax parameter which allows for the variation of income tax allowances according to different industries, asset types and changes in allowances and corporate profit tax rate over time; i_i^t is the nominal internal rate of return; $g_{ik}^t = (p_{ki}^t - p_{ki}^{t-1}) / p_{ki}^t$ captures capital gain or loss due to the revaluation of the asset;

¹⁴ See, for example, Hall and Jorgenson (1967), Jorgenson et. al. (1987) and Jorgenson and Griliches (1967).

d_{ik}^t is the rate of depreciation; x_i^t captures the effective average non-income tax rate on production.

The nominal internal rate of return i_i^t used in the user cost formulation above is solved endogenously following the well-known approach by Hall and Jorgenson (1967) where capital income is derived residually as the difference between gross value added and labour compensation. The depreciation rate d_{ik}^t is derived from dividing the real depreciation (consumption of fixed capital in constant price) by real *net* (wealth) capital stock.

Instead of using the age-efficiency function as for the estimation of productive capital stock, the age-price function (profile) is required to derive the *net* capital stock. This function can be derived using the age-efficiency profile and the retirement pattern as well as a real discount rate. The ABS chooses a real discount rate of 4 per cent, the same as that used by the BLS. This rate approximates the average real 10 year Australian real bond rate.

The estimates of the Tornqvist index of capital services are available for both the individual market-sector industries and the market sector as a whole. The ABS also publishes the estimates of *gross* capital stock and *net* capital stock¹⁵. Since the net capital stock is a measure of wealth, the aggregation across asset types is carried out using market prices as weights as compared with the user cost weights used in the aggregation of productive capital stock.

The major weakness of the estimates of capital services arises from the uncertain quality of the data and various assumptions used in their construction, such as mean asset lives and asset life distributions. Like the capital input estimates published by other national statistical agencies, the ABS capital services and net capital stock estimates are not adjusted for the rate of capital utilisation.

¹⁵ The gross capital stock is a special case of the productive capital stock where assets are treated as new until they are retired (sometimes called 'one-hoss-shay'). The net or wealth capital stock is the current market valuation of an industry's or an economy's productive capital. For a detailed discussion on the method of capital measurement in Australia, see Chapter 16, ABS (2000).

Since the utilisation of capital (and labour) is not adequately captured in the input estimates, swings in demand and output are picked up by the residual productivity measure¹⁶. This is one of the reasons that caution must be exercised in use and interpretation of MFP estimates. However, the pro-cyclical effects of MFP estimates can be mitigated by examining MFP growth between peak-to-peak or trough-to-trough points of business cycle. The drawback of this approach is that it reduces the timeliness of the information on productivity growth. Not adequately adjusting for the rate of input utilisation also reduces the comparability of MFP estimates across counties and industries when their business cycles are not synchronised.

2.3.3 Labour input

The indices of hours worked by industry are used for the measure of labour input in the estimation of industry-level MFP. They are derived as the product of employment and average hours worked in the individual industries. Using the index of hours worked provides a better measure of labour input than using employment, since hours worked capture changes in overtime worked, standard weekly hours, leave taken, and changes in the proportion of part-time employment. However, the estimates of labour input based on hours worked do not capture the differences in skills, education, health and professional experiences as a result of different contribution of different types of labour. This is the issue of quality adjustment for labour input, which is discussed in the following.

At present, the aggregate market-sector MFP estimates use the annual hours worked index. The annual hours worked are derived by subtracting the estimates of non-market-sector hours worked from the estimates for the whole economy (all industries). The corresponding index of the annual hours worked is equivalent to a quantity index of the fixed-weight Laspeyres type:

$$\frac{L^t}{L^{t-1}} = \sum_i w_i^{t-1} \left(\frac{L_i^t}{L_i^{t-1}} \right) \quad (2.21)$$

¹⁶ The issue of capacity utilisation is explicitly dealt with in Chapter 4 where MFP in the mining industry is analysed in detail.

where L_i stands for the hours worked in industry i , and $w_i^{t-1} = L_i^{t-1} / \sum_i L_i^{t-1}$.

Thus, the aggregate market-sector MFP estimates do not adjust for the quality differences in labour inputs. However, the quality change of labour input at the market-sector level can be partially adjusted by aggregating the industry-level hours worked and using each industry's share in total labour compensation as the aggregation weights. Specifically, the following aggregation formula for the growth rate of aggregate hours worked can be used,

$$\frac{L^t}{L^{t-1}} = \sum_i \left(\frac{L_i^t}{L_i^{t-1}} \right)^{\bar{w}_i} \quad (2.22)$$

where $\bar{w}_i = 0.5(w_i^t + w_i^{t-1})$ and $w_i = p_{L_i} L_i / \sum_i p_{L_i} L_i$ is the industry's share in total labour compensation in the market-sector. The quality of aggregate labour input is partially adjusted, since these weights will be comparatively large for industries that pay above-average wages and relatively small for industries with below-average wages, assuming that above-average wages reflect above-average skills of the work force in the industry. This assumption is based on the theory of the firm, stipulating that for a profit maximisation firm under the long-run competitive equilibrium, the cost of an additional hour of labour is just equal to the additional revenue that the labour generates. This equality implies that higher wages are associated with higher marginal productivity. But whether causality runs from productivity to wages or vice versa is not clear. Restrictions on labour mobility due to unions and institutional impediments or inertia suggest that wages do not instantaneously adjust to the long-run equilibrium level. Thus, there are possible biases in the approach purely based on the industry's share of total labour compensation to adjust for labour input quality.

Alternatively, the quality of labour inputs can be adjusted according to different characteristics of the labour involved in the production. Following the method used by the BLS the ABS has produced experimental quality adjusted labour inputs (QALI) for the aggregate market-sector (Reilly and Milne 2000). The experimental

QALI takes account of the effects of the differences in educational attainment and the length of workforce experience on the contribution of hours worked to aggregate labour input. The QALI based MFP estimates for the aggregate market-sector are also available from the ABS. However, at the industry-level, this way of adjusting the quality of labour inputs is not possible due to insufficient industry-level data.

2.3.4 Factor incomes

Estimates of factor incomes are required to derive the shares used in the productivity indices, as shown in equations (2.9) and (2.10). The share of intermediate inputs in gross output can be directly obtained by the current price measures of gross output and intermediate inputs in the supply-use tables. This is, however, not the case for capital and labour, because there are various other expenditure/income items in the current price measure of gross value-added (GVA). As an accounting identity, gross value added at basic prices consists of the following components:

- 1) Compensation of employees (W);
- 2) Other taxes less subsidies (other net taxes) on production and imports (T);
- 3) Gross operating surplus (GOS), and
- 4) Gross mixed income (GMI).

Further,

Compensation of employees (W) \equiv Wages and salaries + Employers' social contributions

Thus, we can write

$$GVA \equiv W + GOS + GMI + T \quad (2.23)$$

In most work on MFP/TFP estimation, the measures of factor income are often used to directly derive the relevant factor income shares. The ABS publishes the estimates of total factor income by industry, where the total factor income is defined as compensation of employees plus gross operating surplus and gross mixed income. Thus, total factor income is different from gross value added because it excludes

other net taxes on production and imports (T in equation (2.23)). In this study, however, the adjusted factor incomes are used to derive the shares by allocating the net taxes on production and imports appropriately to capital and labour, thus preserving the above accounting identity for gross value-added¹⁷.

To derive the adjusted factor incomes, first consider the components of gross mixed income (GMI). This is the income that accrues to unincorporated enterprises owned by members of households, i.e. to self-employed persons. It consists of two major components, wages, salaries and supplements of unincorporated enterprises, and GOS of unincorporated enterprises, both of which are available by industry from the ABS. Accordingly, the former is attributed to GMIL, the labour part of the gross mixed income, and the latter to GMIK, the capital part of the gross mixed income, and $GMI \equiv GMIK + GMIL$.

It follows that GMIK and GOS are naturally the capital part of gross value added, while GMIL and W are the labour part. This leaves T , the other net taxes on production and imports, the only component that needs to be further allocated.

At the aggregate market-sector level, the ABS allocates the net taxes on production and imports to capital and labour according to the specific natures of these taxes. For example, payroll taxes and fringe benefit taxes are related to labour, and taxes on vehicles and building structures are specific to capital. At the industry level, however, the detailed tax information is not complete. Thus, in what follows we allocate the industry-level net taxes on production and imports proportionally, a method recommended by the OECD (OECD 2001). Denoting t_L the share of the net taxes attributable to labour in net taxes and $(1-t_L)$ the share of the net taxes attributable to capital, proportional allocation implies that

$$t_L = \frac{W + GMI_L}{GOS + GMI + W} \quad (2.24)$$

¹⁷ As pointed out by OECD (2001), the alternative approach of using factor cost definition of value-added can avoid the often arbitrary apportionment of other net taxes on production to labour and capital. But it foregoes full consistency between the accounting framework and productivity measures. Note also that in both approaches, net taxes are not treated as a separate cost factor in production.

Thus, the adjusted labour income is $(W + GMI_L + t_L \cdot T)$, while the adjusted capital income is $[GOS + GMI_K + (1 - t_L) \cdot T]$. The corresponding share of labour income in gross value added is given by

$$s_L = \frac{W + GMI_L + t_L \cdot T}{W + GOS + GMI + T} \quad (2.25)$$

The share of capital income in gross value added is given by

$$s_K = \frac{GOS + GMI_K + (1 - t_L) \cdot T}{W + GOS + GMI + T} \quad (2.26)$$

The shares of capital and labour incomes in gross output can be derived accordingly using the adjusted capital and labour incomes. It turns out that using the proportional allocation method has resulted in almost identical aggregate capital and labour income shares to those derived from the detailed net taxes information for the sample period chosen in this chapter. This is shown in Table 2.1.

Table 2.1: Shares of aggregate labour income in gross value added (GVA) in the market-sector

| | Derived from the proportional allocation method | Based on the detailed net taxes information |
|---------|--|--|
| 1990-91 | 0.603 | 0.604 |
| 1991-92 | 0.602 | 0.602 |
| 1992-93 | 0.597 | 0.596 |
| 1993-94 | 0.590 | 0.588 |
| 1994-95 | 0.588 | 0.587 |
| 1995-96 | 0.590 | 0.589 |
| 1996-97 | 0.596 | 0.596 |
| 1997-98 | 0.598 | 0.598 |
| 1998-99 | 0.594 | 0.594 |
| 1999-00 | 0.589 | 0.589 |
| 2000-01 | 0.583 | 0.582 |

Source: The estimates in the second column are derived by the author and those in the third column are used to derive the MFP estimates published in ABS Cat. 5204.0, 2001-02.

2.4 Results

The methods discussed in the previous two sections, particularly equations (2.11) and (2.12) are used to derive the estimates of industry-level MFP based on both gross output and value-added. The results expressed in rates of percentage change are reported in Table 2.2 and Table 2.3 as well as shown in Figure 2.2. As the consistent data for gross output and intermediate inputs are available from 1994-95, a comparison between the value-added and the gross output industry MFP growth estimates is possible only from that period until the end of sample period of 2000-01. Note that the relationship between the two MFP measures as shown in equation (2.13) can also be observed in these estimates.

Table 2.2: Growth rates of MFP based on value added (%)

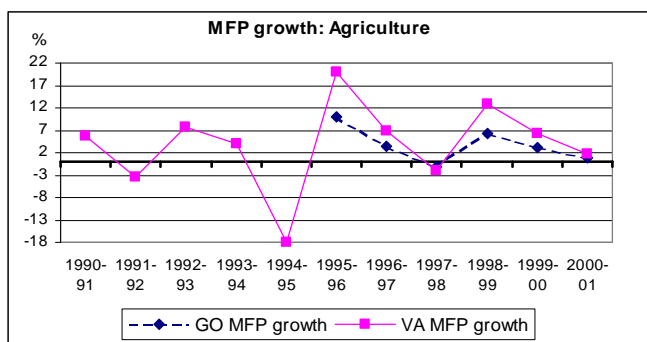
| | 1990-91 | 1991-92 | 1992-93 | 1993-94 | 1994-95 | 1995-96 | 1996-97 | 1997-98 | 1998-99 | 1999-00 | 2000-01 |
|--------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|--------------|
| Agriculture, forestry and fishing | 5.7 | -3.5 | 7.8 | 4.0 | -17.9 | 20.0 | 6.9 | -2.1 | 12.8 | 6.2 | 1.6 |
| Mining | 5.4 | 4.5 | -1.5 | -2.2 | 4.8 | 4.7 | -2.6 | -1.8 | -4.5 | 5.4 | 6.8 |
| Manufacturing | 0.9 | 2.6 | 2.9 | 2.6 | -1.5 | 3.0 | 1.1 | 0.2 | -0.1 | 0.7 | 3.1 |
| Electricity gas and water | 4.5 | 0.3 | 3.9 | 3.4 | 2.5 | 3.0 | 3.1 | 2.7 | -2.6 | -0.4 | -1.7 |
| Construction | -0.8 | -0.1 | 0.1 | 1.7 | -1.5 | 0.2 | 2.9 | 5.9 | 3.3 | -2.4 | -14.9 |
| Wholesale | -9.7 | 2.0 | 0.1 | 1.2 | 12.7 | 4.4 | 7.0 | 3.9 | 0.7 | 0.2 | 2.8 |
| Retail | -0.8 | 3.7 | -0.8 | 2.2 | -2.8 | 1.9 | 4.4 | 2.2 | 1.2 | -0.5 | 0.7 |
| Accommodation, cafes and restaurants | -7.1 | -4.0 | 1.4 | 2.0 | 1.6 | -4.7 | 1.2 | 1.2 | 4.9 | -3.4 | -4.3 |
| Transport and storage | -0.2 | 2.7 | 2.2 | 2.1 | 2.1 | 4.6 | 2.8 | 0.3 | -1.0 | 2.1 | 2.3 |
| Communication | 1.4 | 8.3 | 13.2 | 0.9 | 1.8 | 1.0 | 3.6 | 13.2 | 5.3 | -4.3 | -6.7 |
| Finance and insurance | 0.2 | -3.3 | 3.4 | -0.2 | 4.4 | -0.4 | -1.4 | 0.7 | 4.9 | 0.4 | -4.4 |
| Cultural and recreational | 2.4 | -4.0 | 2.8 | -6.4 | -6.0 | -4.6 | -7.3 | -0.5 | -2.4 | -2.7 | 2.2 |
| Aggregate market-sector | 0.11 | 1.34 | 2.45 | 1.40 | 0.54 | 3.07 | 2.09 | 1.89 | 1.57 | 0.37 | -0.75 |

Table 2.3: Growth rates of MFP based on gross output (%)

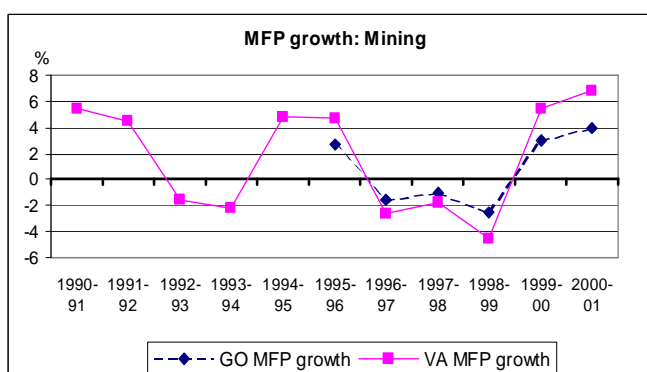
| | 1995-96 | 1996-97 | 1997-98 | 1998-99 | 1999-00 | 2000-01 |
|--------------------------------------|---------|---------|---------|---------|---------|---------|
| Agriculture, forestry and fishing | 9.9 | 3.5 | -1.0 | 6.3 | 3.1 | 0.8 |
| Mining | 2.7 | -1.6 | -1.0 | -2.5 | 3.0 | 4.0 |
| Manufacturing | 0.9 | 0.4 | 0.0 | 0.0 | 0.2 | 0.9 |
| Electricity gas and water | 1.6 | 1.7 | 1.4 | -1.3 | -0.2 | -0.8 |
| Construction | 0.1 | 1.5 | 3.0 | 1.5 | -1.2 | -7.7 |
| Wholesale | 2.3 | 3.6 | 1.9 | 0.3 | 0.1 | 1.4 |
| Retail | 0.7 | 1.8 | 0.9 | 0.5 | -0.2 | 0.3 |
| Accommodation, cafes and restaurants | -1.7 | 0.4 | 0.4 | 1.8 | -1.3 | -1.5 |
| Transport and storage | 2.0 | 1.2 | 0.1 | -0.4 | 0.9 | 1.0 |
| Communication | 0.6 | 2.0 | 7.5 | 3.0 | -2.4 | -3.5 |
| Finance and insurance | -0.2 | -0.9 | 1.3 | 3.1 | 0.3 | -2.7 |
| Cultural and recreational | -2.3 | -3.7 | -0.2 | -1.2 | -1.3 | 1.1 |

Figure 2.2: Estimates of industry-level MFP growth

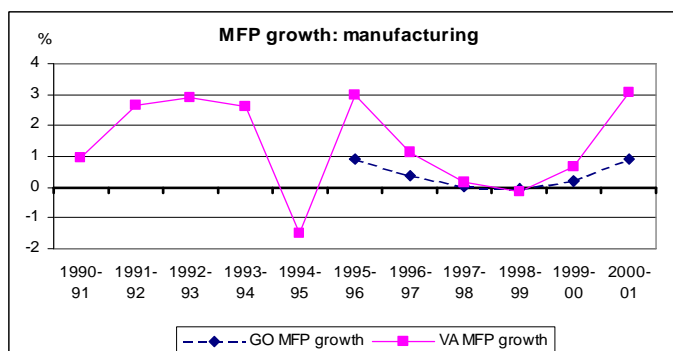
| Agriculture | | |
|-------------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | 5.7 |
| 1991-92 | | -3.5 |
| 1992-93 | | 7.8 |
| 1993-94 | | 4.0 |
| 1994-95 | | -17.9 |
| 1995-96 | 9.9 | 20.0 |
| 1996-97 | 3.5 | 6.9 |
| 1997-98 | -1.0 | -2.1 |
| 1998-99 | 6.3 | 12.8 |
| 1999-00 | 3.1 | 6.2 |
| 2000-01 | 0.8 | 1.6 |



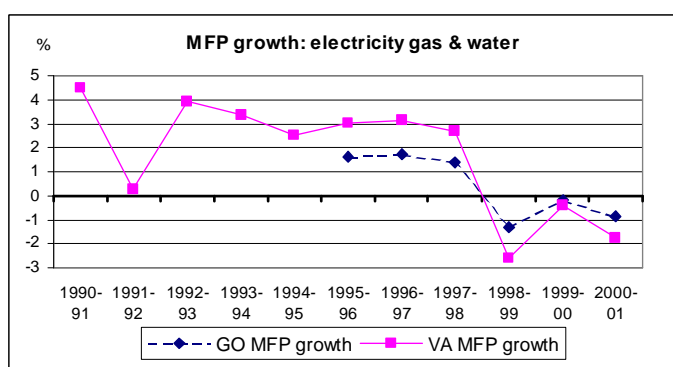
| Mining | | |
|---------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | 5.4 |
| 1991-92 | | 4.5 |
| 1992-93 | | -1.5 |
| 1993-94 | | -2.2 |
| 1994-95 | | 4.8 |
| 1995-96 | 2.7 | 4.7 |
| 1996-97 | -1.6 | -2.6 |
| 1997-98 | -1.0 | -1.8 |
| 1998-99 | -2.5 | -4.5 |
| 1999-00 | 3.0 | 5.4 |
| 2000-01 | 4.0 | 6.8 |



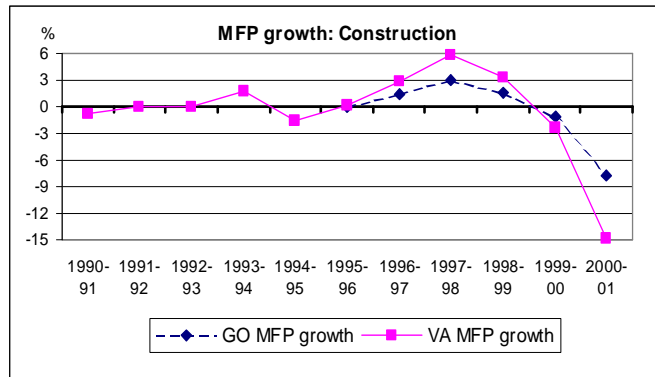
| Manufacturing | | |
|---------------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | 0.9 |
| 1991-92 | | 2.6 |
| 1992-93 | | 2.9 |
| 1993-94 | | 2.6 |
| 1994-95 | | -1.5 |
| 1995-96 | 0.9 | 3.0 |
| 1996-97 | 0.4 | 1.1 |
| 1997-98 | 0.0 | 0.2 |
| 1998-99 | 0.0 | -0.1 |
| 1999-00 | 0.2 | 0.7 |
| 2000-01 | 0.9 | 3.1 |



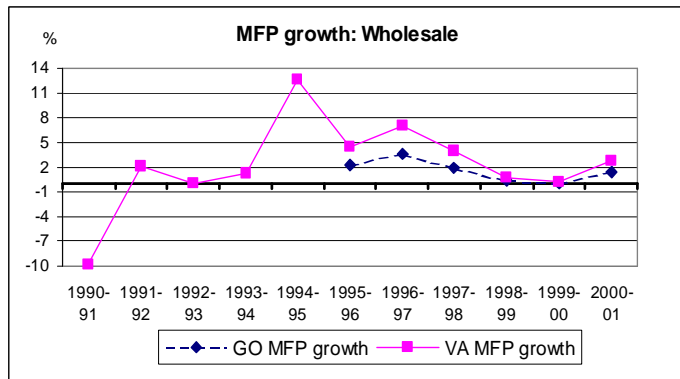
| Electricity gas and water | | |
|---------------------------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | 4.5 |
| 1991-92 | | 0.3 |
| 1992-93 | | 3.9 |
| 1993-94 | | 3.4 |
| 1994-95 | | 2.5 |
| 1995-96 | 1.6 | 3.0 |
| 1996-97 | 1.7 | 3.1 |
| 1997-98 | 1.4 | 2.7 |
| 1998-99 | -1.3 | -2.6 |
| 1999-00 | -0.2 | -0.4 |
| 2000-01 | -0.8 | -1.7 |



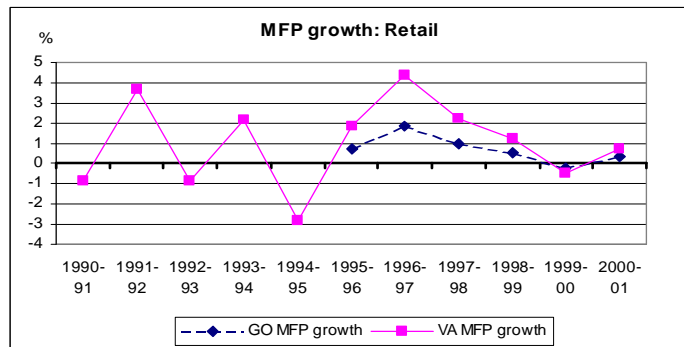
| Construction | | |
|--------------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | -0.8 |
| 1991-92 | | -0.1 |
| 1992-93 | | 0.1 |
| 1993-94 | | 1.7 |
| 1994-95 | | -1.5 |
| 1995-96 | 0.1 | 0.2 |
| 1996-97 | 1.5 | 2.9 |
| 1997-98 | 3.0 | 5.9 |
| 1998-99 | 1.5 | 3.3 |
| 1999-00 | -1.2 | -2.4 |
| 2000-01 | -7.7 | -14.9 |



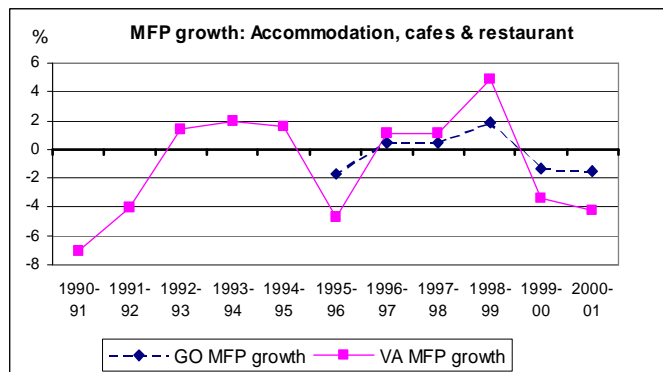
| Wholesale | | |
|-----------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | -9.7 |
| 1991-92 | | 2.0 |
| 1992-93 | | 0.1 |
| 1993-94 | | 1.2 |
| 1994-95 | | 12.7 |
| 1995-96 | 2.3 | 4.4 |
| 1996-97 | 3.6 | 7.0 |
| 1997-98 | 1.9 | 3.9 |
| 1998-99 | 0.3 | 0.7 |
| 1999-00 | 0.1 | 0.2 |
| 2000-01 | 1.4 | 2.8 |



| Retail | | |
|---------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | -0.8 |
| 1991-92 | | 3.7 |
| 1992-93 | | -0.8 |
| 1993-94 | | 2.2 |
| 1994-95 | | -2.8 |
| 1995-96 | 0.7 | 1.9 |
| 1996-97 | 1.8 | 4.4 |
| 1997-98 | 0.9 | 2.2 |
| 1998-99 | 0.5 | 1.2 |
| 1999-00 | -0.2 | -0.5 |
| 2000-01 | 0.3 | 0.7 |



| Accommodation, cafes & restaurant | | |
|-----------------------------------|---------------|---------------|
| | GO MFP growth | VA MFP growth |
| 1990-91 | | -7.1 |
| 1991-92 | | -4.0 |
| 1992-93 | | 1.4 |
| 1993-94 | | 2.0 |
| 1994-95 | | 1.6 |
| 1995-96 | -1.7 | -4.7 |
| 1996-97 | 0.4 | 1.2 |
| 1997-98 | 0.4 | 1.2 |
| 1998-99 | 1.8 | 4.9 |
| 1999-00 | -1.3 | -3.4 |
| 2000-01 | -1.5 | -4.3 |



Under the growth accounting framework, it is also customary to quantify how much output growth is due to productivity change and how much is due to growth in individual inputs. At the industry level, this can be done separately for each industry using either gross output or value added based MFP, while noting the difference between the inputs and outputs associated with the two measures.

As discussed previously, the industry-level results can be aggregated to the market-sector level by applying the aggregation rules of either (2.14) or (2.15), depending on whether it is gross output or value-added based MFP measure. Equation (2.14) are applied to the value-added MFP estimates of Table 2.2. One useful application associated with this aggregation is to measure the industry's contribution to the annual aggregate market-sector MFP growth. The individual industry's percentage point contribution to the aggregate market-sector MFP growth is shown in Table 2.4 in the following page.

As can be seen from the MFP results and those in Table 2.4, during the 1990s the market-sector industries have shown varied rates of productivity growth. They have also had varied levels of contribution to the aggregate market-sector MFP growth. This is reflected by the fact that each industry has made both positive and negative contributions to the aggregate market-sector MFP growth during the eleven year period. Since MFP change is pro-cyclical, it is more appropriate to compare the MFP estimates between growth cycles. However, this is not carried out in this thesis because of the short time span of the experimental series.

Given the rich information contained in the industry-level MFP estimates, we can investigate the relationships between the MFP growth and the growth in gross output or value added-across time and within or across industries, and validate many empirical regularities found in the production and productivity statistics. Issues like whether capital deepening or the growth in MFP is the main contributing factor to the growth in output per hour worked can also be analysed at the industry level by using the data and results from our estimation. However, we have not attempted these exercises here.

Table 2.4: Percentage point contributions to the aggregate market-sector MFP growth

| | 1990-91 | 1991-92 | 1992-93 | 1993-94 | 1994-95 | 1995-96 | 1996-97 | 1997-98 | 1998-99 | 1999-00 | 2000-01 |
|--------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|--------------|
| Agriculture, forestry and fishing | 0.39 | -0.20 | 0.45 | 0.24 | -1.02 | 1.14 | 0.40 | -0.12 | 0.70 | 0.35 | 0.09 |
| Mining | 0.43 | 0.37 | -0.12 | -0.17 | 0.37 | 0.37 | -0.21 | -0.14 | -0.34 | 0.40 | 0.57 |
| Manufacturing | 0.21 | 0.57 | 0.63 | 0.58 | -0.33 | 0.67 | 0.25 | 0.04 | -0.03 | 0.14 | 0.62 |
| Electricity gas and water | 0.24 | 0.01 | 0.22 | 0.18 | 0.13 | 0.14 | 0.14 | 0.12 | -0.11 | -0.02 | -0.07 |
| Construction | -0.08 | -0.01 | 0.01 | 0.16 | -0.15 | 0.02 | 0.28 | 0.59 | 0.33 | -0.26 | -1.51 |
| Wholesale | -0.92 | 0.19 | 0.01 | 0.11 | 1.18 | 0.41 | 0.65 | 0.36 | 0.06 | 0.02 | 0.26 |
| Retail | -0.07 | 0.33 | -0.08 | 0.20 | -0.26 | 0.17 | 0.42 | 0.21 | 0.12 | -0.05 | 0.07 |
| Accommodation, cafes and restaurants | -0.22 | -0.13 | 0.04 | 0.06 | 0.05 | -0.17 | 0.04 | 0.04 | 0.19 | -0.14 | -0.17 |
| Transport and storage | -0.02 | 0.26 | 0.21 | 0.19 | 0.20 | 0.43 | 0.26 | 0.03 | -0.09 | 0.19 | 0.20 |
| Communication | 0.06 | 0.39 | 0.64 | 0.04 | 0.09 | 0.05 | 0.19 | 0.70 | 0.29 | -0.23 | -0.35 |
| Finance and insurance | 0.02 | -0.34 | 0.37 | -0.02 | 0.47 | -0.04 | -0.14 | 0.07 | 0.52 | 0.04 | -0.52 |
| Cultural and recreational | 0.06 | -0.10 | 0.08 | -0.18 | -0.17 | -0.14 | -0.21 | -0.02 | -0.07 | -0.08 | 0.07 |
| Aggregate market-sector | 0.11 | 1.34 | 2.45 | 1.40 | 0.54 | 3.07 | 2.09 | 1.89 | 1.57 | 0.37 | -0.75 |

As these MFP estimates are experimental, it is necessary to assess their quality and plausibility. Bearing in mind the various assumptions and weakness underlying the component series used for the MFP estimation, there are several ways to make such an assessment. One is to compare them directly with those from other studies. However, there are only a limited number of published studies attempting to estimate the industry-level MFP growth for the market-sector industries in Australia.

As mentioned before, the Australian Productivity Commission has published numerous papers covering issues of industry-level productivity. The estimates used to derive the industry-level MFP in these papers are based on unpublished ABS data (e.g. Productivity Commission 1999, Cobbold and Kulys 2003). Other researchers have also derived their own MFP estimates for the Australian market-sector industries (e.g. Simon and Wardrop 2002). However, these studies have different objectives and the MFP estimates in their work are often presented graphically and in some summary measures averaging across the period that does not coincide with that in our study. More importantly, the methods and the data treatment issues associated with the industry-level MFP estimation in these studies are not clearly specified. In some studies, these issues are only mentioned with a few lines of description in a footnote or in an appendix, while the emphasis is placed on discussing the implications and extension of the industry-level MFP results.

Clearly, this is not the approach taken in this study. Our attention is mainly focused on an appropriate choice of the methodology for MFP estimation and on the corresponding data and measurement issues. Thus, a direct, same period comparison of our estimates with the results from these studies is not attempted. Instead, the next section presents the results of a comparison between the aggregate MFP estimates derived from the industry-level results and those directly obtained from the aggregate approach. This comparison is used as a way of assessing the plausibility of the industry-level MFP estimates, while at the same time, also addressing several issues of consistency in aggregation and the difference between the industry-level and aggregate approaches. As will be seen in the next section, this difference has both theoretical and practical implications.

Note that although the word ‘assess’ is used to describe one of the purposes of this comparison exercise, no claim is made that the aggregate MFP estimates based on aggregate approach are the ‘correct’ ones against which the same estimates derived from industry-level approach should be judged. Indeed, it is argued in the literature that purely on the methodological ground, the bottom-up approaches are superior to the aggregate approach (see, e.g. Jorgenson et al. 1987). However, in the actual application, one must take in account the data and measurement issues involved; if the available industry-level data are of less quality than the aggregate data, applying the industry-level approach will of course produce the aggregate MFP estimates of less quality than using the aggregate approach directly¹⁸. It is precisely because of this practical consideration that the exercise of comparison is carried out.

2.5 Consistency between industry-level and aggregate MFP estimates

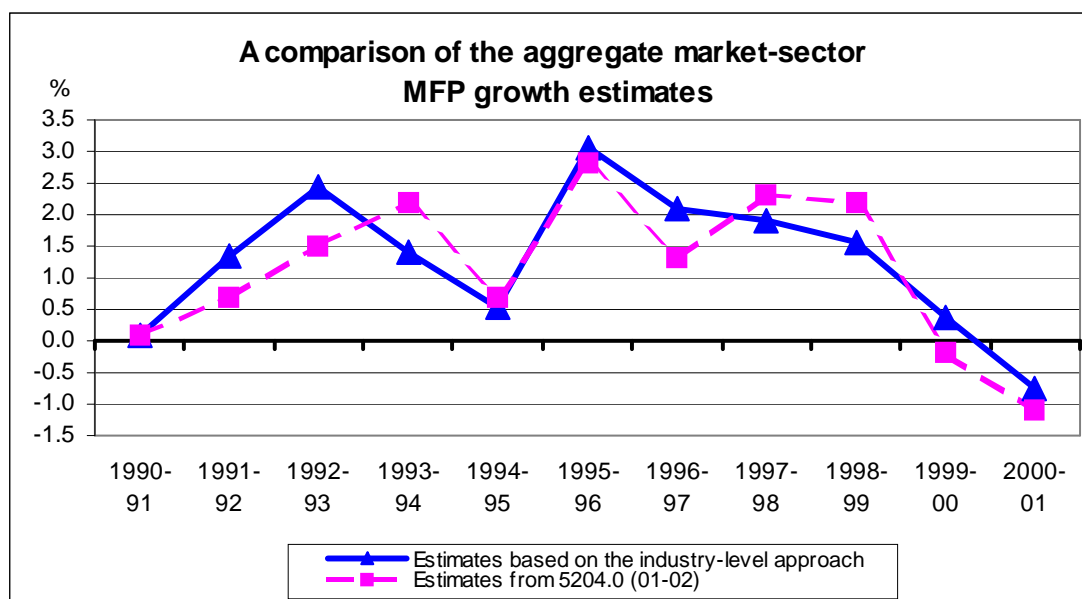
The previous section presents the aggregate MFP estimates for the market-sector as a whole in Table 2.4. These estimates are derived from the industry-level results by applying the aggregation formula of equation (2.14) (summing over the market-sector industries). Note that the ABS has been publishing the aggregate market-sector MFP estimates in the Australian System of National Accounts (ABS Cat. 5204) since the early 1990s. However, they are based on the aggregate approach as outlined in the derivation of the aggregate MFP index in equations (2.3) or (2.4)¹⁹.

The aggregate MFP estimates derived from the two approaches should not be very different. Otherwise, it indicates potential problems in the estimates of industry-level MFP, because the aggregate data used in the aggregate MFP estimation have been known to be of better quality than some of the data at the lower levels of aggregation. This is the basis on which the plausibility of the industry-level MFP estimates is assessed. Figure 2.3 shows the results of the comparison between the MFP estimates derived from the two approaches.

¹⁸ See Diewert (2000) for further comments on the difficulties and measurement problems associated with industry-level MFP estimation.

¹⁹ See Aspden (1990) for details on this aggregate approach used by the ABS.

Figure 2.3: A comparison of the aggregate market-sector MFP growth estimates



As can be seen, the estimates based on the industry-level approach are quite close to those from the aggregate approach, with the largest difference being less than one percentage point in 1992-93. Given the fact that a direct comparison of MFP estimates at the industry-level is not possible for the reasons outlined above, the result from this exercise seems to validate the plausibility of the industry-level MFP estimates. However, the question of what explains these differences, however small, between the two sets of aggregate MFP estimates remains unanswered.

One obvious way of identifying the causes for the difference is to examine each component of the MFP indexes used in the two approaches. The results from this exercise are reported in Appendix B. The main conclusions from this exercise are that the small differences observed above are partly due to different output measures and different index formulae of aggregating labour inputs applied in the two approaches. Despite this, both the industry-level approach applied in this thesis and the aggregate approach used by the ABS are valid methods of estimating aggregate MFP.

Another source of the difference in the aggregate MFP estimates observed above cannot be identified by comparing the component measures and aggregation

formulae applied in the two approaches presented above and in Appendix B. This difference is more systematic and directly related to the difference between the two approaches themselves. This methodological difference in estimating aggregate MFP is captured in a relation derived by Jorgenson et al. (1987), which augments the Domar aggregation formula (Domar 1961, Hulten 1978):

$$\begin{aligned}
\tau_v = & \sum_i \left(\frac{p_{G_i} G_i}{p_V V} \right) \tau_G^i + \left[\hat{V} - \sum_i \left(\frac{p_{V_i} V_i}{p_V V} \right) \hat{V}_i \right] \\
& + \left[\sum_i \sum_k \left(\frac{p_{ki} K_{ki}}{p_V V} \right) \hat{K}_{ki} - \sum_k \frac{p_{Kk} K_k}{p_V V} \hat{K}_k \right] \\
& + \left[\sum_i \sum_l \left(\frac{p_{li} L_{li}}{p_V V} \right) \hat{L}_{li} - \sum_l \frac{p_{Ll} L_l}{p_V V} \hat{L}_l \right]
\end{aligned} \tag{2.27}$$

where τ_v is the MFP growth index based on the aggregate approach,

$\sum_i \left(\frac{p_{G_i} G_i}{p_V V} \right) \tau_G^i = \tau'_v$ is the MFP growth index based on the industry-level approach.

The latter expression is the Domar aggregation formula in its original form as shown in equation (2.15). All other notations are as previously defined.

The augmented Domar formula in equation (2.27) includes terms in the last three square brackets that capture the contributions of changes in the industrial distribution of value-added, all types of capital and labour inputs to the rate of aggregate productivity growth. A derivation of the Domar aggregation formula in both its original and augmented forms is provided in the next section.

In general, $\tau'_v \neq \tau_v$ except in some special cases. One of the cases is that all the industries pay the same prices for their capital and labour inputs, an assumption that is not likely to hold in reality. Aulin-Ahmavaara (2003) and Jorgenson et al. (1987) state that the Domar aggregation formula in its original form also requires this assumption. However, in the next section we show that the original Domar aggregation formula can be derived without using this assumption.

Putting the technical details aside at the moment, equation (2.27) can be used to explain part of the difference between the aggregate MFP estimates derived from the

industry-level and the aggregate approaches that are shown in Figure 2.3. This particular part of the difference is not due to measurement issues. Rather, it is caused by the contributions of reallocations of industry value added and primary factor inputs to the aggregate productivity growth. Assuming that the difference caused by the measurement issues (reported in Appendix B) are negligible, these contributions can be directly estimated using equation (2.27) (by combining capital and labour into primary inputs as a whole) and they are reported in Table 2.5.

Table 2.5: Decomposing aggregate MFP growth estimates using the augmented Domar aggregation formula*

| | MFP growth: aggregate approach (%) | MFP growth: industry-level approach (%) | Contribution of reallocation of industry VA (%) | Contribution of reallocation of industry primary inputs (%) |
|---------|---|---|---|--|
| | (1) | (2) | (3) | (4) |
| 1990-91 | 0.11 | 0.11 | 0.21 | -0.21 |
| 1991-92 | 0.68 | 1.34 | -0.02 | -0.65 |
| 1992-93 | 1.57 | 2.45 | 0.56 | -1.44 |
| 1993-94 | 2.21 | 1.40 | 0.09 | 0.72 |
| 1994-95 | 0.65 | 0.54 | 0.36 | -0.25 |
| 1995-96 | 2.79 | 3.07 | -0.18 | -0.10 |
| 1996-97 | 1.25 | 2.09 | -0.10 | -0.73 |
| 1997-98 | 2.27 | 1.89 | 0.57 | -0.19 |
| 1998-99 | 2.22 | 1.57 | 0.18 | 0.47 |
| 1999-00 | -0.20 | 0.37 | -0.05 | -0.53 |
| 2000-01 | -1.09 | -0.75 | -0.25 | -0.09 |

*Using the augmented Domar aggregation formula of equation (2.27), the MFP growth based on aggregate approach can be decomposed into three main components: the MFP growth based on industry-level approach, the contribution of reallocations of industry value-added and the contribution of reallocations of industry primary inputs. Thus, for the estimates in the columns: (1) = (2) + (3) + (4). Note, however, that the difference between the MFP growth estimates based on the aggregate approach (column (1)) and industry-level approach (column (2)) as well as the term for the industrial reallocation of value-added (column (3)) can also reflect the minor difference between the output measures used in the two approaches. See Appendix B for a detailed comparison of the measures used in the two approaches.

As can be seen from Table 2.5, the effects of reallocation of industry primary inputs have contributed negatively to the aggregate MFP growth in most of the years except in 1993-94 and 1989-99. In some years, these negative contributions have been partially offset by the positive contributions of reallocation of industry value-added. Note, however, that the estimates of these contributions become less important as the differences between the two sets of aggregate MFP estimates are already found

small, which is sufficient for the purpose of assessing the plausibility of the experimental industry-level MFP estimates.

2.6 The relationship between industry-level and aggregate approaches: an augmented Domar aggregation formula

Aulin-Ahmavaara (2003) and Jorgenson et al. (1987) state that the Domar aggregation formula in its original form (Domar 1961) requires the assumption that all the industries pay the same prices for their capital and labour inputs. Indeed, the Domar aggregation rule in its original form is proved formally in a widely cited paper by Hulten (1978), where this assumption is employed implicitly. Jorgenson et al. (1987) derive an augmented Domar aggregation formula in which the original version of the Domar formula is only a special case under this assumption. Without relying on this assumption, the augmented formulation by Jorgenson et al. (1987) also includes terms reflecting the contributions of changes in the sectoral distribution of value-added, as well as contributions of all types capital and labour inputs to the rate of aggregate productivity growth.

This section shows that under the framework of production economics, the Domar aggregation formula in its original form can be derived without requiring the assumption of equal prices for the primary inputs used by the industries. Also derived is the augmented Domar formula that decomposes the MFP growth into several terms, one of which is a weighted sum of sectoral productivity growth, i.e. the Domar aggregation formula in its original form, while the remaining terms reflecting the contribution of changes in sectoral distribution of outputs and inputs.

The augmented Domar aggregation formula essentially provides a systematic explanation for the causes of the difference between the estimates of aggregate MFP derived from the aggregate and industry-level approaches. This way of identifying the sources of the difference also has immediate implications for the exercise of validating the experimental industry-level MFP index as shown in the previous section. As a way of assessing the plausibility of these estimates, they are aggregated to the market-sector level, and then compare the aggregates to the

market-sector MFP estimates derived directly from the aggregate approach. Thus, using the augmented Domar aggregation formula provides an explanation of the systematic part of the difference between the aggregate estimates derived from the aggregate and industry-level approaches.

The derivation of the Domar aggregation formula in this section draws on Gollop (1981). However, special attention is paid to the assumption of equal primary factor prices across industries. A closed economy setting is assumed so that the issue of open versus closed economy MFP estimation is not considered in this section. As the Domar aggregation formula provides a rule that connects the economy-wide and industry/sectoral level MFP growth, both a sectoral/industry model and an aggregate model of production are needed.

2.6.1 Aggregate production and productivity

For a closed economy, an aggregate production possibility frontier is postulated in which the maximum aggregate output is expressed as a function of all quantities of value added, all supplies of primary inputs and time:

$$H(V_1, V_2, \dots, V_n; K_{11}, K_{12}, \dots, K_{mn}; L_{11}, L_{12}, \dots, L_m; t) = \lambda \quad (2.28)$$

where λ is a constant. The function H is homogenous of degree minus one in the quantities of value added, homogenous of degree one in the factor supplies and homogenous of degree zero in quantities of valued added and factor supplies together (Jorgenson et al. 1987, pp 53). The rate of aggregate MFP growth (τ_v) is derived by taking the total logarithmic derivative of the function F with respect to time:

$$\sum_i \frac{\partial \ln H}{\partial \ln V_i} \hat{V}_i + \sum_i \sum_k \frac{\partial \ln H}{\partial \ln K_{ki}} \hat{K}_{ki} + \sum_i \sum_l \frac{\partial \ln H}{\partial \ln L_{li}} \hat{L}_{li} + \tau_v = 0 \quad (2.29)$$

where $\tau_v = \partial \ln H / \partial t$. Clearly, aggregate productivity change can be thought of an expansion in the aggregate production possibility frontier, holding all real primary inputs constant.

Necessary conditions for individual producer under the equilibrium imply that the aggregate output elasticities appearing in equation (2.29) can be represented by value shares:

$$\frac{\partial \ln H}{\partial \ln V_i} = -p_{V_i} V_i / \sum_i p_{V_i} V_i \quad i = 1, 2, \dots, n$$

$$\frac{\partial \ln H}{\partial \ln K_{ki}} = p_{k_i} K_{ki} / \sum_i p_{V_i} V_i \quad k = 1, 2, \dots, m; i = 1, 2, \dots, n$$

$$\frac{\partial \ln H}{\partial \ln L_{li}} = p_{l_i} L_{li} / \sum_i p_{V_i} V_i \quad l = 1, 2, \dots, r; i = 1, 2, \dots, n.$$

where p is the price associated with the quantity of value added and primary inputs.

The rate of aggregate MFP growth can then be written as

$$\tau_V = \sum_i \left(\frac{p_{V_i} V_i}{\sum_i p_{V_i} V_i} \right) \hat{V}_i - \sum_i \sum_k \left(\frac{p_{k_i} K_{ki}}{\sum_i p_{V_i} V_i} \right) \hat{K}_{ki} - \sum_i \sum_l \left(\frac{p_{l_i} L_{li}}{\sum_i p_{V_i} V_i} \right) \hat{L}_{li} \quad (2.30)$$

2.6.2 Industry-level production and productivity

At the sectoral level, the specification of an industry's technology is a production function incorporating all primary and intermediate inputs, and time:

$$G_i = f^i \left(K_{li}, \dots, K_{ki}, \dots, K_{mi}; L_{li}, \dots, L_{li}, \dots, L_{ri}; X_{li}, \dots, X_{ji}, \dots, X_{ni}; t \right) \quad (2.31)$$

where

G_i quantity of the i th industry's gross output;

K_{ki} k th capital input used in the i th industry;

L_{li} l th labour input used in the i th industry;

X_{ji} j th intermediate input used in the i th industry.

Total differentiation in logarithms of the above equation with respect to time implies that the rate of growth in gross output can be decomposed into its source components:

$$\hat{G}_i = \tau_G^i + \sum_k \frac{\partial \ln G_i}{\partial \ln K_{ki}} \hat{K}_{ki} + \sum_k \frac{\partial \ln G_i}{\partial \ln L_{li}} \hat{L}_{li} + \sum_j \frac{\partial \ln G_i}{\partial \ln X_{ji}} \hat{X}_{ji} \quad (2.32)$$

where $\tau_G^i = \partial \ln G_i / dt$ is the measure of MFP growth based on gross output, and it is the rate of growth of gross output while holding all inputs constant.

The assumption of competitive equilibrium in all output and input markets implies that each input is paid the value of its marginal product:

$$\frac{\partial \ln G_i}{\partial \ln K_{ki}} = \frac{p_{ki} K_{ki}}{p_{G_i} G_i} \quad k = 1, 2, \dots, m$$

$$\frac{\partial \ln G_i}{\partial \ln L_{li}} = \frac{p_{li} L_{li}}{p_{G_i} G_i} \quad l = 1, 2, \dots, r$$

$$\frac{\partial \ln G_i}{\partial \ln X_{ji}} = \frac{p_{ji} X_{ji}}{p_{G_i} G_i} \quad j = 1, 2, \dots, n.$$

where p is the price associated with the outputs and inputs. Under these conditions, the gross output MFP growth for the i th industry can be written as

$$\tau_G^i = \hat{G}_i - \sum_j \left(\frac{p_{ji} X_{ji}}{p_{G_i} G_i} \right) \hat{X}_{ji} - \sum_k \left(\frac{p_{ki} K_{ki}}{p_{G_i} G_i} \right) \hat{K}_{ki} - \sum_l \left(\frac{p_{li} L_{li}}{p_{G_i} G_i} \right) \hat{L}_{li} \quad (2.33)$$

Note that all the prices appear in the formulation of aggregate and industry level MFP growth (i.e. in equations (2.30) and (2.33)) are specific to the corresponding quantity measures. No assumption of equal prices for primary inputs across industries is used.

2.6.3 A decomposition of value added growth

To establish the link between the aggregate and industry-level MFP growth, one extra relation is need. This can be derived from either an accounting identity or a sectoral production function assuming value added separability.

Under the assumption of value added separability, the gross output production function (2.31) can be written as

$$G_i = f^i(V_i; X_{li}, \dots, X_{ji}, \dots, X_{ni}) \quad (2.34)$$

where $V_i = h^i(K_{li}, \dots, K_{ki}, \dots, K_{mi}; L_{li}, \dots, L_{li}, \dots, L_{ri}; t)$. Totally differentiating equation (2.34) logarithmically with respect to time, and after rearranging, the rate of growth of real value added for the i th industry can be written as

$$\hat{V}_i = \frac{\partial \ln V_i}{\partial \ln G_i} \hat{G}_i - \frac{\partial \ln V_i}{\partial \ln X_{li}} \hat{X}_{li} - \dots - \frac{\partial \ln V_i}{\partial \ln X_{ji}} \hat{X}_{ji} - \dots - \frac{\partial \ln V_i}{\partial \ln X_{ni}} \hat{X}_{ni} \quad (2.35)$$

Still assuming competitive equilibrium, we have

$$\frac{\partial \ln V_i}{\partial \ln G_i} = \frac{p_{G_i} G_i}{p_{V_i} V_i}, \quad \frac{\partial \ln V_i}{\partial \ln X_{ji}} = \frac{p_{j_i} X_{ji}}{p_{V_i} V_i}$$

Equation (2.35) can then be written as

$$\hat{V}_i = \left(\frac{p_{G_i} G_i}{p_{V_i} V_i} \right) \hat{G}_i - \sum_j \left(\frac{p_{j_i} X_{ji}}{p_{V_i} V_i} \right) \hat{X}_{ji} \quad (2.36)$$

Equation (2.36) also shows how double deflation is consistent with production theory (Oulton 2000).

As mentioned before, the relationship in equation (2.36) can also be derived using the accounting identity of nominal value added in industry i :

$$p_{V_i} V = p_{G_i} G_i - \sum_j p_{j_i} X_{ji}$$

by differentiating it with respect to time while holding prices constant.

2.6.4 Domar aggregation formula in its original form

Without using the assumption that all the industries pay the same prices for their capital and labour inputs, the formulae for aggregate and industry-level MFP growth are derived in equations (2.30) and (2.33). Also derived is the extra relation of value added growth decomposition in equation (2.36) under the framework of production economics.

Using these three equations, it is straightforward to derive the Domar aggregation formula in its original form. Substituting equation (2.36) for value added growth into the aggregate MFP growth formula in equation (2.30) yields

$$\begin{aligned} \tau_v = \sum_i \left(\frac{p_{G_i} G_i}{\sum_i p_{V_i} V_i} \right) \hat{G}_i - \sum_i \sum_j \left(\frac{p_{j_i} X_{j_i}}{\sum_i p_{V_i} V_i} \right) \hat{X}_{j_i} - \sum_i \sum_k \left(\frac{p_{k_i} K_{k_i}}{\sum_i p_{V_i} V_i} \right) \hat{K}_{k_i} \\ - \sum_i \sum_l \left(\frac{p_{l_i} L_{l_i}}{\sum_i p_{V_i} V_i} \right) \hat{L}_{l_i} \end{aligned} \quad (2.37)$$

Substituting equation (2.33) of industry level MFP growth for \hat{G}_i into the above equation gives

$$\begin{aligned} \tau_v = \sum_i \left(\frac{p_{G_i} G_i}{\sum_i p_{V_i} V_i} \right) \tau_G^i \\ + \sum_i \sum_j \left(\frac{p_{j_i} X_{j_i}}{\sum_i p_{V_i} V_i} \right) \hat{X}_{j_i} + \sum_i \sum_k \left(\frac{p_{k_i} K_{k_i}}{\sum_i p_{V_i} V_i} \right) \hat{K}_{k_i} + \sum_i \sum_l \left(\frac{p_{l_i} L_{l_i}}{\sum_i p_{V_i} V_i} \right) \hat{L}_{l_i} \\ - \sum_i \sum_j \left(\frac{p_{j_i} X_{j_i}}{\sum_i p_{V_i} V_i} \right) \hat{X}_{j_i} - \sum_i \sum_k \left(\frac{p_{k_i} K_{k_i}}{\sum_i p_{V_i} V_i} \right) \hat{K}_{k_i} - \sum_i \sum_l \left(\frac{p_{l_i} L_{l_i}}{\sum_i p_{V_i} V_i} \right) \hat{L}_{l_i} \end{aligned} \quad (2.38)$$

The last six terms in the above equation cancel each other out. This leaves the Domar aggregation formula in its original form,

$$\tau_V = \sum_i \left(\frac{p_{G_i} G_i}{\sum_i p_{V_i} V_i} \right) \tau_G^i \quad (2.39)$$

Clearly, in the whole process of deriving equation (2.39), no assumption of equal primary input prices across industries has ever been made. In another word, the conditions $p_{ki} = p_{Kk}$ and $p_{li} = p_{Ll}$ are not required for obtaining the Domar aggregation formula in its original form.

2.6.5 An augmented Domar aggregation formula

The above derivation of the Domar aggregation formula starts from the production possibility frontier in equation (2.28). Instead of this more general case, we now use an aggregate production function with different types of primary inputs while suppressing the industry detail. This way of deriving aggregate MFP growth is called the aggregate approach as opposed to the industry-level approach in the previous section where the aggregate MFP growth is obtained through applying the Domar aggregation formula (in its original form) to the index of industry-level MFP growth. The aggregate production with different types of primary inputs can be expressed as

$$V = F(K_1, K_2, \dots, K_m; L_1, L_2, \dots, L_r; t) \quad (2.40)$$

Going through the same procedure of derivation as before and still assuming competitive equilibrium, the aggregate MFP growth is now equal to

$$\tau'_V = \hat{V} - \sum_k \frac{p_{Kk} K_k}{p_V V} \hat{K}_k - \sum_l \frac{p_{Ll} L_l}{p_V V} \hat{L}_l \quad (2.41)$$

where p_V , p_{Kk} and p_{Ll} are the prices associated with aggregate value added, returns to the k th type of capital and returns to the l th type of labour respectively.

Using the value added growth decomposition in equation (2.36), the rate of gross output growth in industry i is,

$$\hat{G}_i = \left(\frac{p_{V_i} V_i}{p_{G_i} G_i} \right) \hat{V}_i + \sum_j \left(\frac{p_{j_i} X_{ji}}{p_{G_i} G_i} \right) \hat{X}_{ji} \quad (2.42)$$

Substituting \hat{G}_i from the above equation into the formula for MFP growth based on gross output in equation (2.33) yields

$$\tau_G^i = \left(\frac{p_{V_i} V_i}{p_{G_i} G_i} \right) \hat{V}_i - \sum_k \left(\frac{p_{ki} K_{ki}}{p_{G_i} G_i} \right) \hat{K}_{ki} - \sum_l \left(\frac{p_{li} L_{li}}{p_{G_i} G_i} \right) \hat{L}_{li} \quad (2.43)$$

Multiplying both sides of equation (2.43) by $p_{G_i} G_i / p_V V$ and summing over i , it gives

$$\sum_i \left(\frac{p_{G_i} G_i}{p_V V} \right) \tau_G^i = \sum_i \left(\frac{p_{V_i} V_i}{p_V V} \right) \hat{V}_i - \sum_i \sum_k \left(\frac{p_{ki} K_{ki}}{p_V V} \right) \hat{K}_{ki} - \sum_i \sum_l \left(\frac{p_{li} L_{li}}{p_V V} \right) \hat{L}_{li} \quad (2.44)$$

Then subtracting both sides of the above equation from the rate of MFP growth for the economy as a whole in equation (2.41) and after rearranging, yields

$$\begin{aligned} \tau'_V = & \sum_i \left(\frac{p_{G_i} G_i}{p_V V} \right) \tau_G^i + \left[\hat{V} - \sum_i \left(\frac{p_{V_i} V_i}{p_V V} \right) \hat{V}_i \right] \\ & + \left[\sum_i \sum_k \left(\frac{p_{ki} K_{ki}}{p_V V} \right) \hat{K}_{ki} - \sum_k \frac{p_{Kk} K_k}{p_V V} \hat{K}_k \right] + \left[\sum_i \sum_l \left(\frac{p_{li} L_{li}}{p_V V} \right) \hat{L}_{li} - \sum_l \frac{p_{Ll} L_l}{p_V V} \hat{L}_l \right] \end{aligned} \quad (2.45)$$

This is the augmented Domar aggregation formula. It can be expressed in discrete time as that in Jorgenson et al. (1987). The first term on the right hand side of equation (2.45) is the Domar aggregation formula in its original form as in equation (2.39). The last three terms with square brackets reflect respectively the contributions to the rate of aggregate MFP growth of changes in the sectoral distribution of value added, changes in all types of capital input, and changes all types of labour input.

Rather than starting from a production possibility frontier, this augmented form of the Domar aggregation formula in (2.45) is derived using the aggregate production

function while keeping the sectoral level formulations exactly the same as in derivation of the original Domar aggregation formula. Note that this augmented Domar aggregation formula is still without relying on the assumption of equal primary input prices across industries.

The augmented Domar aggregation formula also makes explicit the conditions under which the aggregate and industry-level approaches produce identical MFP estimates at the aggregate level. This is clear from the last three terms in equation (2.45). For the value added term, it is straightforward to see that, provided that the aggregate value added growth is derived from a Divisia index aggregating from the industry-level value added, this term will disappear. The last two terms will also be zero if the Divisia index is repeatedly applied in all levels of aggregation for the capital and labour growth. This is shown for the capital input growth by repeatedly applying the Divisia index,

$$\begin{aligned}
\left[\sum_i \sum_k \left(\frac{p_{ki} K_{ki}}{p_V V} \right) \hat{K}_{ki} - \sum_k \frac{p_{Kk} K_k}{p_V V} \hat{K}_k \right] &= \left(\frac{p_K K}{p_V V} \right) \sum_i \left(\frac{p_{K_i} K_i}{p_K K} \right) \left[\sum_k \left(\frac{p_{ki} K_{ki}}{p_{K_i} K_i} \right) \hat{K}_{ki} \right] \\
&\quad - \left(\frac{p_K K}{p_V V} \right) \left[\sum_k \left(\frac{p_{Kk} K_k}{p_K K} \right) \hat{K}_k \right] \\
&= \left(\frac{p_K K}{p_V V} \right) \left[\sum_i \left(\frac{p_{K_i} K_i}{p_K K} \right) \hat{K}_i \right] - \left(\frac{p_K K}{p_V V} \right) \hat{K} \\
&= \left(\frac{p_K K}{p_V V} \right) \hat{K} - \left(\frac{p_K K}{p_V V} \right) \hat{K} \\
&= 0 \\
(2.46)
\end{aligned}$$

For the labour input, the same result holds.

The above results are crucially dependent on continuous time. If the Tornqvist index is used as the discrete approximation to these indices, the capital and labour terms in equation (2.45) may not equal zero, even if the Tornqvist index is used repeatedly at each stage of the aggregation. Consequently, the difference between the augmented Domar aggregation formula and its original form will not usually disappear.

A more interesting result is that if the assumption of equal primary factor prices across industries is imposed, the augmented Domar aggregation formula of equation (2.45) reduces to the original form of equation (2.39). To see this, observe the following market equilibrium conditions:

$$V = \sum_i V_i; \quad K_k = \sum_i K_{ki}; \quad L_l = \sum_i L_{li} \quad (2.47)$$

Expressing the above conditions in terms of growth rate and substituting each of them into the corresponding variables in equation (2.45) and after some manipulation, equation (2.45) can be expressed in the form of

$$\begin{aligned} \tau'_v = & \sum_i \left(\frac{p_{G_i} G_i}{p_V V} \right) \tau_G^i + \sum_i \left[\frac{(p_V - p_{V_i}) V_i}{p_V V} \right] \hat{V}_i \\ & + \sum_i \sum_k \left[\frac{(p_{ki} - p_{Kk}) K_{ki}}{p_V V} \right] \hat{K}_{ki} + \sum_i \sum_l \left[\frac{(p_{li} - p_{Ll}) L_{li}}{p_V V} \right] \hat{L}_{li} \end{aligned} \quad (2.48)$$

Assuming that the prices of industry-level value added are identical $p_V = p_{V_i}$, the above equation clearly reduces to the Domar aggregation formula in its original form, provided that all industries pay the same prices for capital and labour inputs, i.e. $p_{ki} = p_{Kk}$ and $p_{li} = p_{Ll}$. This may be the reason behind the statement by Aulin-Ahmavaara (2003) and Jorgenson et al. (1987) that the Domar aggregation formula in its original form requires the assumption of equal primary input prices across industries. However, as is shown above, equation (2.39) can be derived without using this assumption.

The difference between the original Domar aggregation formula τ_v and its augmented form τ'_v can also be interpreted as a measure of departures from the assumptions that underlie the aggregate approach to MFP in which an aggregation production is assumed (Jorgenson et al. 1987). These assumptions include that there exist value added functions for each sector and they are identical up to a scalar multiple. In addition, capital and labour inputs are identical functions of their components for all industries. Finally, all industries pay the same prices for capital and labour inputs and the prices of industry-level value added are identical.

Now it is clear that comparing the aggregate MFP growth estimates derived from the industry-level and aggregate approaches must take into account the effects of contributions of industrial reallocations of value added and the primary factor inputs to the rate of aggregate MFP growth, as these contributions are captured in the augmented Domar aggregation formula. In other words, there are inherent differences between the aggregate and industry-level approaches that will cause the divergence between the aggregate MFP estimates, which must be taken into account in assessing of the plausibility of the industry-level MFP estimates.

2.7 The open versus the closed economy MFP index

So far, no a clear distinction is made between the MFP index under the closed economy and that under the open economy. This distinction, however, is important if MFP index is intended to correctly reflect the productivity and efficiency changes generated from domestic production.

In an open economy, many of the intermediate inputs are not produced by domestic industries and are imported from other countries. Thus, in theory they should not be treated the same as those domestically produced intermediate inputs in productivity measurement. Rather, they should be classified as primary inputs along with capital and labour, which are considered exogenous to the economy viewed as an input-output system. This is the motivation behind the delivery to final demand model of aggregate MFP growth developed by Gollop (1983, 1987).

In Section 2.2, the measure of MFP based on the deliveries to final demand is presented as an alternative to value added based aggregate MFP index. According to Gollop (1983, 1987), the aggregate MFP growth formulation as presented in equation (2.5) is the index adjusted for the effects of the open economy, while the aggregate model of MFP growth based on value added as shown in equation (2.3) is its closed economy counterpart. The relationship between the two aggregate MFP indices is quite simple,

$$\tau_{FD} = \left(\frac{P_V V}{P_{FD} FD} \right) \tau_V \quad (2.49)$$

As mentioned in Section 2.2, the value of aggregate deliveries to final demand exceeds the value of aggregate value added by an amount equal to the value of imported intermediate inputs. Thus, in general the rate of growth of aggregate MFP index based on deliveries to final demand is less than that based on value-added, i.e. $\tau_{FD} < \tau_V$, unless the value of imported intermediate inputs is zero as is the case under the closed economy²⁰.

Both the values of the market-sector aggregate value added and aggregate deliveries to final demand can be derived from the national accounts. Thus, the weights in equation (2.49) can be calculated and estimates of MFP growth for the open economy are obtained. They are presented in Table 2.6, along with their closed economy counterpart.

Table 2.6: The open versus the closed economy MFP estimates*

| | MFP growth from Cat. 5204 (01-02) τ_V | Open economy MFP growth τ_{FD} |
|---------|--|--|
| | % | % |
| 1990-91 | 0.11 | 0.10 |
| 1991-92 | 0.68 | 0.59 |
| 1992-93 | 1.57 | 1.37 |
| 1993-94 | 2.21 | 1.92 |
| 1994-95 | 0.65 | 0.56 |
| 1995-96 | 2.79 | 2.39 |
| 1996-97 | 1.25 | 1.08 |
| 1997-98 | 2.27 | 1.95 |
| 1998-99 | 2.22 | 1.90 |
| 1999-00 | -0.20 | -0.17 |
| 2000-01 | -1.09 | -0.93 |

* The open economy MFP growth, τ_{FD} is derived using equation (2.49).

²⁰ As pointed out by Balk from one of his comments on this chapter, the deliveries to final demand based MFP measure as that of Gollop (1983, 1987) is nothing but the gross output based measure at the level of the entire economy. This point is also implied in Balk (2003a, footnote 5). It can also be seen more clearly by comparing equation (2.49) with equation (2.13).

It must be noted, however, that the model of aggregate MFP growth developed by Gollop (1983, 1987) is not the only framework of measuring MFP under the open economy. There are several other approaches that have appeared in the literature, which give special consideration to the issues of open economy MFP measurement. For example, Diewert and Morrison (1986), Fox and Kohli (1998) and Kohli (1990, 2003) suggest correcting the productivity indices by a terms of trade effect, as if an improvement in the terms of trade of the economy is equivalent to an outward movement of the economy's production possibility frontier.

In contrast to Gollop's (1983, 1987) approach where imported intermediate inputs are treated as primary inputs, Durand (1996) and Cas and Rymes (1991) consider alternative ways of closing the economy on imported inputs. Their objective is that the additional productivity gains generated by imported inputs are attributed appropriately to an economy under the input-output based MFP framework. Their approaches are based on the argument that looking at the productivity of the integrated set of economies that are trading together, treating their imported inputs as primary inputs as done by Gollop (1987) results in productivity estimates for each of these economies that do not aggregate to the productivity gains of all the economies taken as a whole.

However, the direct application of these approaches within the framework of the non-parametric MFP estimation employed in this thesis is not as straightforward as the method proposed by Gollop (1983, 1987). Thus, a generally accepted solution to the open economy issue, particularly for the MFP estimates derived for the purposes of statistical production, has yet to crystallise. This may be the topic for future work.

2.8 Conclusions

This chapter discusses several issues associated with estimating industry-level MFP. Two approaches to estimating industry-level MFP are considered. First, the input-output based approach, which was developed by Statistics Canada (Durand 1996, Cas and Rymes 1991). Second, the approach recently recommended by the OECD

(OECD 2001). The latter approach is closely related to that developed by Jorgenson et al. (1987), which is also a bottom-up, non-parametric approach based on production economics. After considering the current ABS data environment, estimation of industry-level MFP is based on the approach recommended by the OECD. The experimental estimates of MFP are presented for both gross output and value added for the 12 market-sector industries in Australia.

Since aggregate market-sector MFP indices can also be derived from the industry-level estimates, comparisons of the estimates are used as a way of assessing the plausibility of the industry-level MFP index. To understand the causes of the differences observed in the validation exercise, issues of consistency in aggregation are also considered. Comparing the components of the two indices shows that the small differences are partly due to different output measures and different index formulae for aggregating labour inputs applied. A more important source of the differences is, however, directly related to the models of production underlying the two approaches to the measurement of aggregate MFP. This is revealed by an aggregation relation derived by Jorgenson et al. (1987), which augments the Domar aggregation formula of linking industry-level and aggregate MFP indices.

Using the augmented Domar aggregation formula, the estimates of MFP growth derived from the aggregate approach are decomposed into a weighted sum of industry-level MFP growth and weighted sums of rates of growth of value added, capital input and labour input, which reflect the contributions of the reallocations of these outputs and inputs among industries.

Under the framework of production economics, a derivation of the Domar aggregation formula in its original form is provided without relying on the assumption of equal prices for the primary inputs used by the industries. The Domar aggregation formula is derived in the augmented form according to Jorgenson et al. (1987).

The open economy MFP estimates for the aggregate market-sector are also estimated using an approach developed by Gollop (1983, 1987). While there are several other approaches dealing with the open economy MFP measurement, a generally accepted

solution to the open economy issue within the non-parametric growth accounting framework for estimating MFP has yet to crystallise. This may be the topic for future work.

Chapter 3

Returns to industry R&D in Australia

3.1 Introduction

Australia's total spending on R&D investment has quadrupled in real terms over the past three decades, from \$3.1 billion in 1976-77 to \$12.2 billion in 2002-03. R&D intensity — R&D expenditure as a proportion of GDP — has also increased from 0.95 per cent to 1.63 per cent over the same period. Between 1976-77 and 2002-03, labour productivity and multifactor productivity in Australia have increased by 69 per cent and 33 per cent, respectively. While there is a substantial body of research that quantifies the relationship between R&D and productivity, the number of studies that focus on using the Australian data, particularly at the industry level, is quite limited. Moreover, given the rapid changes in the Australian economy and the substantial improvement in productivity growth in recent years, the results from previous Australian studies may require further validation and updating. The additional evidence based on the updated study may be of greater importance if it is to be used for guiding the R&D related policies.

This chapter draws on a large study by Shanks and Zheng (2006) that focuses on econometric modelling of R&D and productivity in Australia. It uses the updated Australian data at the one digit (ANZSIC division) level to estimate the returns to R&D in several industries. Due to the limitations of the available R&D expenditure data, the estimation is confined to the following four industries: Manufacturing, Mining, Wholesale and retail trade and Agricultural, forestry and fishing. The data for the four industries contain 29 years of annual observations ranging from 1974-75 to 2002-03.

While the empirical models used in the chapter are based on the conventional Cobb-Douglas production function, an alternative specification that specifically adjusts for the effects of double counting and expensing biases is also derived and applied

(Schankerman 1981). The biases in the estimates are the result of using the double-counted R&D expenditure data as well as using the output measures from national accounts in which the expenditure on R&D is treated as a current expense, rather than as an investment.

Using various estimation procedures and model specifications, some evidence is found of a positive relationship between the industry's own R&D capital stock and its productivity growth. However, the estimated returns in some industries appear implausibly high. Also, the results are highly sensitive to the choice of the control variables. This may reflect the problems of small sample and the quality of the industry-level data used in the regressions.

The Chapter is structured as follows. Section 3.2 reviews the main results from the previous Australian industry-level studies. Section 3.3 specifies the empirical models and derives an alternative specification that takes account of the effects of double-counting and expensing biases due to the use of mismeasured data in the R&D regressions. Section 3.4 discusses the estimation issues, while the results are presented in Section 3.5. The last section provides a few concluding remarks.

3.2 Previous Australian industry-level studies

The number of Australian studies on R&D that focus on broad industry sectors is quite limited. Most other studies tend to use data at a lower level of aggregation, in particular, for the sub-industries within manufacturing. Detailed manufacturing data are relatively easy to obtain, and of relatively better quality, as they have fewer measurement issues compared with data on other sectors.

Industry Commission (1995) and Connolly and Fox (2006) estimate models at the one-digit ANZSIC level. Productivity Commission (2003) uses manufacturing data at the 3-digit and 4-digit levels, while Chand et al. (1998) use the Gretton and Fisher (1997) dataset. This dataset is based on unpublished ABS data and it provides time series of productivity, capital and labour for eight manufacturing subdivisions.

The estimated elasticities and implied rates of return to R&D vary widely across the studies (Table 3.1). The rate of return to industry own R&D in manufacturing (at the one-digit level) is estimated to be only 13 per cent in Industry Commission (1995). Productivity Commission (2003) produces an estimate that is twice as high, although various factors, such as different specifications and data, may explain the difference.

Since some of the studies include R&D as a control variable rather than as the variable of primary interest, the estimated R&D effects could be classified as ‘incidental’, as opposed to thoroughly investigated. The studies of Chand et al. (1998) and Connolly and Fox (2006) focus on industry protection and the role of ICT in productivity growth, respectively. Both studies present elasticity estimates for R&D that are very large and negative in some industries.

Some studies do not include control variables or other sources of growth in their regressions. Other studies include various control variables or other sources of growth that differ greatly, even where the regressions are based essentially on the same overall framework and data. Despite the fact that various justifications are given, there is a degree of arbitrariness — which may be unavoidable — in choosing different control variables.

As the estimated R&D elasticities in these studies are wide-ranging, and even negative in some cases, clearly they are highly sensitive to the changes in data, methods, and the focus of the issues under investigation. A lack of robustness in estimates seems to be a common weakness that is shared by many R&D empirical studies (Diewert 2005).

Table 3.1: The effect of own-industry and foreign R&D on productivity growth in Australian industry-level studies

| <i>Study</i> | <i>Dataset and time period</i> | <i>Dependent variable</i> | <i>Key findings, Elasticity (γ) rates of return (ρ)</i> | <i>Key findings and comments</i> |
|------------------------------------|--|---------------------------|--|--|
| Industry Commission (1995) | Various industries, 1976-77 to 1989-90 | $\ln(\text{MFP})$ | Broadacre agriculture: γ for own R&D not available; $\gamma = 0.066$ and $\rho = 1.9\%$ for the stock of foreign R&D. Manufacturing: $\gamma = 0.014$ and $\rho = 13\%$ for own R&D and $\gamma = 0.066$ and $\rho = 7\%$ for foreign R&D. Mining: both own and foreign R&D stocks are excluded from the regression, as they are not significant. Other services: $\gamma = 0.052$ and $\rho = 263\%$ for own R&D; $\gamma = 0.030$ and 3% for foreign R&D. Wholesale and retail trade: negative γ is estimated, but overall fit and specification of the model are questioned. | R&D has some positive effect on productivity at the industry level. The rates of return to R&D appear to vary among the sectors. Most industries in the study appear to receive spillover benefits from foreign R&D and from R&D undertaken in other sectors. Despite various control variables being used, questions can still be raised about the robustness of the results. |
| Chand, McCalman and Gretton (1998) | Manufacturing, Gretton and Fisher (1997) dataset | $\Delta \ln(Y)$ | $\gamma = 0.06$ (not significant at the 10 per cent level) two digit-manufacturing panel (using the economy-wide stock of R&D performed by both domestic private and public sectors), $\gamma = -1.55$ (not significant) in Printing etc industry, $\gamma = 2.45$ (a significant at 10 per cent level) in Transport equipment. | Trade liberalisation raises output growth, although the estimated elasticities w. r. t. R&D capital, public infrastructure and human capital are negative in several industries. The effect of foreign R&D spillovers is not considered. |
| Productivity Commission (2003) | Manufacturing, various levels of aggregation, using 3 digit manufacturing data to quantify the effect of R&D intensity on labour productivity growth | $\Delta \ln(Y/L)$ | In the regression using 3-digit ANZSIC manufacturing data, the estimated coefficient associated with R&D intensity is 0.26. This implies that an additional 0.26 percentage points of labour productivity growth can be attributed to every percentage point of higher R&D intensity. | The most statistically robust result of the modelling indicates that industries categorised as having high R&D intensities, or characterised as 'high technology', had labour productivity growth rates that were significantly higher than other industries. |

(continued on next page)

Table 3.1 (continued)

| <i>Study</i> | <i>Dataset and time period</i> | <i>Dependent variable</i> | <i>Key findings, Elasticity (γ) rates of return (ρ)</i> | <i>Key findings and comments</i> |
|-------------------------|--|---------------------------|--|---|
| Connolly and Fox (2006) | 10 one-digit market-sector industries and aggregate market-sector, mainly based on ABS data: 1966-2002 | ln(MFP) ln(Y) | The industry's own R&D stock is used as a control variable in the regression for the two market-sector industries, Accommodation, cafes & restaurants and Cultural and recreational services, but the coefficients are both negative and significant in the preferred, ln(MFP) based regressions, $\gamma = -0.772$ and -0.485 . | The focus of the study is placed on the impact of IT capital on productivity. The issue of the significantly negative estimates of R&D elasticities found in the two industries is not discussed. |

3.3 Methodology

Following common practice, the strategy for specifying an equation for estimation is to start from a theoretical model and augment it with the most relevant control variables. The theory underlying the analysis is a conventional one. It is based on production economics in which the stock of knowledge or R&D capital is treated as a separate input in production along with traditional capital and labour²¹.

3.3.1 MFP-based empirical models

The Cobb-Douglas production function is the most popular form used in the empirical work on R&D and productivity (Griliches 1998). A Cobb-Douglas production function with R&D stock as a separate input in industry i can be written as

$$Y_i = Ae^{ut} K_i^\alpha L_i^\beta R_i^\gamma \prod_{j=1}^q Z_{ij}^{\omega_j} \quad (3.1)$$

²¹ Rather than relying on the traditional production functions, recent research on R&D based on the micro-productivity studies uses the citation weighted count of patents granted to a unit as a measure of its innovation output and R&D capital stock as its input (see, for example, Bottazzi and Peri 2005).

where A is a constant, e is the base of natural logarithms, $e^{\mu t}$ can be considered as a neutral technology term, Y , K and L are output, the traditional capital stock and labour, respectively. R is R&D capital stock. Z_j ($j = 1$ to q) are other inputs that determine the level of output. All inputs and output are in quantity (volume) measures. All the exponential coefficients associated with the variables are elasticities of output with respect to the corresponding inputs.

The Cobb-Douglas production function is somewhat restrictive, since it imposes an elasticity of substitution between each pair of inputs equal to one. In the empirical models, interaction terms can be included to allow for the changes in the relationships between inputs (for example, between the domestic and foreign R&D stocks). Other more sophisticated forms, such as the constant elasticity of substitution (CES) or the translog production functions can also be used. Cost functions have also been used for estimating the relationship between R&D and productivity. These alternative approaches describe more complex production processes, but introduce more parameters to be estimated compared with the Cobb-Douglas form. This is a disadvantage when degrees of freedom are restricted by the small numbers of observations, as is the case in this study.

Taking the natural log of equation (3.1) (after dropping the industry index, i for clarity) gives

$$\ln Y = \ln A + \mu t + \alpha \ln K + \beta \ln L + \gamma \ln R + \sum_{j=1}^q \omega_j \ln Z_j \quad (3.2)$$

Adding an error term and using the appropriate measures of output and inputs, equation (3.2) can be used directly for estimation. Alternatively, if we assume constant returns to scale in conventional capital and labour ($\alpha + \beta = 1$) with value added as a measure of output, equation (3.2) can then be written as

$$\ln MFP = a + \mu t + \gamma \ln R + \sum_{j=1}^q \omega_j \ln Z_j \quad (3.3)$$

where $\ln MFP = \ln Y - \alpha \ln K - (1 - \alpha) \ln L$, $a = \ln A$. Note that $\ln MFP$ is the conventional MFP (or TFP) index based on value added. At the industry-level, it can be derived from the data on quantity indexes of industry value added, capital and labour inputs as well as the relevant factor income shares, as shown in Chapter 2.

As before, adding an error term and using the appropriate measures of output and inputs, equation (3.3) can also be used directly for estimation. Note that (3.3) contains two less right hand side variables than (3.2) does. With a small sample, this clearly is an advantage. However, to use equation (3.3) for estimation, the MFP index has to be derived in a consistent fashion first. The difficulties and various measurement issues associated with estimating industry-level MFP have been addressed in Diewert (2000) and a general methodology for estimating industry-level MFP has been discussed in Chapter 2.

The MFP index is based on the assumptions of constant returns to scale and competitive equilibrium in both input and output markets so that the factor income shares can be used to replace the elasticities in deriving the index. Despite these limitations, the MFP/TFP based regression models have been used frequently in many empirical studies on R&D. It is also the approach adopted in this chapter.

3.3.2 Intensity forms

One variant of equation (3.3) is in growth rate terms,

$$\tau = \mu + \gamma \hat{R} + \sum_{j=1}^q \omega_j \hat{Z}_j \quad (3.4)$$

where $\tau = \frac{d \ln MFP}{dt}$; $\hat{X} = \frac{\dot{X}}{X} = \frac{d \ln X}{dt} \approx \ln X_t - \ln X_{t-1}$ is the rate of growth for any variable X .

Notice the absence of the time trend in equation (3.4). This specification can be extended further by noting the following relationships,

$$\gamma = \frac{\partial Y}{\partial R} \frac{R}{Y} = \rho \frac{R}{Y} \quad (\text{define } \rho = \frac{\partial Y}{\partial R})$$

Thus $\gamma \hat{R} = \rho \frac{\dot{R}}{Y}$. The R&D capital stock is constructed by the perpetual inventory method (PIM), the same methodology used to form conventional capital stocks. It follows that $\dot{R} \approx R_t - R_{t-1} = I_t^R - \delta R_{t-1}$, where I_t^R is the real investment in R&D at time t , δ is the rate of R&D depreciation. Thus $\gamma \hat{R} \approx \rho \left(\frac{R_t - R_{t-1}}{Y} \right)$ and equation (3.4) can be written as

$$\tau = \mu + \rho \left(\frac{R_t - R_{t-1}}{Y} \right) + \sum_{j=1}^q \omega_j \hat{Z}_j \quad (3.5)$$

Note that the coefficient ρ is defined as the marginal product of R&D capital, and it is also called the rate of return to R&D capital²². In some studies, the rate of depreciation is assumed to be zero, which implies that $\left(\frac{R_t - R_{t-1}}{Y} \right) = \frac{I_t^R}{Y}$. Thus equation (3.5) becomes,

$$\tau = \mu + \rho \left(\frac{I_t^R}{Y} \right) + \sum_{j=1}^q \omega_j \hat{Z}_j \quad (3.6)$$

As before, equations (3.5) and (3.6) can be used to directly estimate the rate of return to R&D capital. Specifications similar to equations (3.2) to (3.6) have been used frequently in the empirical literature — for example, Terleckyj (1980) and Lichtenberg and Siegel (1991).

Compared with the level specifications (3.2) and (3.3), which involve the coefficient of R&D elasticity, equations (3.5) and (3.6) use variables in growth rates (except for the intensity variable). As a result, some information contained in the (log) level variables may be lost when the intensity forms are applied. Despite the same

²² Strictly speaking, when the depreciation of R&D capital is non-zero, ρ is known as the *gross* rate of return to R&D. The *net* rate of return to R&D capital is simply the gross rate minus the rate of depreciation.

coefficient γ being associated with the R&D stock variable in both equations (3.2) and (3.3), the estimates of γ will generally not be identical from the two models because of different variables involved in the estimation. This is also true for estimated ρ using specifications (3.5) and (3.6).

3.3.3 A specification adjusting for double-counting and expensing biases

As mentioned in Section 3.1, since the capital and labour used in R&D activity are part of the investment expenditure used to form R&D capital stock as well as part of capital and labour inputs to an industry's production, there is an element of double counting of these inputs. The obvious approach to solving this problem is to net out the capital and labour used for R&D from the traditional measures, and then derive the estimates accordingly. But this is not always possible due to the data and methodological constraints, particularly at the industry level. Another way to get around this problem is to interpret the estimated returns to R&D under the double-counting as the returns above and beyond the normal remuneration to traditional capital.

This excess returns interpretation is quite popular in many empirical studies on R&D. However, it has been demonstrated by Schankerman (1981) that the double-counting bias can be potentially offset by another source of bias that arises from the mismeasurement of value added. The latter bias is called the expensing bias, since R&D is treated as an intermediate expense rather than as an investment in the formation of capital asset. The corresponding output, and therefore productivity, is mismeasured and the resulting estimates of elasticity and return to R&D are biased. The expensing bias could be either positive or negative. Schankerman demonstrates that because of the existence of the expensing bias, the excess returns interpretation is conceptually incorrect, even though it appears to be valid empirically based on an example using the data from Griliches (1980).

Following Schankerman's approach, a specification is derived that adjusts for the biases and can be used directly for econometric estimation. However, it is argued

that the correction to the expensing bias may not be as straightforward as the treatment given in Schankerman's paper.

Measured value added

The expensing bias identified by Schankerman is the result of mismeasurement of value added. Schankerman (1981, pp. 455) states that 'since current R&D is typically expensed (subtracted from gross product as an intermediate input), measured value added is too small by that amount.' To correct this, Schankerman adds the amount of R&D expenditure back to the measured value added, and then derives the term that captures the expensing bias.

At the industry level, some of the industry-level volume measures of value added are derived from the double-deflation procedure under the framework of national accounts (ABS 2000). The procedure partly involves the subtraction of the value of intermediate inputs from the value of gross output. Let us focus on the quantity terms and denote gross output by GO and intermediate inputs by IM . With a prime (') to indicate a measured, rather than the 'true' value, the accounting identity linking gross output and value added is

$$Y' = GO' - IM'$$

There are several ways to look at the measured gross output. One could argue that gross output is in fact measured correctly, but the measured intermediate inputs are incorrect because they include R&D expenditure. Once R&D expenditure is re-allocated to be part of measured value added, the resulting value added will be the correct one. This appears to be the basis for Schankerman's adding back solution.

However, one can also argue that there are also problems with the measured gross output, Y' , as it is quite likely that gross output will also change once R&D is capitalised in the national accounts. Thus, rather than using the assumption that gross output based on the current framework of national accounts is measured correctly in the presence of R&D, attention is turned to the measured value added directly. Since the current-price measure of value added is equal to the value of

measured capital and labour income (assuming no net taxes, or they have been allocated properly to capital and labour), the ‘true’ value added could then also exclude R&D capital and labour. This is opposite to Schankerman’s adding back correction.

This way of correcting for expensing R&D may be equally simplistic as that suggested by Schankerman. However, it does highlight the fact that the problem of treating R&D investment expenditure as intermediate inputs may not be resolved simply by re-classifying it as part of value added. It requires more complex work both at conceptual and practical levels to bring about changes to the current framework of national accounts²³. Given the importance of the expensing bias, the following analysis of the effects of mismeasurement is based on our (the second) argument about the measured value added.

The effects of mismeasurement

the Cobb-Douglas production function of equation (3.1) is used to illustrate the effects of the biases due to double counting and expensing of R&D. To simplify, the control variables and time in equation (3.1) are omitted, although the inclusion of these variables does not change the results. Based on the simplified version of equation (3.1) and using the definition of MFP,

$$\ln MFP = \ln Y - \alpha \ln K - \beta \ln L = \gamma \ln R \quad (3.7)$$

Now suppose that capital and labour are measured inclusive of the primary inputs and those used for R&D,

$$\begin{aligned} K' &= K + K_R \\ L' &= L + L_R \end{aligned} \quad (3.8)$$

where, as before, a prime denotes a measured variable, and K_R and L_R represent R&D capital and labour, respectively. The measured productivity under the growth accounting is

²³ For a recent exploratory work on this issue at the economy-wide level in the U.S., see Fraumeni and Okubo (2005).

$$\ln MFP' = \ln Y' - \alpha' \ln K' - \beta' \ln L' \quad (3.9)$$

Note that the measured factor shares in (3.9) are also biased by double-counting. They are assumed to be $\alpha' = \alpha(1+s)$ and $\beta' = \beta(1+d)$, where $s = K_R/K$ and $d = L_R/L$. One of the assumptions used to derive MFP is constant returns to scale, thus $\alpha' + \beta' = 1$. This implies that $\alpha + \beta < 1$.

If we use our argument about the measured gross value added as discussed above, we have

$$Y' = Y + I_R \quad (3.10)$$

Using equations (3.8) and (3.10), we can express the measured variables (in log) as

$$\begin{aligned} \ln K' &= \ln K + \ln(1 + K_R/K) \approx \ln K + s \\ \ln L' &= \ln L + \ln(1 + L_R/L) \approx \ln L + \mu \\ \ln Y' &= \ln Y + \ln(1 + I_R/Y) \approx \ln Y + \theta \end{aligned} \quad (3.11)$$

where $\theta = I_R/Y$ is the R&D intensity. The approximate equality in (3.11) uses the fact that s , μ and θ are small. Substituting the measured variables in (3.11) for those in (3.9) and using (3.7), we obtain the following equation,

$$\ln MFP' = \gamma \ln R - \alpha s \ln K' - \beta \mu \ln L' + \theta - (\alpha s + \beta \mu) \quad (3.12)$$

Assuming that s and μ are constant coefficients, the last term in the right hand side of (3.12) becomes part of the intercept in a regression equation. Adding an error term, equation (3.12) can be used directly for the regressions to correct for the use of the R&D stock variable that is double counted and inappropriately treated in value added.

By ignoring the mismeasurement, the output elasticity of R&D, γ is estimated in the MFP based regression equation without including variables $\ln K'$, $\ln L'$ and θ as in (3.12). To derive the biases on the estimated elasticity and the return to R&D, we use the formula for omission of relevant variables. The bias for γ from the misspecified equation is

$$E(\hat{\gamma}) - \gamma = -\alpha s B_{K'R} - \beta \mu B_{L'R} + B_{\theta R} \quad (3.13)$$

where the ‘hat’ indicates an estimated coefficient; the B ’s represent coefficients in auxiliary regressions of the omitted variables on $\ln R$. Multiplying (3.13) by Y/R and noting that rate of return to R&D, $\pi = \gamma(Y/R)$, we obtain,

$$E(\hat{\pi}) - \pi = -[(\alpha s B_{K'R} + \beta \mu B_{L'R})(Y/R)] + B_{\theta R}(Y/R) \quad (3.14)$$

The terms in the square bracket represent the double counting bias. It is a downward bias, as it is most likely that $B_{K'R} > 0$ and $B_{L'R} > 0$. The last term in (3.14) represents the expensing bias, and it may be either positive or negative, and it can also be zero if R is uncorrelated with θ . Thus, the total bias may also be positive or negative and will depend on sample characteristics. Note that here we use equation (3.10) based on our argument on measured value added rather than Schankerman’s adding back correction. The resulting difference is only in the sign associated with θ in equations (3.12) to (3.14), while the ambiguity about the direction of the total bias remains.

3.4 Regressions

Several measures of R&D capital stock at the one-digit industry-level have been constructed. While the main focus of the chapter is on the estimates of returns to industry’s own R&D, there are various R&D related activities outside the industry that may also have an effect on the industry’s productivity performance. The following R&D variables are intended to capture these effects, but not all of them are included in the preferred specifications, which is discussed in the next sub-section²⁴.

3.4.1 R&D variables

The following set of R&D variables is used in the regressions:

²⁴ See Appendix C for the description and analysis of the data used in this chapter. See also Chapter 5 in Shanks and Zheng (2006) for a detailed discussion of data issues and the construction of R&D stocks.

- *Own R&D.* The industry's own R&D stock measure is based on R&D that is performed as well as financed by the industry, with an assumed annual rate of decay of 15 per cent²⁵. The coefficient associated with this variable is the main interest of our study.
- *Inter-industry R&D.* This stock measure is based on the R&D performed by other Australian industries, weighted by either inter-industry trade or technological distance.
- *Foreign.* This stock measure is based on R&D performed in other countries, weighted by either the share in Elaborately Transformed Manufactures imports to Australia or technological distance. It can be aggregate or industry-specific foreign R&D (see appendix F in Shanks and Zheng 2006 for details).
- *Public.* This stock measure is based on R&D performed by higher education, government and private non-profit institutions.

As the appropriate data on R&D expenditure in Agriculture, forestry & fishing are not available, the variable measuring public expenditure on R&D is used in the regressions for this industry. The measure of public R&D is only available for the economy as a whole. Its use in the regressions for Agriculture, forestry & fishing may be interpreted as capturing the total public R&D effect on the industry's productivity.

3.4.2 Other Control Variables

Several variables are used to control for productivity enhancing factors other than industry's own R&D capital stock. A time trend is included in the empirical models, except in Agriculture, because many variables in log level form display clear, upward, linear trends (see Appendix C for the unit root tests). In Agriculture, the intensity specification of equation (3.5) is used, in which the time trend is naturally eliminated. The linear time trend in the level specification also captures the causes

²⁵ Regressions with a stock measure based on the R&D performed by the industry, including all sources of finance, are also estimated. The estimated elasticities are not statistically different. Also, the implied rates of return do not seem very sensitive to changes in the assumed rate of decay used in the construction of the industry's own R&D stocks.

of measured productivity growth that are not related to growth in R&D capital stock. These causes may include economies of scale, market power, and factors from other methods of improving efficiency in the production that are not captured by the other control variables included in the regression equations. As there are only 29 years of data, only a small set of control variables could be included in the regression models.

A variable measuring the inter-industry R&D capital stock weighted by either inter-industry trade or technological distance is constructed to control for the effects of spillovers and inter-industry technology flows on the industry's productivity growth. It turns out that this variable is highly insignificant (p -value > 50 per cent) with a negative sign in most of the regressions. But a priori this type of spillover among industries is likely to be important. This raises questions as to whether the effect has been adequately captured by the constructed variables under the current measurement framework. The industry-level results suggest that the current indicator of this highly aggregated, imprecise measure introduces more 'noise' into the models. Thus, inter-industry R&D stocks are excluded from the reported regressions²⁶.

It is well-known that measured MFP is pro-cyclical. Some empirical studies include a variable to control for this effect in the regression equations in which MFP is used as the dependent variable. However, there is more than one measure that can be used to control for this effect. In some studies, for example Dowrick and Nguyen (1989), a measure of capacity utilisation is used, which is based on the residuals from the regression of a volume measure of value added on a time trend. An increase in this variable approximates the effect of a higher rate of capacity utilisation²⁷. Other measures to control for the cyclical effect include the real GDP gap and a variable simply measuring real GDP growth (for example, Engelbrecht 1997).

²⁶ In the manufacturing panel regressions of appendix J in Shanks and Zheng 2006, inter-industry stocks are highly significant, but it is not possible to obtain consistent signs in the estimates in the MFP and labour productivity based models.

²⁷ There is no consensus approach to measuring capacity utilisation. See Hulten (1986 and 1990) and Berndt and Fuss (1986) for a detailed discussion. For a recent discussion of measuring capacity utilisation within the framework of national accounts, see Durand (2002).

Clearly, all these cycle variables are proxies. The exact impact of using different proxies to control for the same effect on the econometric estimates is generally unknown²⁸. In experiments using either the capacity utilisation index or the growth rate of real gross value added to control for the cyclical effect in the regressions for each industry, both measures performed poorly. Thus, they are both dropped from the reported industry-level regressions.

The foreign R&D capital stock is often treated as a variable of main interest in many empirical studies, because it is intended to capture the effect of international R&D knowledge transfer that is considered to be an important source of domestic productivity growth. As with the measure of domestic R&D capital stocks, foreign R&D stocks can be constructed for the whole economy (or market sector) and for particular industries. For the industry-level analysis, the construction of foreign R&D stocks can take account of inter-country relationships or both inter-industry and inter-country relationships (see Shanks and Zheng 2006 for details).

It is usually more difficult to construct industry-specific foreign R&D stocks because of data constraints. For Manufacturing and Wholesale & retail trade, foreign stocks were constructed from both foreign aggregate business expenditure on R&D (BERD) data and from industry-level data. For the Agriculture and Mining industries, the foreign R&D stocks were based only on aggregate BERD. The foreign R&D stocks are weighted across countries by the US Patent and Trademark Office's patent grants data (foreign).

The remaining control variables included in the regression equations are the usage of public infrastructure, change in oil price, an index of trade openness, CPI, a measure of rainfall, IT capital, use of communication infrastructure and farmers' terms of trade. Apart from the variable of usage of public infrastructure, which appears in all

²⁸ Coe and Helpman (1995) do not control for the business cycle effect in their macro-level regression models, while Engelbrecht (1997) uses a variable measuring real GDP growth to control for business cycle effect. Controlling for the business cycle effect could be one of the contributing factors for the negative elasticities on foreign R&D for a number of OECD countries, including Australia, in the study by Engelbrecht (1997). Engelbrecht (1997) uses the same dataset as that of Coe and Helpman (1995), but the latter does not obtain any negative elasticities.

the four regression equations, the remainder of the control variables were only included in some industry regressions.

The amount of rainfall and farmers' terms of trade are included as being relevant factors affecting productivity in Agriculture, forestry & fishing. The CPI and the change in oil price are included to control for the cyclical effects in Wholesale & retail trade and Mining, respectively. The Wholesale & retail industry's MFP (based on value added) is closely linked to the changes in final consumption, while the demand in final consumption can be strongly influenced by the changes in CPI. In the absence of an appropriate price index for Mining as a whole, the oil price index is used as a proxy to control for some major cycles that may have a direct impact on the world energy market and the mining industry in particular.

As in other Australian studies, (for example, Chand et al. 1998, Chand 1999 and Oczkowski and Sharma 2001), an index of trade openness is included in the manufacturing productivity regression. The variables of IT capital and use of communication infrastructure were included for Wholesale & retail trade.

3.4.3 The modelling strategy

Ruling out panel techniques

It is reasonable to expect that the models for different industries contain some industry-specific control variables, while any common control variables used in different industries may attract different estimated coefficients, reflecting the considerable amount of heterogeneity across industries. The kind of econometric technique applied should allow for these differences.

While panel data techniques are very powerful in dealing with data in both cross-section and time-series dimensions, they may not be the best tool in this instance. They impose a common set of control variables and the same elasticities across different industries, with the differences only being explicitly captured by the intercept terms (in the fixed effects models). Although the elasticities with respect to R&D across industries can be allowed to differ under panel regressions by

introducing various interaction terms (see, for example, Cameron 2004), this approach is not attempted here due to the small sample size available²⁹.

The ‘test down’ procedure

As hinted previously, the strategy that we have used to select the control variables is based on the consideration of their economic as well as statistical significance in regression models. Starting the regression with an initial large set of control variables, if any coefficient of the control variable did not have the expected sign, and/or its presence adversely affected the overall fit of the model or the significance of the coefficient associated with the main variable of interest, then it was deleted. For example, an index of the level of education for each industry’s labour input was included in the industry regressions as a proxy for the measure of human capital and as a control for the quality of labour input. However, the estimated coefficient associated with this variable was either negative or highly insignificant. As a result, this variable was excluded from further regressions. The estimates shown in the next section are the result of this ‘test down’ procedure.

This way of selecting the control variables may be said to be ‘data mining’. However, since there are no specific theories to draw on in determining which variables should be included and excluded in many empirical studies, it is common practice to choose control variables that are based on some level of subjective judgment as well as on data availability. This may also be one of the reasons that it is often difficult to replicate the estimates from other empirical studies using a similar dataset.

3.5 Results

The results for Manufacturing, Mining and Wholesale & retail trade are based on the MFP level specification of equation (3.3), while the intensity form of equation (3.5) is used for Agriculture. Regression models based on the specification of equation

²⁹ In addition, experiments with panel estimation do not yield economic and statistically significant results, indicating that the data may not be ‘poolable’.

(3.2), where value added output is the dependent variable, were also estimated. But the results from these models are rather problematic. Thus, the specifications of (3.3) and (3.5) are preferred. The choice of specification for Agriculture is an empirical outcome. Because the intensity specification tends to reduce the level of volatility in output and productivity observed in this industry, it yields more plausible results.

3.5.1 Results based on individual industry regressions

The results in Table 3.2 are based on the regressions run separately for each industry. The estimated effect of own-industry R&D on MFP is positive for each of the 3 industries for which log levels are used (Table 3.2). For example, in Manufacturing, the estimates imply that a 10 per cent increase in the industry's stock of R&D capital results in a 0.38 per cent increase in MFP. In Agriculture, the estimated return to public R&D is 32 per cent based on the results in Table 3.2.

The aggregate foreign R&D stock measure is tested in each of the four industries. The coefficient on foreign R&D is significant (but negative) in Manufacturing only when the aggregate measure is used, whereas it is not significant (also negative) in other industries when either the aggregate or the industry-specific foreign R&D measures were used. As a result, the foreign R&D stock is retained only in Manufacturing, and is in the form of an aggregate measure.

A negative foreign spillover effect has been observed in other aggregate-level studies on R&D, for example, in the cross-country studies by Engelbrecht (1997) and Madden et al. (2001), and in the Australian study by Rogers (1995). It is also found in some aggregate market-sector regression models in Shanks and Zheng (2006)³⁰.

While the estimated models in Table 3.2 pass major diagnostic tests, including no heteroskedasticity (not shown in the table), there are still some results that are quite 'unsatisfactory'. For example, in Manufacturing the coefficients associated with public and foreign R&D stocks are both negative, and the coefficients associated with public R&D in Manufacturing and in Mining are also quite large in magnitude.

³⁰ See pp. 139 in Shanks and Zheng (2006) for some possible explanations for a weak or negative effect of foreign R&D on Australia's productivity.

Although the negative public R&D coefficient in Manufacturing is somewhat counter-intuitive, the high level of statistical significance of this variable indicates that it may not be appropriate to exclude it from the regression equation.

Wholesale & retail trade is the only industry for which the coefficients on IT capital and usage of communication services by industry are significant and of the expected sign. This supports the conclusion that the heavy use of ICT is one of the major determinants of the productivity changes in this industry, a well-known result that is found in many other studies. For the other industries, this effect does not seem strong enough to warrant the variables being included in their regression equations.

One variable that is significant in each of the four industry-level regressions is the use of public infrastructure. The positive effect of public infrastructure on productivity in Australia is found in other studies (for example, Otto and Voss 1994; Connolly and Fox 2006). It is also found at the market-sector level in Shanks and Zheng (2006).

Table 3.2: Regression results for the four market-sector industries^a

| | <i>Log (MFP) as the dependent variable</i> | | | <i>Δlog(MFP) as the dependent variable</i> |
|--|--|--------------------------------|---|--|
| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade^b</i> | <i>Agriculture, forestry & fishing^c</i> |
| <i>R&D capital stocks</i> | | | | |
| Own | 0.038** (0.0168) | 0.077** (0.035) | 0.055** (0.019) | |
| Public | -2.46** (0.455) | 4.07** (0.814) | | |
| Foreign | -0.2125** (0.0785) | | | |
| <i>R&D intensity</i> | | | | |
| Public | | | | 0.317** (0.135) |
| <i>Other control variables</i> | | | | |
| Time | 0.076** (0.015) | -0.153** (0.021) | -0.058** (0.009) | |
| Usage of public infrastructure | 0.165* (0.0924) | 1.23** (0.082) | 0.844** (0.165) | 0.993** (0.059) |
| Change in oil price | | 0.059** (0.020) | | |
| Trade openness | 0.077* (0.0443) | 0.355** (0.113) | | |
| CPI | | | -0.421** (0.094) | |
| IT capital (hardware and software) | | | 0.179** (0.035) | |
| Use of communication infrastructure | | | 0.511** (0.102) | |
| Rain | | | | 0.015** (0.007) |
| Farmers' terms of trade | | | | 0.159** (0.064) |
| Test statistics | | | | |
| Sample | 1974/75-2002/03 | 1974/75-2002/03 | 1974/75-2002/03 | 1974/75-2002/03 |
| R ² | 0.81 | 0.95 | 0.96 | 0.97 |
| DW | 2.2 | 1.7 | 2.4 | 2.2 |
| AIC | -183.5 | -124.7 | -162.6 | -124.4 |
| RESET F(2, T-K-3) | 0.28 | 0.84 | 2.16 | 0.64 |
| | Pr > F: 0.76 | Pr>F: 0.45 | Pr > F: 0.14 | Pr > F: 0.54 |
| Unit root test (Phillips-Perron) for the residual: | rejected with p-value < 0.0001 | rejected with p-value < 0.0001 | rejected with p-value < 0.0001 | rejected with p-value < 0.0001 |

** indicates the p-value associated with the estimated coefficient is less than 5 per cent, while * indicates the p-value is between 5 and 10 per cent. ^a Standard errors are in parentheses. ^b For Wholesale & retail trade, the results are based on the Yule-Walker estimates after adjusting for autocorrelation of order 3. ^c The intensity specification of equation (5) is used for Agriculture. The R&D intensity is defined as the change in R&D capital stock divided by the real output, and the relevant control variables used for this industry are in first difference.

The regression equations used above do not contain any lagged variables. However, lags do exist between an investment in R&D and its impact on production and productivity³¹. It could be argued that since the perpetual inventory method (PIM) used to construct the R&D stocks includes current as well as past investment expenditure on R&D, there is no need to use lags of the R&D stock variables. On the other hand, one could also argue that since current expenditure on R&D is assigned the largest weight (which is one, because of no depreciation) in PIM and it has the strongest single impact on the current period R&D stock, lagged R&D stock variables may be required in the regression equations to fully reflect the lags between R&D and productivity.

To accommodate the argument about the lags between R&D activity and its effects on productivity, the models are re-estimated with lags on all the R&D stock variables. The results in Table 3.3 show that a one-period lag seems most appropriate, as it largely maintains the level of significance for the majority of coefficients. Nevertheless, the estimates on the lagged R&D variables are not significantly different from those without lags in Table 3.2³².

³¹ The same argument may also apply to traditional capital. But in general, the lags associated with R&D are likely to be much longer than with traditional capital.

³² With the exception of Wholesale & retail trade where the coefficient on the industry's own R&D becomes insignificant when the lagged R&D variable is used in the regression.

Table 3.3: Results from the regressions using the lagged R&D capital stocks^a

| | <i>Log (MFP) as the dependent variable</i> | | | <i>Δlog(MFP) as the dependent variable</i> |
|-------------------------------------|--|---------------------|---|--|
| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade^b</i> | <i>Agriculture, forestry & fishing^c</i> |
| <i>R&D capital stocks</i> | | | | |
| Own (t-1) | 0.036* (0.0195) | 0.081** (0.037) | 0.034 (0.024) | |
| Public (t-1) | -2.12** (0.50) | 3.81** (0.986) | | |
| Foreign (t-1) | -0.128 (0.086) | | | |
| <i>R&D intensity</i> | | | | |
| Public (t-1) | | | | 0.332** (0.145) |
| <i>Other control variables</i> | | | | |
| Time | 0.063** (0.017) | -0.146** (0.025) | -0.075** (0.012) | |
| Usage of public infrastructure | 0.217* (0.102) | 1.26** (0.084) | 0.556** (0.224) | 0.919** (0.052) |
| Change in oil price | | 0.055** (0.021) | | |
| Trade openness | 0.074 (0.051) | 0.38** (0.116) | | |
| CPI | | | -0.423** (0.114) | |
| IT capital (hardware and software) | | | 0.219** (0.047) | |
| Use of communication infrastructure | | | 0.705** (0.118) | |
| Rain | | | | 0.015** (0.007) |
| Farmers' terms of trade | | | | 0.149** (0.064) |

(continued on next page)

Table 3.3 (continued)

| | <i>Log (MFP) as the dependent variable</i> | | | <i>Δlog(MFP) as the dependent variable</i> |
|------------------------|--|-----------------|---|--|
| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade^b</i> | <i>Agriculture, forestry & fishing^c</i> |
| Test statistics | | | | |
| Sample | 1974/75-2002/03 | 1974/75-2002/03 | 1974/75-2002/03 | 1974/75-2002/03 |
| R ² | 0.77 | 0.95 | 0.95 | 0.97 |
| DW | 2.0 | 1.7 | 2.2 | 2.1 |
| AIC | -174 | -123 | -151 | -124 |
| RESET F(2, T-K-3) | 0.67 | 0.56 | 1.48 | 0.96 |
| | Pr > F: 0.52 | Pr>F: 0.57 | Pr > F: 0.25 | Pr > F: 0.40 |

** indicates the p-value associated with the estimated coefficient is less than 5 per cent, while * indicates the p-value is between 5 and 10 per cent. ^a Standard errors are in parentheses. ^b For Wholesale & retail trade, the results are based on the Yule-Walker estimates after adjusting for autocorrelation of order 3. ^c The intensity specification of equation (5) is used for Agriculture. The R&D intensity is defined as the change in R&D capital stock divided by the real output, and the relevant control variables used for this industry are in first difference.

3.5.2 Results from joint estimation

The previous results were obtained from regression equations that were estimated separately for each industry. The models can also be estimated jointly using seeming unrelated regression equations (SURE), which takes account of the contemporaneous correlation in the errors (with error variances able to differ across industries) to possibly improve the quality of the estimates, compared with independent estimation of each of the industries.

The SURE estimator produces similar results to those from the linear regression estimated separately for each industry, but it results in the coefficients for industry's own R&D elasticity in Manufacturing and Wholesale & retail becoming insignificant (Table 3.4). However, the condition under which SURE improves on the results from equations estimated separately is the existence of contemporaneous correlation. If contemporaneous correlation does not exist, least square estimation applied

separately to each equation is fully efficient and there is no need to employ SURE. Thus, it is useful to test whether the contemporaneous covariances are zero.

In the four-equation system used above, the null hypothesis for the test is that all the contemporaneous cross-model covariances are zero, while the alternative is that at least one of the covariances is nonzero. The test indicates that the evidence for the existence of the contemporaneous correlation in the equation system is somewhat weak³³. Thus, the results from independently estimated equations are preferred to those based on SURE.

³³ The Lagrange multiplier test statistic suggested by Breusch and Pagan, λ , takes a value of 12.39. Under the null, λ has an asymptotic χ^2 distribution with 6 degrees of freedom. At the 5 per cent level of significance, its critical value is 12.59, which is just above the test statistic, while the 10 per cent critical value is 10.64.

Table 3.4: SURE results for the four market-sector industries^a

| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade</i> | <i>Agriculture, forestry & fishing^b</i> |
|--|----------------------|---------------------|---|--|
| <i>R&D capital stocks</i> | | | | |
| Own | 0.027 (0.016) | 0.077** (0.032) | 0.038 (0.044) | |
| Public | -2.53** (0.462) | 3.81** (0.758) | | |
| Foreign | -0.222** (0.085) | | | |
| <i>R&D intensity</i> | | | | |
| Public | | | | 0.314** (0.132) |
| <i>Other control variables</i> | | | | |
| Time | 0.094** (0.016) | -0.134** (0.019) | -0.042** (0.020) | |
| Usage of public infrastructure | 0.102 (0.090) | 1.211** (0.075) | 0.789** (0.382) | 0.955** (0.056) |
| Change in oil price | | 0.072** (0.018) | | |
| Trade openness | 0.085* (0.045) | 0.361** (0.105) | | |
| CPI | | | -0.413** (0.174) | |
| IT capital (hardware and software) | | | 0.181** (0.071) | |
| Use of communication infrastructure | | | 0.533** (0.242) | |
| Rain | | | | 0.018** (0.006) |
| Farmers' terms of trade | | | | 0.117** (0.060) |

** indicates the p-value associated with the estimated coefficient is less than 5 per cent, while * indicates the p-value is between 5 and 10 per cent. ^a Standard errors are in parentheses. ^b The intensity specification of equation (5) is used for Agriculture. The R&D intensity is defined as the change in R&D capital stock divided by the real output, and the relevant control variables used for this industry are in first difference.

3.5.3 Results based on an alternative specification

As discussed in detail in Section 3.3, R&D expenditure, which is the basis for constructing R&D capital stock, is double counted in the measured capital and labour, and it is also expensed as an intermediate input. In the absence of an appropriate procedure to tackle these measurement problems, the estimates based on the MFP-R&D regressions may suffer from the double counting and expensing biases. Equation (3.12) derived in Section 3.3.3 can be used directly for the MFP based regressions by taking into account the two possible sources of bias. The equation is re-produced for convenience.

$$\ln MFP' = C + \gamma \ln R - A \ln K' - B \ln L' + \theta \quad (3.15)$$

where C is a constant collecting various constant terms in (3.12), $\theta = I_R / Y$ is the R&D intensity and A and B are coefficients associated with the measured capital and labour, respectively. Notice that in comparison to (3.3), i.e. the equation without adjustment for the biases, (3.15) contains three additional right hand side variables (with the same set of control variables, including time). Also, both the measured capital and labour are expected to have negative coefficients.

Using the same set of control variables for each industry as that in the previous regressions, the results under this alternative specification are shown Table 3.5. The three additional variables are included in the initial regressions, but some are tested out and their coefficients do not appear in table 3.5. In particular, the coefficient θ is found to be insignificant in all of the regressions³⁴.

³⁴ In Agriculture, the public R&D stock is used for regressions. However, similar to industry's own R&D stock, the public R&D stock is also double counted and expensed. The estimation of the intensity specification adjusted for the biases in Agriculture should include \hat{K}' , \hat{L}' and $\hat{\theta}$ implied by equation (3.15).

Table 3.5: Results based on an alternative specification ^a

| | <i>Log (MFP) as the dependent variable</i> | | | <i>Δlog(MFP) as the dependent variable</i> |
|-------------------------------------|--|---------------------|---|--|
| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade^b</i> | <i>Agriculture, forestry & fishing^c</i> |
| <i>R&D capital stocks</i> | | | | |
| Own | 0.055** (0.016) | 0.061** (0.026) | 0.055** (0.019) | |
| Public | -1.21** (0.205) | 2.55** (0.69) | | |
| <i>R&D intensity</i> | | | | |
| Public | | | | 0.237** (0.110) |
| <i>Other control variables</i> | | | | |
| Time | 0.030** (0.005) | -0.082** (0.023) | -0.059** (0.010) | |
| Usage of public infrastructure | 0.495** (0.099) | 1.066** (0.071) | 0.864** (0.189) | 1.026** (0.048) |
| Change in oil price | | 0.036** (0.016) | | |
| Trade openness | 0.106** (0.038) | 0.187* (0.092) | | |
| CPI | | | -0.436** (0.115) | |
| Hours worked | -0.207** (0.049) | | | -0.342** (0.092) |
| Capital stock | | -0.477** (0.109) | -0.053* (0.242) | |
| IT capital (hardware and software) | | | 0.191** (0.065) | |
| Use of communication infrastructure | | | 0.508** (0.106) | |
| Rain | | | | 0.012** (0.006) |
| Farmers' terms of trade | | | | 0.156** (0.051) |
| <i>Test statistics</i> | | | | |
| R ² | 0.86 | 0.97 | 0.91 | 0.98 |
| DW | 2.5 | 1.6 | 2.4 | 1.7 |
| AIC | -192.3 | -141.3 | -142.23 | -136.1 |
| RESET F(2, T-K-3) | 0.13 (0.88) | 2.51 (0.11) | 2.22 (0.14) | 3.14 (0.07) |

** indicates the p-value associated with the estimated coefficient is less than 5 per cent, while * indicates the p-value is between 5 and 10 per cent. ^a Standard errors are in parentheses. ^b For Wholesale & retail trade, the results are based on the Yule-Walker estimates after adjusting for autocorrelation of order 3. ^c The intensity specification of equation (5) is used for Agriculture. The R&D intensity is defined as the change in R&D capital stock divided by the real output, while the relevant control variables used for this industry are in first difference.

Inclusion of these new variables impacts on the significance levels of other coefficients previously included in the regressions. For example, the coefficient on the foreign R&D stock in Manufacturing becomes insignificant, and thus is excluded from the regression (see Tables 3.3 and 3.4). Under this alternative specification, the coefficient on the own R&D capital stock in the Wholesale & retail trade becomes significant at the 5 per cent level. Inclusion of the traditional capital stock in this industry regression does not change the estimates and the levels of significance for the other variables in the equation.

All the coefficients in the regressions (Table 3.5) are significant, with p -values below 5 per cent for most of the variables and p -values between 5 and 10 per cent for the rest. All the coefficients included in the regression equations are also of the expected signs.

Comparing the above results with those in Table 3.2, which were obtained from the specification that does not adjust for the measurement biases, the estimated output elasticity with respect to R&D has increased from 0.038 to 0.055 in Manufacturing, but it has decreased in Mining from 0.077 to 0.06, and the estimated return to public R&D in Agriculture has decreased from 32 to 24 per cent. There is no change for Wholesale & retail trade.

3.5.4 Estimates of rate of return to R&D

While the level of the estimated elasticity is informative by itself, it is of more interest to know the rate of return to R&D. As derived in section 3.3.2, the relationship $\rho_t = \gamma \left(\frac{Y_t}{R_t} \right)$ can be used for this purpose. Notice that the subscript t is included here to highlight the time index associated with the variables, while the elasticity variable is time-free, as it represents the *average* estimated elasticity across the sample period. Thus, at a given estimated elasticity, the rate of return to R&D is inversely related to the level of R&D intensity (defined as $\frac{R_t}{Y_t}$). In other words, as

R&D intensity rises, the annual rate of return to R&D will decrease at a given estimated elasticity in the sample period. However, the common practice is to average the intensity over the sample period and then derive the rate of return accordingly. This is also the approach adopted here.

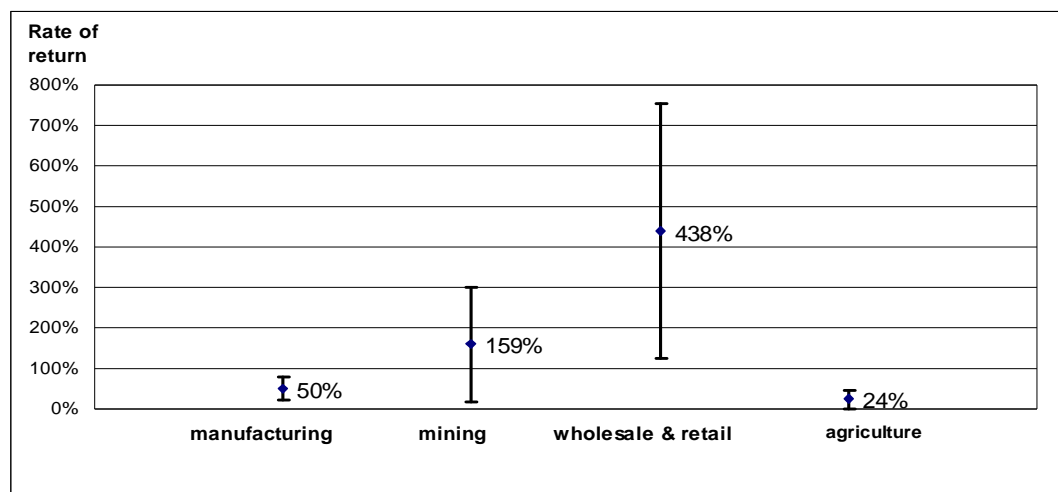
The rate of return reported in Table 3.6 should be interpreted as the gross rate, as the R&D capital stocks used in the regressions are based on a 15% rate of depreciation. The following figure presents a 95 percent confidence interval for the estimated rate of return in the four industries.

Table 3.6: Gross rate of return to industry R&D^a

| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade</i> | <i>Agriculture</i> |
|-----------------------------------|----------------------|---------------|-------------------------------------|--------------------|
| Industry real R&D intensity (K/Y) | 0.11 | 0.038 | 0.013 | |
| Elasticity of R&D | 0.055* | 0.061* | 0.055* | |
| Rate of return (%) | 50 | 159 | 438 | 24* |

^a The figures marked by * are based on results from Table 3.5. The return to public sector Agriculture R&D was estimated directly.

Figure 3.1: The 95% confidence intervals for the rate of return to R&D



The estimated return in Manufacturing falls within reasonable bounds at 50 per cent. The return is higher than the 13 per cent found in Industry Commission (1995). The return to the industry's own R&D stock in Mining and Wholesale & retail trade is unexpectedly high, although it is not uncommon to obtain high rates of return for empirical studies below the one-digit level.³⁵

The estimate of the return to public R&D in Agriculture also falls within reasonable bounds. The return in Agriculture is a return to the public R&D stock. Given that the returns to research in broadacre agriculture in Australia have been estimated to be in the range of 15 to 40 per cent (Mullen and Cox 1995), the rate of 24 per cent for Agriculture estimated in this study seems reasonable.

While the confidence intervals are quite wide for Mining and Wholesale & retail, they do not contain zero for each industry (i.e. the hypothesis of a zero estimated rate of return in each industry is rejected at the 5 per cent level of significance). It suggests that there is some evidence of a positive relationship between the industry's own R&D activity and its productivity growth. However, such evidence cannot withstand the changes in the control variables used in many of the regressions with which we experiment. As such, the results from this study should be considered as only indicative.

3.6 Concluding remarks

For the four one-digit industries investigated in the chapter, some evidence is found of a positive relationship between each industry's own R&D capital stock and its productivity growth. But for the R&D capital stocks outside the industry, the estimated R&D effects on the industry's productivity are somewhat unexpected. This could be due to unresolved issues in data quality, the small sample size and a lack of robustness in the main results. Thus, there are still doubts about precision and reliability of the estimated returns to R&D at the industry level.

³⁵ Nadiri (1993) surveys mainly US studies at the firm level and at one-digit industry level and finds estimated returns to R&D varying widely from 3 to 143 per cent.

Several observations are worth noting. First, the estimation of the effect of R&D on productivity at the industry level is subject to greater data constraints than at the aggregate level. The measurement of industry inputs, outputs and productivity all face the long-standing, difficult issues that affect the quality of the data. The measurement of the R&D capital stocks is also subject to greater uncertainty (Diewert 2005). The measurement issues may be even more severe for some proxy and control variables, as they are often constructed from some ad-hoc data sources and methods without much quality control and scrutiny. The effects of using these poorly measured variables in econometric estimation are generally not clear.

Second, despite an increased sample size compared to some previous work, the number of observations in this study is still limited, and many econometric tests under small samples have very low power.

Third, while the theory linking R&D and productivity based on the production function used in this study is of some help for model specification, it may not be sufficiently specific for industry analysis at the one-digit level. In particular, the theory says little about the selection of different control variables. The selection process in empirical modelling remains somewhat arbitrary, but in many cases, it strongly influences the main results.

Chapter 4

Australia's recent mining boom and the productivity paradox: another lesson for the MFP measurement

4.1 Introduction

The industry-level MFP estimates derived in Chapter 2 are based on the standard non-parametric, growth accounting approach. These estimates are intended to capture the changes of overall efficiency in an industry. As is well known, productivity growth is fundamentally driven by technological progress, which is determined by R&D effort and outcomes. However, as demonstrated in Chapter 3, based on a number of Australian industries for which the required data are available, the quantitative evidence for the link between R&D and productivity performance at the industry-level is somewhat weak.

Apart from various econometric issues, the measured industry-level MFP itself may also be one of the factors contributing to the non-robust results. This is because the MFP estimates are derived under the standard approach without taking specific account of the different ways in which productivity is related to the technology in different industries. In other words, it is possible that measured MFP is biased for certain industries.

One notable example is the mining industry. Different mines and oil and gas fields are diverse in terms of the quality of the deposits and the level of engineering difficulties with which mineral and energy products can be extracted and transformed into economic goods. Another related factor that may impact on mining productivity is the condition of natural reserves. These factors are generally called the natural resource inputs and they are crucial in determining which extraction techniques are most appropriate to use and how the production is organised for different mines and fields, thus they are the integral part of the mineral and energy production.

One would expect that the most easily accessible deposits are exploited first, followed by deeper or less-accessible reserves. In the absence of the discovery of

new deposits, more production leads to fewer easily accessible reserves, and greater amount of labour, capital and intermediate inputs have to be used to maintain the same level of output with a given technology. Thus, measured productivity would decline.

However, natural resource inputs do not generally have a market price and are difficult to be quantified properly both from producer and statistical perspectives. Consequently, they are usually left out from the conventional MFP calculations. While the general issue of missing inputs in the measurement of MFP also exists for other industries, the level of severity caused by this problem could be much higher in mining due to the importance of natural resource inputs in its production.

The issue of excluding natural resource inputs and the resulting effect on measured MFP in mining have been known for quite some time in the literature. Wedge (1973) observes this problem and challenges earlier estimates of low productivity growth in Canadian mining. Using an index of ore grades as a proxy for natural resource inputs, Wedge finds a sizable increase in measured rate of productivity growth. Lasserre and Ouellette (1988) include the resource input as an explicit factor in the mining production function and also use the changes in ore grade to approximate the changes in quality of the resource input. Young (1991) uses regression techniques to estimate the impact of ore grade and geological accessibility of a deposit (proxied by cumulative production) on measured MFP and finds evidence that lower ore grade and higher cumulative production (thus lower geological accessibility) reduce measured MFP in Canadian copper-mining firms.

More recently, Rodriguez and Arias (2008) derive a decomposition of the Solow residual that consists of the 'true' MFP growth, the effects of non-constant returns to scale, capacity utilisation and the level of reserves of natural resources. They further estimate a variable cost function for Spanish coal mining that enables them to quantify each component in their decomposition formula. Their results show that the depletion of the coal reserves lowers the MFP growth in Spanish coal mining by 1.3 percentage points per annum on average over the sample period.

Also recently, a study by Topp et al. (2008) focuses exclusively on Australian mining productivity and the related measurement issues. Their paper provides a comprehensive literature review on the effect of natural resource inputs on mining productivity and concludes that the studies they have reviewed are not well known and ‘the issue is not well established in the literature’ (pp. 38). In the paper, the authors estimate a ‘yield’ index to capture the effect of resource depletion and an alternative capital input index that allows for longer lead time from investment to forming productive capital stock used in production.

The yield index in the Topp et al. study aggregates the changes in ore grade, oil and gas flow rates and the ratio of saleable to raw coal. With the yield index being included in the MFP calculation to remove the depletion effect, the MFP growth in Australian mining is estimated by the authors to be 2.5% per annum on average over the period 1974-75 to 2006-07. By further including the alternative capital input index, the re-estimated MFP growth for Australian mining becomes 2.3%. These results are very different from the measured MFP growth of 0.01% over the same period based on the conventional MFP calculations.

The work by Topp et al. (2008) reviewed above appears to have been the only major Australian study that systematically addresses the issue of resource inputs in relation to the measurement of mining productivity. While there may have been many reasons for this to be the case – for example, the published estimates of Australian mining MFP have only been available for a relatively short period of time – the level of attention paid to this issue in Australia still seems inadequate, given the importance of mining in Australia in terms its contribution to exports, GDP growth, taxation revenue and overall prosperity of the nation.

The mining industry in Australia has recently experienced a strong surge in production, investment and employment activities due to the rise in commodity prices and higher demand for mineral and energy products from China. This is the recent mining boom, starting roughly from the end of 2001-02 to the beginning of 2008-09. One would expect that the mining boom would have also boosted mining’s productivity performance. However, measured MFP in Australian mining during

this boom period has in fact deteriorated substantially. This mining productivity ‘paradox’ is one of the motivations for the study by Topp et al. (2008). This chapter also investigates this issue. Additionally, one of our main objectives is to explore the usefulness of the interactions between economic measurement and production economics, as is highlighted in the previous two chapters.

The next section provides some statistical information about the growth in commodity prices and measured MFP in Australia’s mining industry, which puts the scale of the recent mining boom into some perspective. Some possible explanations for the puzzling productivity performance during this boom period are also outlined. Section 4.3 presents a more formal approach that unravels the various factors that may ‘contaminate’ measured MFP, particularly in relation to the natural resource inputs in mining. Here, again, we seek to explore the links between productivity measurement and various concepts in production economics. This is the main section of the chapter, and due to its importance, it consists of several subsections, each dealing separately with the conceptual and empirical issues. The last section concludes.

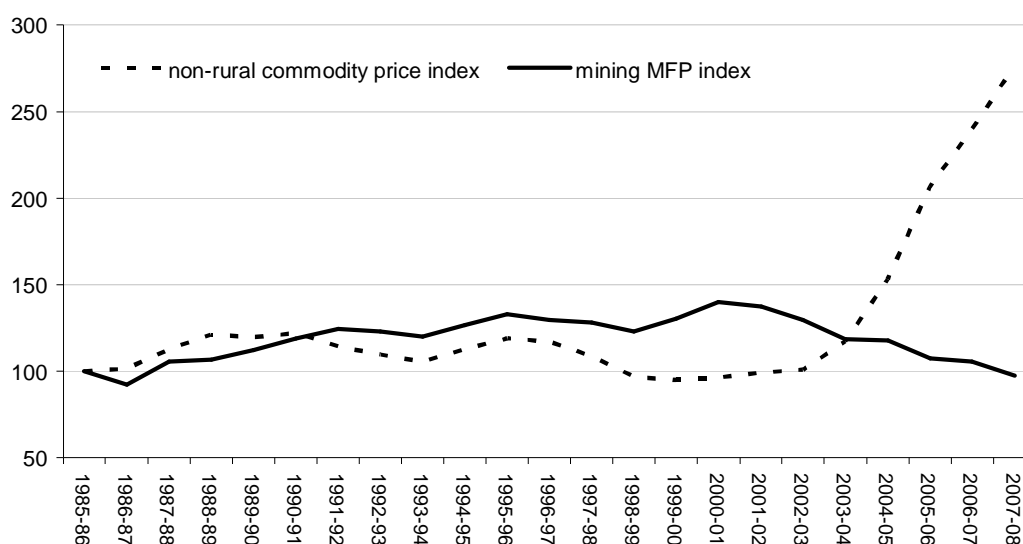
4.2 Australia’s recent mining boom

While there is no technical definition for a mining boom³⁶, it is obvious to see the scale of the recent surge in the non-rural commodity prices as shown at Figure 4.1. Between 2001-02 and 2007-08, the average annual growth of the Australian non-rural commodity prices is 16.8%. But the same price index records an annual decrease of 0.1% on average during the period 1985-06 to 2000-01. In contrast, the annual average growth in measured MFP in Australian mining is -5% between 2001-02 and 2007-08, while the average growth of measured MFP is 2.4% per annum in the period 1985-06 to 2000-01. The correlation coefficient between the index of the non-rural commodity prices and the index of measured MFP is -0.49. This inverse

³⁶ The mining boom is also called the ‘commodity price boom’ by some commentators, such as the RBA. However, the recent boom reflects the increased level of activity originated from the mining industry, which was driven by the steep rise in prices for the mineral and energy products due the demand surge in China, whereas the term, ‘commodity price’ used to describe the boom can also include the prices of agricultural products. Thus, here preference is given to the term, ‘mining boom’.

relationship between the two indices during the period 2001-02 and 2007-08 is quite clear from Figure 4.1.

Figure 4.1: Australia’s mining commodity prices and productivity performance



Data Source: RBA: index of commodity prices and ABS Cat. No. 5260.0.55.002 (Nov 2008)

It is well known that at aggregate MFP tends to be pro-cyclical, implying that MFP at the economy-wide level tends to be higher when the economy is at a boom cycle, while it tends to be lower when the economy is in a negative growth or recession period (OECD 2001). However, this empirical relationship cannot be carried over to the industry-level. As shown in Figure 4.1, measured MFP in mining is in fact counter-cyclical – when the industry is booming as reflected by the price surge, its productivity performance is deteriorating; and to a less extent, measured productivity is increasing when there is a decline in output prices.

This paradoxical relationship between industry’s productivity performance and its general activity level is quite prominent during the recent mining boom in Australia. There are several possible causes that have been suggested to explain this paradox. Apart from the effect of resource inputs on measured MFP, which is analysed formally in much detail in the next section, a few of intuitive explanations are outlined below.

As explained by Perry (1999) regarding the US coal mines, when the prices of the mining products rise, those previously closed mines now become profitable again so

that they resume operations. However, their productivity level may still be lower than that of the existing mines. New mines and companies entering the industry to take advantage of the high prices may also have a lower level of productivity compared with the existing ones. This will bring down the overall level of productivity in the industry.

As mentioned before, investment in mining usually has a long lead time due to the lags between capital expenditure and the forming of productive capital stock. While industrial machinery and equipment - one of the asset categories of productive capital stock - may be purchased and assembled within a relatively short period of time, the new mining infrastructure, which largely belongs to the non-dwelling construction in the mining capital stock, usually takes a much longer time to complete. However, the current level of investment takes the largest weight in the current-period capital services index based on the perpetual inventory method (PIM). Thus, it overestimates the actual amount of capital used in production and underestimates the MFP growth if the investment surges strongly during the period of a mining boom.

During the recent mining boom, the volume of gross fixed capital formation in mining has increased significantly, with the fastest growth in capital assets coming from non-dwelling construction. The share of rental prices for non-dwelling construction has also increased (ABS 2007a). In terms of capital services, the average annual growth during the period 1985-86 and 2000-01 is 3.9%, and it accelerates to 6.5% during the period 2001-02 and 2007-08, which largely coincides with the duration of the mining boom. With the income share of capital at more than 80% in recent years and also with a high growth in labour (at an average of 8.8% in hours worked per annum between 2001-02 and 2007-08), but only a moderate output volume growth (an average of 1.6% in valued added per annum between 2001-02 and 2007-08), the resulting MFP growth is bound to be negative (an average of minus 5.2% per annum between 2001-02 and 2007-08). The results from Topp et al. (2008) show that by lagging the investment for a further 3 years in the PIM formula used for estimating productive stock, the re-estimated MFP in 2007-08 was -3%

under this alternative capital services measure (without adjusting for the effect of resource inputs), rather than -8% based on the conventional capital services measure.

The recent negative growth of measured MFP in Australia is also due to the low rate of growth in value added since 2000-01, which is caused by the decline in the output of oil and gas, as a result of depletion of the mature oil fields and the impact of cyclones on oil production (ABS 2007b).

Another possible explanation for a declined MFP growth is the infrastructure constraints, which features in the recent discussions about the mining boom (see, for example, Topp et al. 2008). As infrastructure is part of the capital, the issue of infrastructure constraints is therefore closely related to the problem of long lead time between investment and production use of capital stocks as discussed above. This is also a specific case that is associated with the general issue of the difference between capacity utilisation in the short run and that in the long run, which will be analysed formally in the next section.

4.3 A more formal approach

The various explanations presented in the previous section provide some general indications of the likely causes for the poor productivity performance in Australian mining as measured by the conventional MFP index during the recent mining boom. While it is known that measured MFP omits natural resource inputs that are important to mining operation and production, there have been relatively few attempts to systematically quantify the influence of resource inputs on measured MFP in Australia. The study by Topp et al. (2008) is one of the very few studies that focus on this issue in relation to Australia's mining sector. As mentioned above, in their study the volume of output is scaled by a 'yield' factor to take account of the effect of missing resource inputs and the mining capital services are re-estimated by increasing the lengths of lags with which investment contributes to the productive capital stock.

These adjustments have provided some useful ways of gauging the biases in measured mining MFP. The following analysis addresses the problem in measured MFP not only in terms of measurement, but also in terms of the MFP measure itself in relation to the concepts in production economics. It shows that dealing with the measurement problem alone cannot address the systematic weaknesses embedded in the conventional MFP measure.

The major conceptual weakness of MFP tends to lie in the two assumptions that are used in deriving the measure under the non-parametric, growth accounting approach. As discussed in Chapter 2, the assumptions of competitive markets and constant returns to scale are crucial in the derivation of the conventional MFP measure. They allow us to derive the MFP index without estimating some forms of a production function, thus less data are required. Clearly, this is the practical benefit of applying the Solow residual or the non-parametric approach to the measurement of MFP. However, the potential pitfall of relying on the two assumptions is that when they are strongly violated, the MFP estimates could contain the level of biases that may be large enough to misinform us about the true level and direction of MFP growth, with the latter being of a more serious concern. The problem is further exacerbated by the missing resource inputs when estimating MFP for the mining industry.

Another potential source of bias stems from the fact that the conventional MFP index is based on the long-run equilibrium framework where the inputs used in production can be adjusted sufficiently fast so that the marginal product is always equal to the real price for each input. This may be a reasonable assumption for certain inputs, such as labour and intermediate inputs, which can be adjusted relatively quickly. But capital input usually has a long lead time from the period of investment to the period of providing full productive services. In other words, capital should be treated as a quasi-fixed input, as it is fixed in the short run, while it is flexible in the long run.

In the short run, the prevailing market price for the capital may not be equal to the value of its marginal product due to the quasi-fixity. It also means that the level of output in the short run is different from that determined by the long-run equilibrium, and the firm or industry can operate below or above its optimal capacity that is

determined only in the long-run equilibrium³⁷. The conventional MFP index implicitly assumes that the level of output produced by a firm or industry is always at the optimal, long-run level. Clearly, the capacity utilisation effect originating from the presence of quasi-fixed inputs in production is a potential source of biases in measured MFP.

Each of the four factors mentioned above - the existence of market power, non-constant returns to scale, the quasi-fixity of capital and missing inputs – may also exist in other industries. But one expects that the problem of missing natural resource inputs in the MFP calculation can be more severe for mining for the reasons discussed above. Also, some of the factors that contribute to the biases in measured MFP may be more prominent during a growth cycle in the industry, like the recent mining boom in Australia. Nonetheless, the extent to which each of these factors biases measured MFP is an empirical question.

Before attempting to answer this question in relation to Australia's mining industry, we need first to establish an analytical relationship between the 'true' and measured MFP. This amounts to decomposing measured MFP into the 'true' MFP component and various other components that are influenced by the existence of market power, non-constant returns to scale, quasi-fixity of capital and natural resource inputs.

4.3.1 A decomposition of measured MFP

This section derives a decomposition of measured MFP. So far in this thesis production functions are used to analyse the issues related to MFP. This section uses a cost function to derive the MFP measure. As is well known, the cost function contains essentially the same information on technology that the production function contains, as long as producers are at a cost-minimising equilibrium and facing fixed input prices. This is the property of duality in production economics.

³⁷ Here we use 'firm' or 'industry' interchangeably to refer to the industry as a whole. This essentially treats the industry as a representative firm. Thus, various properties associated with its optimisation behaviour postulated in production economics can be readily applied. No attempt is made in this study to formally address the issues of firm entry and exit, and the corresponding costs and productivity implications for the industry.

The dual approach to the measurement of MFP has also been widely used (see, e.g. Berndt and Fuss 1986 and Hulten 1986). As will be seen, this approach can also reveal many important aspects of production that are not obvious if only the production function is used. In the following, some results are derived that resemble to those in Morrison and Schwarz (1994 and 1996) and in Rodriguez and Arias (2008). However, there are dissimilarities between the results here and those in the previous studies, as the four factors discussed above are incorporated in one formulation, and consideration is also given to a further complication in the MFP measurement. This complication stems from the fact that the aggregate and industry-level MFP indices are often based on a capital rental price that is derived endogenously by national statistical agencies to overcome the data limitations.

Cost minimisation and the variable cost function

In the short run, the firm is minimising the total costs under the constraint. This short-run cost minimisation problem can be written as:

$$\begin{aligned}
 C(w, r, K, R, Y, t) &= G(w, K, R, Y, t) + rK + vR \\
 &= \underset{L}{\text{Min}}\{wL \text{ s.t. } Y = F(K, L, R, t), \text{ and } K, R \text{ given}\} \quad (4.1) \\
 &\quad + rK + vR
 \end{aligned}$$

where $C(w, r, K, R, Y, t)$ captures the total costs, $G(w, K, R, Y, t)$ is the variable cost function that minimises variable cost (labour cost in this case) subject to the production technology at the given level of fixed inputs in the short run, and R is the (composite) resource inputs for which the firm pays the price, v . This price represents the cost to firm for the use of one unit of resource input. However, unlike capital and other conventional inputs, the resource input does not have a market to determine its price.

One can think of the resource input costs as the firm's spending on maintaining or improving the current conditions in the existing mines, the expenditure on exploration activities to discover new deposits, including the costs of acquiring the licenses for exploration and also those costs associated with maintaining the mine sites and organising the production process to meet certain environmental standards.

Alternatively, v can be thought of as the opportunity cost of using the resource input today rather than keeping it in situ for use in the future. The empirical approximation for v will be discussed further in the next section where a variable cost function is estimated.

In the short run, both K and R are fixed, and r is the aggregate rental price of capital or the user cost, which is determined by aggregation over the prices of different asset types. Thus, in our formulation of the cost minimisation problem, capital and resource inputs are treated symmetrically. The difference between these two variables lies only in their empirical contents and interpretations. Consequently, the resulting decomposition formula to be derived in the following has different form and interpretation from the one that treats the resource input as an unpaid input for which there is no observed cost incurred to the firm and only shadow price can be estimated³⁸. In reality, however, the case may lie somewhere in between - part of the resource inputs used have to be paid by the firm, such as those activities outlined above, while the other part is free to the firm.

As usual, time t is used to capture neutral, exogenous technical progress. The Lagrangian associated with the minimisation of the variable costs defined in (4.1) is given by

$$\ell = wL + \lambda[Y - F(K, L, R, t)] \quad (4.2)$$

The first-order condition for the cost minimisation problem is

$$w = \lambda F_L \quad (4.3)$$

By the envelope theorem, the marginal cost is equal to the multiplier, λ

$$\lambda = \frac{\partial C}{\partial Y} = \frac{\partial G}{\partial Y} = \frac{\partial \ell}{\partial Y} \quad (4.4)$$

The elasticity of total cost with respect to output can be written as the ratio of marginal to average cost,

³⁸ Morrison and Schwartz (1996) include the public infrastructure as an unpaid input in the variable cost function to derive their productivity decomposition formula. Rodriguez and Arias (2008) include the level of coal reserves in the same way as the public infrastructure that is treated in Morrison and Schwartz (1996) in the development of their decomposition formula.

$$\varepsilon_{C,Y} \equiv \frac{\partial C}{\partial Y} \frac{Y}{C} = \frac{\lambda}{C/Y} \quad (4.5)$$

This elasticity is often used as an alternative measure of returns to scale (see, e.g. Diewert and Fox 2008), as it measures the cost responsiveness to changes in output, which depends inversely on output's responsiveness to changes in factor inputs, a common measure of returns to scale.

Using (4.3) and noting that the share of labour in total cost is defined as $S_L \equiv wL/C$ and that the elasticity of output with respect to labour is defined as $\varepsilon_{Y,L} \equiv F_L L/Y$, (4.5) becomes

$$\varepsilon_{C,Y} = \frac{w}{F_L} \frac{Y}{C} = \frac{wL}{F_L L} \frac{Y}{C} = \frac{S_L}{\varepsilon_{Y,L}} \quad (4.6)$$

Thus, the output elasticity of the short-run cost function is equal to the inverse of the elasticity of output with respect to labour input multiplied by the share of labour (variable cost) in total cost.

Alternatively, (4.6) can be written as

$$\varepsilon_{Y,L} = \frac{S_L}{\varepsilon_{C,L}} \quad (4.7)$$

We now define the shadow price of capital, Z_K , and the shadow price of the resource inputs, Z_R , and note that both capital and resource inputs are fixed in the short-run. These shadow prices are defined in terms of their marginal contributions to the reduction of variable costs. Using the envelope theorem again, we have

$$Z_K \equiv -\frac{\partial G}{\partial K} = -\frac{\partial \ell}{\partial K} = \lambda F_K \quad (4.8)$$

$$Z_R \equiv -\frac{\partial G}{\partial R} = -\frac{\partial \ell}{\partial R} = \lambda F_R \quad (4.9)$$

Similar to the share of labour input in total cost, the shadow cost shares of the two inputs can be defined as

$$S_K^* \equiv \frac{Z_K K}{C} \text{ and } S_R^* \equiv \frac{Z_R R}{C} \quad (4.10)$$

Results similar to (4.7) can now be obtained regarding the relationships between the elasticity of output with respect to these two inputs and the output elasticity of the short-run cost function. Using (4.5) and (4.8) to (4.10) yields,

$$\varepsilon_{Y,K} \equiv F_K \frac{K}{Y} = \frac{\mu F_K K}{C} \frac{C/Y}{\lambda} = \frac{Z_K K}{C} \frac{C/Y}{\lambda} = \frac{S_K^*}{\varepsilon_{C,Y}} \quad (4.11)$$

$$\varepsilon_{Y,R} \equiv F_R \frac{R}{Y} = \frac{\mu F_R R}{C} \frac{C/Y}{\lambda} = \frac{Z_R R}{C} \frac{C/Y}{\lambda} = \frac{S_R^*}{\varepsilon_{C,Y}} \quad (4.12)$$

The relationship between the primal and dual measures of technical progress

As discussed in Chapter 2, the rate of technological progress can be defined as the rate of growth in output that follows from the passage of time with factor inputs being fixed. Differentiating the production function in (4.1) totally with respect to time, dividing through by Y and rearranging terms yields,

$$\varepsilon_{Y,t} \equiv \frac{F_t}{Y} = \hat{Y} - \varepsilon_{Y,K} \hat{K} - \varepsilon_{Y,L} \hat{L} - \varepsilon_{Y,R} \hat{R} \quad (4.13)$$

where $F_t = \partial F / \partial t$ and \hat{X} denotes the rate of growth for variable X . Note that the production function used here includes the resource inputs, R , while previously they are omitted in the discussion of the MFP measures. The conventional MFP index that corresponds to the production function in (4.1) is

$$\hat{A} = \hat{Y} - S_K \hat{K} - S_L \hat{L} - S_R \hat{R} \quad (4.14)$$

This index is equal to the measure of technical change, $\varepsilon_{Y,t}$ in (4.13) under the assumptions of perfectly competitive input and output markets and constant returns to scale. As discussed previously, the advantage of using this index is that no explicit knowledge of the production function or no estimated elasticities are required to estimate the technical progress.

The dual measure of technological progress has also been used widely in productivity analysis (see, e.g. the Berndt and Fuss 1986 and Hulten 1986). It is defined as the rate of cost reduction while holding the level of output, input prices and quantities constant. Relating to the short-run cost minimisation problem of (4.1), the dual measure of technical progress has the following relationships,

$$-\varepsilon_{C,t} \equiv -\frac{\partial C}{\partial t} \frac{1}{C} = -\frac{\partial G}{\partial t} \frac{1}{C} = -\frac{\partial \ell}{\partial t} \frac{1}{C} = \frac{\lambda F_t}{C} \quad (4.15)$$

Rearranging terms in the last equality in (4.15) and using (4.5) and the identity in (4.13) yields

$$-\varepsilon_{C,t} = \frac{\lambda}{C/Y} \frac{F_t}{Y} = \varepsilon_{C,Y} \varepsilon_{Y,t} \quad (4.16)$$

Equation (4.16) shows that the dual index of technical progress is related to the primal one through a measure of returns to scale. The relationship between the primal and dual measures of technical progress is first derived by Ohta (1974).

To use (4.16) for our purposes, first note the relationships between the cost and shadow cost shares, the elasticities of output with respect to various inputs and the returns to scale measure in (4.7), (4.11) and (4.12). The primal productivity index $\varepsilon_{Y,t}$ of (4.13) can be written as

$$\varepsilon_{Y,t} = \hat{Y} - \frac{S_K^*}{\varepsilon_{C,Y}} \hat{K} - \frac{S_L}{\varepsilon_{C,Y}} \hat{L} - \frac{S_R^*}{\varepsilon_{C,Y}} \hat{R} \quad (4.17)$$

Substituting this expression into (4.16) yields

$$-\varepsilon_{C,t} = \varepsilon_{C,Y} \hat{Y} - S_K^* \hat{K} - S_L \hat{L} - S_R^* \hat{R} \quad (4.18)$$

Rearranging terms to express (4.18) in terms of the MFP index in (4.14), we obtain

$$\begin{aligned} -\varepsilon_{C,t} &= \hat{A} - (\hat{Y} - S_K \hat{K} - S_L \hat{L} - S_R \hat{R}) + \varepsilon_{C,Y} \hat{Y} - S_K^* \hat{K} - S_L \hat{L} - S_R^* \hat{R} \\ &= \hat{A} + (\varepsilon_{C,Y} - 1) \hat{Y} + (S_K - S_K^*) \hat{K} + (S_R - S_R^*) \hat{R} \end{aligned} \quad (4.19)$$

This expression captures the biases in the conventional MFP measure, or the biases associated with the Solow residual. It shows that both non-constant returns to scale

and differences between the shadow and observed cost shares for the quasi-fixed inputs are causes of the biases. As there are other measurement issues in the application of MFP index, a few more steps are needed to go through to identify more biases associated with the measured MFP index.

The endogenous rental price of capital

As discussed in Chapter 2, a basic identity used in national accounts equates the value of output to the value of input. Using the value added measure, the value of output is distributed between the cost of capital and the remuneration of labour. At the aggregate level, the value of capital services - also called gross operating surplus (GOS) - represents the remuneration of fixed assets (capital) in the national accounts. In terms of the quantity of capital, the ABS applies the conventional perpetual inventory method with hyperbolic depreciation schedule to measure the volume of capital services (see Chapter 2 for details). In terms of the value, the cost of capital is derived residually by subtracting labour income/cost from the total value of output, as it is relatively easy to estimate the cost of labour input and difficult to directly measure the value of capital. While this practice preserves the accounting identity between the value of input and the value of output, it essentially determines that the rental price of capital (also called the user cost) has to be measured endogenously. This can be seen in the following identity,

$$pY \equiv r^m K + wL \quad (4.20)$$

where r^m indicates the endogenously derived rental price of capital (or user cost), and it emphasises its difference from the true rental price, which is determined outside the above identity. Note that in the productivity calculation for the mining industry, the standard practice in the national accounts is not to identify the resource inputs as a separate item of value added, thus (4.20) does not include the price and quantity of the resource inputs.

From equation (4.20), the endogenous rental price of capital can then be represented by

$$r^m = (pY - wL) / K \quad (4.21)$$

The corresponding measure of MFP growth is

$$\hat{A}^m = \hat{Y} - \left(\frac{r^m K}{pY} \right) \hat{K} - \left(\frac{wL}{pY} \right) \hat{L} \quad (4.22)$$

where \hat{A}^m indicates the measured MFP index.

Now it is straightforward to derive a relationship between \hat{A} and \hat{A}^m . Substituting \hat{Y} of (4.22) into (4.14) and simplifying yields

$$\hat{A} = \hat{A}^m + \left(\frac{wL}{C} - \frac{wL}{pY} \right) (\hat{K} - \hat{L}) + S_R (\hat{K} - \hat{R}) \quad (4.23)$$

The above equation shows that measured MFP will be identical to the Solow residual if there is no missing factor in the measured inputs; and if the share of labour in total cost is equal to the share of labour in the total value of output. Also, the two measures of MFP will be identical if the volumes of capital, labour and the missing inputs (i.e. the natural resource inputs in our case) are all growing at the same rate.

Incorporating the effects of mark-up factor and capacity utilisation

So far we have assumed perfectly competitive behaviour in both output and factor input markets. Now we relax this assumption to allow for imperfect output market. This generalisation is also necessary for the existence of non-constant returns to scale, as it is well known that competitive profit maximisation breaks down in the presence of increasing returns to scale (see, e.g. Hall 1988).

It is necessary to set up the following profit maximisation problem faced by a monopoly firm in the short run:

$$Max_y \{ p(Y)Y - C(w, r, K, R, Y, t) \} \quad (4.24)$$

where $p(Y)$ is the inverse demand function. The first-order, necessary condition for (4.24) is

$$\frac{\partial C}{\partial Y} = Y \frac{dp}{dY} + p = p \left(1 + \frac{dp}{dY} \frac{Y}{p}\right) \equiv p\mu \quad (4.25)$$

The optimisation behaviour of a producer under imperfect output market implies that output price of the producer is no longer equal to its marginal cost; rather, there is a mark-up of price over cost. This mark-up is captured by the factor $\mu \equiv \left(1 + \frac{dp}{dY} \frac{Y}{p}\right)$, $0 < \mu \leq 1$.

Using (4.25) and the definition of the elasticity of total cost with respect to output in (4.5), we obtain

$$\varepsilon_{C,Y} \equiv \frac{\partial C}{\partial Y} \frac{Y}{C} = \frac{\mu p Y}{C} \quad (4.26)$$

Using this result to replace pY in (4.23) yields

$$\begin{aligned} \hat{A} &= \hat{A}^m + \left(\frac{wL}{C} - \frac{wL}{C} \frac{\mu}{\varepsilon_{C,Y}} \right) (\hat{K} - \hat{L}) + S_R (\hat{K} - \hat{R}) \\ &= \hat{A}^m + S_L \left(1 - \frac{\mu}{\varepsilon_{C,Y}} \right) (\hat{K} - \hat{L}) + S_R (\hat{K} - \hat{R}) \end{aligned} \quad (4.27)$$

Replacing \hat{A} in (4.19) with the expression after the second equality in (4.27), we obtain

$$\begin{aligned} \hat{A}^m &= -\varepsilon_{C,t} + S_L \left(1 - \frac{\mu}{\varepsilon_{C,Y}} \right) (\hat{L} - \hat{K}) + (1 - \varepsilon_{C,Y}) \hat{Y} \\ &\quad + (S_K^* - S_K) \hat{K} + (S_R^* - S_R) \hat{R} + S_R (\hat{R} - \hat{K}) \\ &\equiv -\varepsilon_{C,t} + \Omega \end{aligned} \quad (4.28)$$

The expression after the first equality in (4.28) shows the decomposition of measured MFP growth, and it consists of six components. The first component ($-\varepsilon_{C,t}$) can be regarded as the ‘true’ or unbiased productivity growth. The second component reflects the combined effect of market power and returns to scale in the industry or firm. The third component measures the remaining effect of returns to scale. The fourth and fifth components capture the effect of capacity utilisation that is defined in

Hulten (1986) or Berndt and Fuss (1986), which will be discussed further next. The last component captures the remaining effect of the resource inputs or resource depletion on measured MFP.

Equation (4.28) also shows that the presence of the resource inputs can potentially increase the divergence between the measured and the true MFP from two different, but related sources. The first reflects the missing input effect, as the resource inputs are not accounted for in the conventional MFP measurement, despite the fact that they are used and implicitly paid by the firm or industry in its production. The second is the capacity utilisation effect, which is due to the quasi-fixity of the resource inputs, similar to the conventional capital. This stems from the fact that capital and resource inputs are treated symmetrically in our formulation of the cost minimisation problem, as discussed above. In the short run resource inputs are fixed while in the long run they are variable through the effect of depletion from cumulative production and the (opposite) effect of discoveries of new deposits. If the level of resource inputs can also be changed in the short run, like labour, the capacity utilisation effect from the resource inputs will disappear, but the missing input effect still remains.

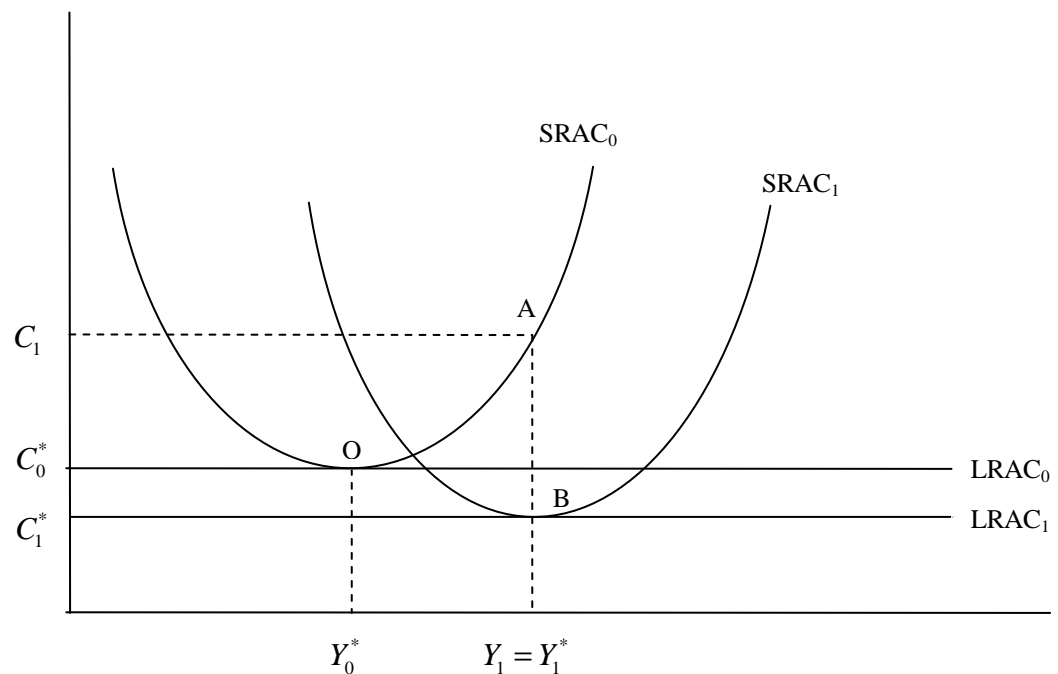
In the following discussion of the issues of capacity utilisation, the focus is on one of the quasi-fixed inputs, the conventional capital. The analogous analysis can be carried over to the natural resource inputs. While the quasi-fixity is common to the conventional capital and the natural resource inputs, there are many differences between the two types of inputs. For example, it can be argued that the firm or industry has limited scope to adjust the nature resource inputs to a desired level even in the long run despite continuous effort in exploration activities. However, these differences, apart from the measurement issues, seem unimportant in our model presented above, as it is intended to explain a mainly short-run phenomenon. In the short run, the issue of capacity utilisation is prominent in an industry that is highly sensitive to the amount of capital and resource inputs available for production uses.

From (4.28), if $S_K^* > S_K$, which is equivalent to $Z_K > r$, then the marginal contribution of capital is greater than its market price. Thus, the firm has incentives

to invest in additional stock of capital. This situation can arise because capital stock is quasi-fixed. When the firm produces the output at a level that is greater than its long-run equilibrium level ($Y > Y^*$), where Y^* denotes long-run equilibrium level of output, a greater quantity of variable inputs has to be applied to the quasi-fixed stock of capital in the short run, thus in this sense, the capacity is over-utilised. As a result, the capital stock earns a quasi-rent that exceeds the market rent, r , which may be thought of as a long-run rent earned if output is at its long-run equilibrium level.

This concept of capacity utilisation is due to Berndt and Fuss (1986) who define that the rate of capacity utilisation is greater (less) than unity, when $Y > Y^*$, or equivalently $Z_K > r$ or $S_K^* > S_K$ ($Y < Y^*$ or $Z_K < r$ or $S_K^* < S_K$). Based on this definition, Berndt and Fuss (1986) and Hulten (1986) further analyse the effect of capacity utilisation on the difference between the true and measured MFP. The following diagram illustrates the effects of capacity utilisation on the measured productivity growth.

Figure 4.2: Effects of capacity utilisation on measured MFP when the ‘true’ productivity growth is positive



For illustrative purposes, assume that the firm operates under the conditions of constant returns to scale and constant input prices in the long run. This implies that the firm's long-run average cost function (LRAC) is a horizontal line as shown in Figure 4.2. As the input prices remain constant, vertical shifts in LRAC curves represent the true changes in MFP. The short-run average cost curves (SRAC) are U-shaped because capital is quasi-fixed in the short run³⁹. The position and shape of the SRAC curves are dependent on technology, output quantity, input prices and quantities. It is well known that each SRAC curve is tangent to the LRAC curve at an output level that is associated with the minimum level of short-run cost.

The initial equilibrium level of production and cost are at point $O(C_0^* Y_0^*)$ where $SRAC_0$ is tangent to $LRAC_0$. Now suppose that under a demand driven boom, the firm increases the level of production in period 1 to Y_1 with the increased average cost at C_1 on the initial SRAC curve. For clarity in illustration, it is assumed that Y_1 is also the new equilibrium level of output (i.e. $Y_1 = Y_1^*$). Based on Berndt and Fuss (1986)'s notion of capacity utilisation as outlined above, at point $A(C_1 Y_1)$, the period 0 capacity is over utilised, as the level of output is above the initial long-run equilibrium level of production Y_0^* . This also implies that the shadow price of capital is greater than the market price, and the firm has incentives to invest in additional capital stock.

When the firm increases the stock of capital to the desired level in period 1, the SRAC curve shifts to the right to $SRAC_1$. The average cost is decreased to the level where the new short-run average cost curve ($SRAC_1$) is tangent to the new long-run average cost curve ($LRAC_1$) at point $B(C_1^* Y_1^*)$, which is lower than point $O(C_0^* Y_0^*)$ due to technological progress. This implies that at point $B(C_1^* Y_1^*)$, the capacity is fully utilised in period 1. Thus, the rate of capacity utilisation has to decrease moving from point A (a point associated with over-utilised capacity) to point B. However, if capital does not reach the desired level in period 1 and/or the level of

³⁹ The underlying short-run total cost is a cubic function of output.

output does not reach Y_1^* (i.e. $Y_1 < Y_1^*$), the capacity can be underutilised in period 1. This means further adjustments are required to reach the new long-run equilibrium.

If only the two data points $O(C_0^* Y_0^*)$ and $A(C_1 Y_1)$ are observed in the two periods under the consideration and if it is incorrectly assumed that both points represent the long-run equilibrium where the capacity is fully utilised, the traditional Solow residual measures the MFP growth as the negative of the logarithm of C_1 / C_0^* , which is negative, indicating a decline in productivity. But the true MFP growth should involve points $O(C_0^* Y_0^*)$ and $B(C_1^* Y_1^*)$, which is positive as the long-run average cost decreases ($C_1^* < C_0^*$) over time. The ‘true’ measure of MFP growth, $-\varepsilon_{C,t}$ in (4.19) should also be positive in this case, as it is invariant to the short-run utilisation effect.

Going back to equation (4.28), it is clear that measured MFP will overstate/understate the true level of productivity growth if Ω is positive/negative. However, the sign of Ω cannot be determined a priori, and it has to be estimated with the data. In the special case where there are constant returns to scale, perfect competition and a full capacity utilisation, the first four terms in Ω will be zero. If the resource inputs also decline over time ($\hat{R} < 0$), but with a positive growth in capital stock, then measured MFP will understate the true productivity growth (i.e. $\Omega < 0$ in (4.28)).

In another special case where there are constant returns to scale, perfect competition and the same rate of changes in capital and resource inputs, the sign of Ω is then determined by whether the capacity is over or under utilised. Measured MFP will understate the true productivity growth if the rate of capacity utilisation is less than unity (i.e. $S_K^* < S_K$ and $S_R^* < S_R$, thus $\Omega < 0$). This situation corresponds to the case in which the level of output is below Y_1^* in period 1 (i.e. $Y_1 < Y_1^*$). However, the extent of this underestimation is determined by the magnitude of various parameters, which has to be obtained empirically.

In the next section, a variable cost function is estimated for Australia's mining industry. While it would be superior to estimate a separate function for each of the sub-industries in Australia's mining, the data limitation means that the only possible focus is on the aggregate mining. The estimated coefficients from the variable cost function are used to determine the magnitude of various components in the decomposition formula in (4.28).

A similar approach is adopted by Rodriguez and Arias (2008) in their study on estimating the effects of resource depletion on coal mining productivity in Spain. However, the decomposition formula used here is different from theirs in two respects. First, the effect of market power is incorporated in the decomposition, while Rodriguez and Arias (2008) ignore this effect. Second, the way in which the rate of return to capital is commonly measured by national statistical agencies, thus how MFP growth is measured in practice, is taken into account specifically here, while Rodriguez and Arias (2008) do not consider any measurement issues in their decomposition of MFP growth.

4.3.2 Estimating a variable cost function

The various components in the decomposition equation (4.28) can be derived by estimating a variable cost function. In practice, however, we are constrained by the available data that can be used for the estimation. Particularly, as discussed previously, the resource inputs contain many intangible factors that cannot be quantified in a systematic fashion. As such, a proxy variable has to be used in econometric estimation in order to gain some quantitative insights into the impact of natural resource inputs on measured productivity.

Among the recent studies as reviewed previously, Rodriguez and Arias (2008) use the level of coal reserves to control for the effect of resource depletion (i.e. the decline in natural resource inputs) in their estimation of the biases associated with the Solow residual for the Spanish coal industry. The study by Topp et al. (2008) constructs a yield index that is largely based on the ore grades for various minerals in

the sub-sectors of Australian mining. This yield index is intended to capture the changes in resource inputs.

Here, the part of productive capital stock in mining that is attributed to mineral and petroleum exploration is used as a proxy for resource inputs. This amounts to separating the measure of mining capital services into two parts - one is the conventional productive capital stock similar to that used in other industries⁴⁰, and the other is accumulated only by the investment in mineral and petroleum exploration, which is unique to mining. This also implies that the resource inputs used here are also subject to depreciation, the same as the conventional capital stock⁴¹.

Like any proxy variables used in other studies, the productive capital stock from mineral and petroleum exploration does not correspond strictly to a measure of the resource inputs. While not all exploration activities result in discoveries of new deposits, they are a prerequisite for maintaining as well as enhancing the quality and quantity of resource inputs that are essential for mining production. The increase in investment in mineral and petroleum exploration partly reflects the decrease in natural resource inputs, as more exploration activity can be seen as a response to the decline in quantity and quality of mineral and petroleum reserves. From a practical perspective, this proxy variable is directly available from the ABS, which is based on the measurement framework that is consistent with that for the other variables used in this study⁴².

The following sub-section presents a translog variable cost function in which the proxy variable for resource inputs plays an important role.

⁴⁰ In mining, they include computer software, computers, electrical and electronic equipment, industrial machinery and equipment, other plant and equipment, other transport equipment, road vehicles, non-dwelling construction, non-farm inventories and land.

⁴¹ See OECD (2001) for a discussion of how the rate of depreciation is related to the age-price profile and the age-efficiency profile that is outlined in Chapter 2.

⁴² For future work, it might be useful to also explicitly allow for depletion, the amount tied to the level of cumulative production, which may not be adequately captured by the depreciation measure in the stock of mineral and petroleum exploration.

The translog variable cost function

The translog cost function is one of the popular choices of functional form in empirical production economics. Its broad applicability is largely due to its correspondence to a flexible underlying production technology that places minimum *a priori* restrictions. Recent applications of this functional form in the studies of mining industry include the work by Azzalini, et al. (2008) and Rodriguez and Arias (2008), where the latter employs a variable cost function. Various econometric issues associated with specifying and estimating a translog cost function are discussed extensively in Berndt (1991).

The variable cost function used in this study only contains one variable input, namely labour, while both capital and resource inputs are treated as fixed inputs in the short run. This is the result of the value added output measure used in the study and our emphasis on the short-run and long-run distinctions, as discussed above. This translog variable cost function can be written as

$$\begin{aligned}
 \ln VC = & \beta_0 + \beta_w \ln w + \beta_Y \ln Y + \beta_R \ln R + \beta_K \ln K \\
 & + \frac{1}{2} \left[\beta_{ww} (\ln w)^2 + \beta_{KK} (\ln K)^2 + \beta_{RR} (\ln R)^2 + \beta_{YY} (\ln Y)^2 \right] \\
 & + \beta_{Kw} \ln K \ln w + \beta_{Rw} \ln R \ln w + \beta_{KR} \ln K \ln R \\
 & + \beta_{KY} \ln K \ln Y + \beta_{RY} \ln R \ln Y + \beta_{wY} \ln w \ln Y \\
 & + \beta_{tw} t \ln w + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \beta_{Yt} t \ln Y
 \end{aligned} \tag{4.29}$$

where t is a time index and all other variables are as defined previously. This translog form is similar to what is used in Rodriguez and Arias (2008)⁴³. Differentiating (4.29) with respect to $\ln w$ yields

$$\frac{\partial \ln VC}{\partial \ln w} = \beta_w + \beta_{ww} \ln w + \beta_{Kw} \ln K + \beta_{Rw} \ln R + \beta_{wY} \ln Y + \beta_{tw} t \tag{4.30}$$

Shephard's Lemma implies that $\partial VC / \partial w = L$, thus

⁴³ But for some unspecified reasons, the interaction term between capital and resource input and that between capital and output are excluded in their unrestricted translog variable cost function. See equation (23) on page 403 in Rodriguez and Arias (2008).

$$\frac{\partial \ln VC}{\partial \ln w} = \frac{wL}{VC} = 1 \quad (4.31)$$

since labour is the only variable input in the short run in our specification.

Economic theory requires that the variable cost function is homogenous of degree 1 in variable input prices, given K , R and Y . This implies that $\beta_w = 1$, $\beta_{ww} = 0$, $\beta_{Kw} = 0$, $\beta_{Rw} = 0$, $\beta_{wY} = 0$. Combined with (4.30) and (4.31), the homogeneity gives rise to the following full set of restrictions

$$\beta_w = 1, \beta_{ww} = 0, \beta_{Kw} = 0, \beta_{Rw} = 0, \beta_{wY} = 0, \beta_{tw} = 0 \quad (4.32)$$

Applying the above restrictions, the translog cost function (4.29) can be simplified to

$$\begin{aligned} \ln VC = & \beta_0 + \ln w + \beta_Y \ln Y + \beta_R \ln R + \beta_K \ln K \\ & + \frac{1}{2} \left[\beta_{KK} (\ln K)^2 + \beta_{RR} (\ln R)^2 + \beta_{YY} (\ln Y)^2 \right] \\ & + \beta_{KR} \ln K \ln R + \beta_{KY} \ln K \ln Y + \beta_{RY} \ln R \ln Y \\ & + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \beta_{Yt} t \ln Y \end{aligned} \quad (4.33)$$

Although this reduces the number of coefficients that need to be estimated from 19 to 12, it is still large relative to the sample size that is available⁴⁴. As a further necessary step, the equilibrium condition of competitive output pricing behaviour is imposed, which can be expressed as

$$\begin{aligned} p_Y = \frac{\partial VC}{\partial Y} = \frac{VC}{Y} \frac{\partial \ln VC}{\partial \ln Y} \\ = \frac{VC}{Y} (\beta_Y + \beta_{YY} \ln Y + \beta_{KY} \ln K + \beta_{RY} \ln R + \beta_{wY} \ln w + \beta_{Yt} t) \end{aligned} \quad (4.34)$$

Using the restrictions contained in (4.32), the above equilibrium condition is reduced to

$$p_Y = \frac{VC}{Y} (\beta_Y + \beta_{YY} \ln Y + \beta_{KY} \ln K + \beta_{RY} \ln R + \beta_{Yt} t) \quad (4.35)$$

⁴⁴ The annual data available are from 1974-75 to 2006-07, which forms 33 annual observations. The data sources and the related issues will be discussed in the next sub-section.

Note that the variable cost in our case is just equal to the value of labour input. Thus, the above equilibrium condition is equivalent to

$$\frac{1}{S_L} = \beta_Y + \beta_{YY} \ln Y + \beta_{KY} \ln K + \beta_{RY} \ln R + \beta_{Yt} t \quad (4.36)$$

Appending the error terms to the inverse share equation (4.36) and the restricted translog cost function (4.33), the relevant coefficients can be estimated with more precisions using this two-equation system than using (4.33) alone.

While the above equation system approach seems practical given the available sample size, the downside of this is that the effect of the producer's market power on measured MFP growth cannot be estimated, as the pure competition in the output market is reflected by the optimal condition that is used in (4.36). Despite this limitation, the remaining factors of measured MFP can still be decomposed.

Data and variable constructions

There are 33 annual observations available, from 1974-75 to 2006-07, for estimating the parameters in (4.33) and (4.36). The following table contains a summary of data sources for each of the variables used in the estimation and it also outlines how the variables are constructed.

Table 4.1: Data sources and construction

| Variable | Source | Notes |
|---|---|--|
| Variable cost, <i>VC</i> | <p>a) 1989-90 to 2006-07: ABS Cat. No. 5204.0 Australian System of National Accounts, Table 48. Compensation of Employees, by Industry - Current prices</p> <p>b) 1974-75 1988-89: ABS unpublished national accounts data on total labour income from incorporated and un-incorporated businesses</p> | The variable cost is just the cost of obtaining labour services. The data are spliced to connect the two periods and then indexed to 1 at the starting of the sample period |
| Nominal wage rate, <i>w</i> | <p>a) 1984-85 to 2006-07: ABS Cat. No. 6302.0 Average Weekly Earnings, Australia, Table 10I. Average Weekly Earnings, Industry, Australia (Dollars) - Original - Persons, Total Earnings - mining</p> <p>b) 1974-75 to 1983-84: ABS Cat. No. 6350.0, Average weekly earnings, Table 5 Full-time adult non-managerial employees, average weekly earnings, industry, Australia, at November 1974-1990 (dollars) – persons - mining</p> | The earlier period data are provided by ABS customer service, as they are not available on the ABS website. The data are spliced to connect the two periods and then indexed to 1 at the starting of the sample period |
| Conventional capital services <i>K</i> | <p>Productive capital stock by assets, chain volume measure, excluding mineral and petroleum exploration and the corresponding rental prices for the different assets</p> <p>a) 1985-86 to 2006-07, ABS Cat. No. 5260.0.55.002 Experimental Estimates of Industry Multifactor Productivity, Australia: Detailed Productivity Estimates, Nov 2009.</p> <p>b) 1974-75 to 1984-85: ABS unpublished data on productive capital stock by asset and the corresponding data on rental prices</p> | Aggregation also includes the assets from unincorporated businesses. Applying the Tornqvist index for capital services and the corresponding weights as shown in equation (2.18) of Chapter 2. The weights are based on the rental prices. The index is scaled to 1 at the starting of the sample period |

| | | |
|---|--|---|
| Proxy for resource inputs: mineral and petroleum exploration, R | Productive capital stock for mineral and petroleum exploration, chain volume measure a) 1985-86 to 2006-07, ABS Cat. No. 5260.0.55.002 Experimental Estimates of Industry Multifactor Productivity, Australia: Detailed Productivity Estimates, Nov 2009 b) 1974-75 to 1984-85: ABS unpublished data on productive capital stock, chain volume measure | Indexed to 1 at the starting of the sample period |
| Volume of output, Y | Gross value added, Productivity Commission productivity database, which is based on both published and unpublished ABS data on the chain volume index of gross value added | Indexed to 1 at the starting of the sample period |

Results

A popular technique to estimate a system of equations in applied econometrics is to use the Seemingly Unrelated Regression (SUR)⁴⁵. This estimation procedure produces more efficient estimates of parameters than OLS when the errors across the equations in the system are contemporaneously correlated. In Chapter 3, this technique is applied to the estimation of R&D equations across different industries. Here the same procedure is used to estimate the coefficients in equations (4.33) and (4.36).

In the estimation of a variable cost function with multiple variable inputs, the cost share equations must add up to unity. To avoid singularity in the error covariance matrix, one of the share equations has to be dropped. This issue does not arise here as there is only one variable input in our specification, and no share equation needs to be estimated. However, the equilibrium condition (4.36) is introduced in order to improve the efficiency of estimating the coefficients in equation (4.33) by using SUR.

⁴⁵ Many original references on SUR, together with many early applied studies using this method can also be found in Berndt (1991).

As a common practice, the errors associated with the two equations are assumed to be multivariate normally distributed. EViews 6's Iterative SUR function is used to estimate the coefficients. This estimation procedure updates the estimates of the error covariance matrix and repeats the SUR until changes from one iteration to the next in the estimated coefficients and estimated error covariance matrix become arbitrarily small. The parameter estimates using the Iterative SUR are numerically equivalent to those of the maximum likelihood estimation (Berndt 1991).

Like many other studies that estimate the translog cost function, the possible non-stationarity in the data is assumed to be unimportant, particularly given the lack of power for the unit root tests in a small sample. The main purposes here are focused on obtaining some plausible estimates of the relevant coefficients for carrying out the decomposition exercise. Furthermore, as the time index has been included in the system, this is appropriate for estimating a trend-stationary process. If the data were indeed non-stationary, the log-level relationships could be seen as some long-run conditions that are based on producer's optimal behaviour in the equilibrium states. While the variable cost function includes the short-run behaviour by construction, (4.36) is based on the equilibrium condition that imposes competitive output pricing behaviour.

Similar to Topp et al. (2008), experiments are conducted with using lags for capital services and resource inputs in order to take account of the long lead time from the investment in capital goods to their use in production. It turns out that it is appropriate to lag both capital variables by one year in the empirical variable cost function.

The estimation results are presented in Table 4.2, while the detailed estimation output directly from EViews 6 is reported in Appendix D. The adjusted R-squared for the variable cost function (4.33) is 0.925 and for the equilibrium condition (4.36) is 0.806. The values of Durbin-Watson statistic are 2.16 for (4.33) and 1.18 for (4.36). This indicates that autocorrelation is not a serious issue, although its presence does not bias the estimates.

Table 4.2: Estimation results for the restricted translog variable cost function

| Parameter | Estimate | Standard error | <i>t</i> -statistic | probability |
|--------------|----------|----------------|---------------------|-------------|
| β_0 | 0.1555 | 0.1822 | 0.8537 | 0.3973 |
| β_K | -4.2796 | 3.1396 | -1.3631 | 0.1788 |
| β_R | 6.5798 | 2.0080 | 3.2768 | 0.0019 |
| β_Y | 4.3024 | 0.3011 | 14.2898 | 0.0000 |
| β_{KK} | 1.8363 | 3.1430 | 0.5842 | 0.5616 |
| β_{RR} | -5.0914 | 7.2774 | -0.6996 | 0.4873 |
| β_{KR} | -6.1139 | 4.7173 | -1.2961 | 0.2008 |
| β_{KY} | 8.8343 | 1.8357 | 4.8124 | 0.0000 |
| β_{RY} | -3.8101 | 0.5850 | -6.5125 | 0.0000 |
| β_t | -0.0914 | 0.0640 | -1.4280 | 0.1594 |
| β_{tt} | 0.0100 | 0.0049 | 2.0592 | 0.0446 |
| β_{Yt} | -0.2677 | 0.0821 | -3.2594 | 0.0020 |
| β_{YY} | 0.3138 | 0.6159 | 0.5095 | 0.6126 |

The estimated elasticity of variable cost with respect to resource inputs, β_R is large and significantly different from zero, indicating the importance of resource inputs in the mining production. Note that the coefficients for several variables in Table 4.2 are statistically insignificant. However, a test that all these coefficients are jointly zero is strongly rejected.

The requirements for a well behaved cost function include that it is non-decreasing and concave in input prices. A non-decreasing cost function implies that the first derivative of a cost function with respect to input prices must be non-negative. As the variable cost function in our case only contains one variable input, that is labour, this requirement is satisfied by the imposed restriction, $\beta_w = 1$, as shown in (4.33).

Concavity of the cost function in input prices requires that the matrix of substitution elasticities be negative semi-definite. Again, due to the single variable input in our variable cost function of (4.29), this requirement is trivially satisfied.

Several parameters of interest cannot be obtained directly from the results in Table 4.2 and they are derived in the following along with the standard errors. The first major component in the decomposition of measured MFP in (4.28) is the dual

measure of technological change, $-\varepsilon_{C,t}$. Taking the partial derivative with respect to time, t for both sides of the variable cost function (4.33) yields

$$\frac{\partial \ln VC}{\partial t} = \beta_t + t\beta_{tt} + \beta_{Yt} \ln Y \quad (4.37)$$

Using (4.15) and (4.37), we obtain

$$\begin{aligned} -\varepsilon_{C,t} &\equiv -\frac{\partial C}{\partial t} \frac{1}{C} = -\frac{\partial G}{\partial t} \frac{1}{C} = -\frac{\partial \ln VC}{\partial t} \frac{VC}{C} \\ &= -(\beta_t + \beta_{tt}t + \beta_{Yt} \ln Y) \frac{VC}{C} \\ &= -(\beta_t + \beta_{tt}t + \beta_{Yt} \ln Y) S_L \end{aligned} \quad (4.38)$$

To obtain the standard errors for the estimates of $-\varepsilon_{C,t}$, the following formula is used to calculate the variance,

$$\begin{aligned} \text{var}(\varepsilon_{C,t}) &= \text{var}[(\beta_t + \beta_{tt}t + \beta_{Yt} \ln Y) S_L] \\ &= (S_L)^2 [\text{var}(\beta_t) + t^2 \text{var}(\beta_{tt}) + (\ln Y)^2 \text{var}(\beta_{Yt}) \\ &\quad + 2t \text{cov}(\beta_{\beta_t}, \beta_{tt}) + 2 \ln Y \text{cov}(\beta_t, \beta_{Yt}) + 2t \ln Y \text{cov}(\beta_{tt}, \beta_{Yt})] \end{aligned} \quad (4.39)$$

The results of these calculations using the sample mean are shown in Table 4.3.

The estimate for $\varepsilon_{C,Y}$, the inverse of the returns to scale measure, can also be derived using the observed data. Based on the definition of the inverse of returns to scale in (4.5), and taking the partial derivative with respect to the log of value added, $\ln Y$ for both sides of the variable cost function (4.33), we obtain

$$\begin{aligned} \varepsilon_{C,Y} &\equiv \frac{\partial \ln C}{\partial \ln Y} = \frac{\partial C}{\partial Y} \frac{Y}{C} = \frac{\partial VC}{\partial Y} \frac{Y}{C} = \frac{\partial \ln VC}{\partial \ln Y} \frac{VC}{Y} \frac{Y}{C} \\ &= (\beta_Y + \beta_{YY} \ln Y + \beta_{KY} \ln K + \beta_{RY} \ln R + \beta_{Yt}t) S_L \end{aligned} \quad (4.40)$$

Similarly, the standard errors for $\varepsilon_{C,Y}$ can be calculated using

$$\begin{aligned}
\text{var}(\varepsilon_{C,Y}) = & (S_L)^2 [\text{var}(\beta_Y) + (\ln Y)^2 \text{var}(\beta_{YY}) + (\ln K)^2 \text{var}(\beta_{KY}) \\
& + (\ln R)^2 \text{var}(\beta_{RY}) + t^2 \text{var}(\beta_{Yt}) + 2 \ln Y \text{cov}(\beta_Y, \beta_{YY}) \\
& + 2 \ln K \text{cov}(\beta_Y, \beta_{KY}) + 2 \ln R \text{cov}(\beta_Y, \beta_{RY}) + 2t \text{cov}(\beta_Y, \beta_{Yt}) \\
& + 2 \ln Y \ln K \text{cov}(\beta_{YY}, \beta_{KY}) + 2 \ln Y \ln R \text{cov}(\beta_{YY}, \beta_{RY}) + 2t \ln Y \text{cov}(\beta_{YY}, \beta_{Yt}) \\
& + 2 \ln K \ln R \text{cov}(\beta_{KY}, \beta_{RY}) + 2t \ln K \text{cov}(\beta_{KY}, \beta_{Yt}) + 2t \ln R \text{cov}(\beta_{RY}, \beta_{Yt})]
\end{aligned}
\tag{4.41}$$

The results of these calculations based on the sample mean are also shown in Table 4.3.

Table 4.3: Estimates of technological change and inverse of returns to scale

| | Dual measure of technical change $-\varepsilon_{C,t}$ | Inverse of returns to scale $\varepsilon_{C,Y}$ |
|-------------------|--|--|
| Point estimate | 0.020 | 1.089 |
| Standard error | 0.011 | 0.026 |
| Interval estimate | (0.00, 0.04) | (1.04, 1.14) |

As the above estimates are non-linear combinations of the random variables, they may not be normally distributed. It follows that the standard significance test using the t-statistic may not be applicable in this case. The above table also includes the interval estimates that are calculated using the point estimate plus or minus 2 times the standard error. However, since the distribution may not be normal, the interval may not be associated with a 95% confidence level, as in the normally distributed case. While it may be possible to use Monte Carlo simulations to estimate the empirical distributions and produce alternative interval estimates for the variables of interest, this is left as a topic for future work, as the point estimates presented above are sufficient in applying the decomposition formula to explain the mining productivity paradox, which is the main focus of this chapter. Nevertheless, the interval estimates presented in the table are indicative of the value ranges within which the estimates may lie.

The above results show that the ‘true’ rate of technological change in Australian mining is about 2.0% per annum between 1974-75 and 2006-07, while the returns to scale is 0.93 ($\approx 1/1.089$), indicating a moderate level of decreasing returns to scale. Based on the same sample period as in this study, Topp et. al. (2008) estimate that the average annual MFP growth in Australian mining is 2.5% with depletion effects removed, and is 2.3% with the removal of depletion effects as well as adjusting for investment lags in capital services.

Despite the fact that various coefficients and variables are involved in estimating the dual measure of technical change and returns to scale as shown in equations (4.38) and (4.40), the estimates for the two measures seem plausible, and are quite stable over the entire sample. This is shown in the following table⁴⁶.

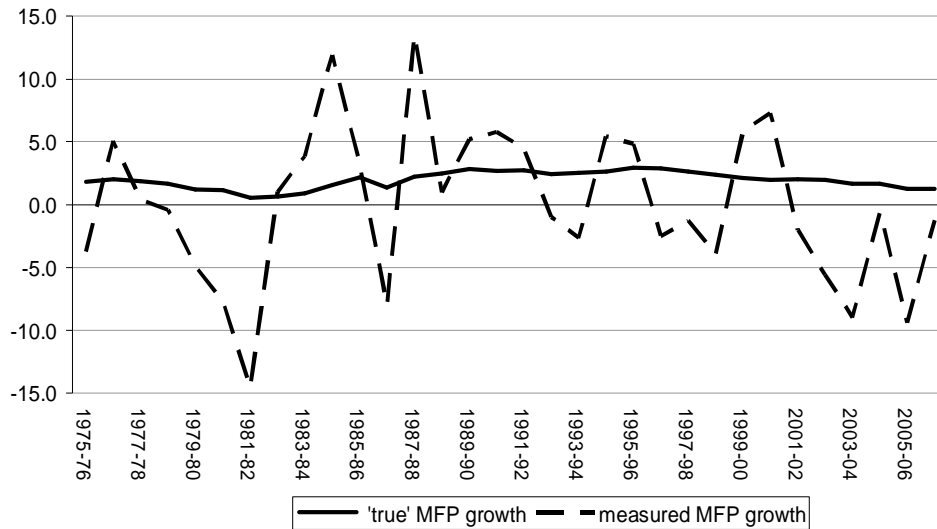
⁴⁶ However, the estimated coefficients for the translog variable cost function are sensitive to the changes in specifications. This problem may be caused by the lack of degrees of freedom in the estimation, which is typically encountered in the estimation of the translog form using low frequency data.

Table 4.4: Annual estimates of the ‘true technical change and returns to scale

| | Dual measure of technical change (%) | Returns to scale |
|----------------|--------------------------------------|------------------|
| 1974-75 | 2.6 | 0.8 |
| 1995-76 | 1.8 | 0.9 |
| 1976-77 | 2.0 | 1.0 |
| 1977-78 | 1.9 | 1.0 |
| 1978-79 | 1.7 | 1.0 |
| 1979-80 | 1.2 | 1.1 |
| 1980-81 | 1.2 | 0.9 |
| 1981-82 | 0.6 | 0.8 |
| 1982-83 | 0.6 | 0.8 |
| 1983-84 | 0.9 | 0.9 |
| 1984-85 | 1.6 | 1.1 |
| 1985-86 | 2.2 | 1.0 |
| 1986-87 | 1.4 | 0.9 |
| 1987-88 | 2.2 | 0.9 |
| 1988-89 | 2.5 | 0.9 |
| 1989-90 | 2.9 | 0.9 |
| 1990-91 | 2.7 | 1.0 |
| 1991-92 | 2.7 | 1.0 |
| 1992-93 | 2.5 | 1.0 |
| 1993-94 | 2.5 | 0.9 |
| 1994-95 | 2.6 | 1.0 |
| 1995-96 | 2.9 | 0.9 |
| 1996-97 | 2.9 | 0.8 |
| 1997-98 | 2.6 | 0.8 |
| 1998-99 | 2.4 | 0.8 |
| 1999-00 | 2.1 | 0.9 |
| 2000-01 | 2.0 | 1.1 |
| 2001-02 | 2.0 | 1.0 |
| 2002-03 | 2.0 | 0.9 |
| 2003-04 | 1.7 | 0.8 |
| 2004-05 | 1.7 | 0.8 |
| 2005-06 | 1.2 | 0.9 |
| 2006-07 | 1.3 | 0.9 |
| Average | 2.0 | 0.9 |

Figure 4.3 compares the two sets of estimates of MFP growth in Australian mining; one is based on the dual measure of technological change that is estimated using the variable cost function, while the other is the measured MFP index published by the ABS (ABS 2008).

Figure 4.4: ‘True’ versus measured MFP growth (%)



As can be seen, the measured MFP growth is much more volatile than the MFP growth estimated by the variable cost function that includes a proxy variable for resource inputs with lagged variables for capital and resource inputs. Intuitively, if MFP index truly reflects technological progress as is intended by this measure, then the measured MFP growth shown in Figure 4.3 seems subject to large biases, as it has recorded more years of technological *regress* than the years of progress (17 versus 15), which appears quite unlikely.

The difference between the ‘true’ and measured MFP growth (which is about 1.96% on average over the sample period) is the biases that can be attributed to various factors. They are captured by the decomposition formula (4.28) presented above. As discussed previously, the second and third components in (4.28) reflect the effects of market power and returns to scale. As perfect competition is assumed to derive one of the equations for the estimation, this leaves only the scale effect in the components, as the mark-up factor equals one, i.e. $\mu = 1$.

In order to obtain the other components in the decomposition formula (4.28), estimates for the shadow cost shares for the conventional capital and resource inputs need to be derived. Again, using the variable cost function (4.29) and the definitions

for the corresponding shadow cost shares, the following equations relate the shadow cost shares to the observed data and estimated coefficients.

$$S_K^* \equiv \frac{Z_K K}{C} = \frac{-\left(\frac{\partial VC}{\partial K}\right) K}{C} = \frac{-\left(\frac{\partial \ln VC}{\partial \ln K}\right) VC}{C} = -\frac{\partial \ln VC}{\partial \ln K} S_L \quad (4.42)$$

$$= -(\beta_K + \beta_{KK} \ln K + \beta_{KR} \ln R + \beta_{KY} \ln Y) S_L$$

$$S_R^* \equiv \frac{Z_R R}{C} = \frac{-\left(\frac{\partial VC}{\partial R}\right) R}{C} = \frac{-\left(\frac{\partial \ln VC}{\partial \ln R}\right) VC}{C} = -\frac{\partial \ln VC}{\partial \ln R} S_L \quad (4.43)$$

$$= -(\beta_R + \beta_{RR} \ln R + \beta_{KR} \ln K + \beta_{RY} \ln Y) S_L$$

Using equations (4.38) to (4.43), we can now decompose measured MFP growth into four major components according to (4.28), namely, the true MFP growth, $-\varepsilon_{C,t}$; the component reflecting scale effect, $S_L \left(1 - \frac{1}{\varepsilon_{C,Y}}\right) (\hat{L} - \hat{K}) + (1 - \varepsilon_{C,Y}) \hat{Y}$, the capital utilisation component, $(S_K^* - S_K) \hat{K}$, and the remaining component capturing the effect of resource inputs, $(S_R^* - S_R) \hat{R} + S_R (\hat{R} - \hat{K})$, which can be derived residually. The decomposition results using the average values over the sample are shown in Table 4.5.

Table 4.5: Decomposition of measured MFP (evaluated at the sample mean)

| Measured MFP growth | MFP growth based on the dual measure | Scale effect | Capital utilisation effect | Resource input effect |
|---------------------|--------------------------------------|--------------|----------------------------|-----------------------|
| 0.0001 | 0.0197 | -0.0022 | -0.0060 | -0.0114 |

All three components - scale effect, capacity utilisation effect and resource input effect - are negative, thus reducing the 'true' MFP growth. The negative scale effect is largely due to the presence of a moderate level of decreasing returns to scale. The resource input effect is the largest in absolute value compared with the other components. As discussed before, the resource input effect is a combination of the effects due to its quasi-fixity and the fact that natural resource inputs are excluded from measured MFP (as missing inputs). An alternative decomposition combines the capacity utilisation effects due to capital and resource inputs and attributes the remaining effect to missing resource inputs. This is reported in Table 4.6.

Table 4.6: A decomposition of measured MFP with capacity utilisation from both capital and resource inputs (evaluated at the sample mean)

| Measured MFP growth | MFP growth based on the dual measure | Scale effect | Capacity utilisation effect | Effect of missing resource inputs |
|---------------------|--------------------------------------|--------------|-----------------------------|-----------------------------------|
| 0.0001 | 0.0197 | -0.0022 | -0.0109 | -0.0065 |

The negative capacity utilisation effect from both capital and resource inputs is due to the fact that the respective shadow price is less than the corresponding market price, thus the rate of capacity utilisation is below unity, according to the definition of capacity utilisation discussed above. This implies that output is also below the new long-run equilibrium level. This situation is discussed above in relation to

Figure 4.2 and equation (4.28). Further adjustments may result in an overestimation of the ‘true’ MFP growth, as the short-run average cost is reduced when the industry increases the quasi-fixed inputs over time to approach the new long-run equilibrium output level.

In either case reported in the above tables, changes in resource inputs contribute negatively to measured MFP growth. This is consistent with the findings in other studies, which show a negative relationship between measured MFP and resource inputs, whether the latter is measured by a yield index in the case of Topp et. al. (2008), or captured by the cumulative output as in Young (1991) and Rodriguez and Arias (2008).

4.4 Conclusions

This chapter has investigated the main causes for the mining industry’s poor productivity performance as measured by the conventional MFP growth during the recent mining boom in Australia. It has long been known in the literature that the measure of productivity change in the extraction industry can be affected by the evolution of natural resource inputs. This has provided some useful clue to our investigation of this mining productivity paradox that appeared recently in Australia. It points to some underlying issues associated with measured MFP in mining, which can only be addressed appropriately by correcting for the biases arising from the measurement and from the simplifying assumptions used in deriving the measure.

To this end, a relationship is derived between the measured and ‘true’ MFP growth that separates the effects of returns to scale, market power, capacity utilisation and resource inputs on measured MFP. Also incorporated is the effect of the endogenously derived rental price for capital, a common practice by the national statistical agencies, in the derivation of our decomposition equation. A translog variable cost function is then estimated that provides the parameter estimates for the various components in the decomposition formula.

The results show that the average MFP growth in Australian mining based on the dual measure of technical change over the sample period is nearly 2%, rather than 0.01% from the published index. Also, the model-based MFP growth has been quite stable, in contrast to the large positive and negative swings observed in the official mining MFP statistics. The results indicate that changes in natural resource inputs have subtracted the 'true' MFP growth by 1.14 percentage points, while the effects of capacity utilisation and returns to scale also have sizable, but relatively less negative impact on the measured MFP growth in Australian mining.

As stated in Chapter 2, measured MFP growth reflects not only technological progress, but also non-constant returns to scale, efficiency changes, variations in capacity utilisation and measurement errors. The results in this chapter are concrete examples for this statement. More importantly, they highlight the concern that focusing on measured MFP alone may give us misleading information about the true extent of productivity improvement in the mining industry. Consequently, caution should be exercised in using the MFP estimates based on the conventional measure. Particularly, great care has to be taken in using these estimates in policy decisions for the mining industry.

Chapter 5

Summary and conclusions

5.1 Summary of the major findings

The thesis has covered three major topics on the industry-level productivity growth in Australia. While there are distinctive issues and focuses associated with each of these topics, one common theme throughout the thesis is to explore the interactions between economic measurement and production economics.

First, the thesis has discussed several issues associated with measuring industry-level MFP. Two approaches to estimating the industry-level MFP index have been considered: the input-output based approach, which is developed by Statistics Canada (Durand 1996, Cas and Rymes 1991), and the one recommended by the OECD (OECD 2001). The latter one is closely related to the approach developed by Jorgenson et al. (1987), which is also a bottom-up, non-parametric approach based on production economics. After considering the current ABS data environment, estimation of industry-level MFP follows the approach recommended by the OECD (2001). Experimental estimates of MFP are presented based on both gross output and value added for the 12 market-sector industries in Australia.

Since the aggregate market-sector MFP indices can also be derived from the industry-level estimates, this is used as a way of assessing the plausibility of the industry-level MFP estimates. It is found that the differences are small based on a comparison between the MFP estimates aggregated from the industry-level results and those currently published by the ABS. This tends to validate the plausibility of the industry-level MFP index derived in the thesis.

To understand the causes for the differences observed in the validation exercise, issues of consistency in aggregation are also investigated. The components of the two indices are compared and it is found that the small differences are partly due to

different output measures and different index number formulae for aggregating labour inputs applied in the two approaches.

A more important source of the differences is, however, directly related to the models of production underlying the two approaches to the measurement of aggregate MFP. This is revealed by an aggregation relation derived by Jorgenson et al. (1987), which augments the Domar aggregation formula (Domar 1961) that links the industry-level MFP index with the aggregate one. Using the augmented Domar aggregation formula, estimates of MFP growth derived from the aggregate approach are decomposed into a weighted sum of industry-level MFP growth and weighted sums of rates of growth of value added, capital input and labour input, which reflect the contributions of the reallocations of these outputs and inputs among industries.

Under the framework of production economics, a derivation of the Domar aggregation formula in its original form is provided without relying on the assumption of equal prices for the primary inputs used by the industries. The Domar aggregation formula in the augmented form is also derived according to Jorgenson et al. (1987).

The open economy MFP estimates for the aggregate market-sector are also estimated using an approach developed by Gollop (1983, 1987). While there are several other approaches dealing with the open economy MFP measurement, a generally accepted solution to the open economy issue within the non-parametric growth accounting framework for estimating MFP has yet to crystallise. This may be the topic for future work.

Having analysed the various conceptual and practical issues in the estimation of the industry-level MFP index, the second major part of the thesis focuses on using the recent Australian data at the one-digit (ANZSIC division) level to estimate the returns to R&D in several Australian industries.

The empirical models used for the estimation of the returns to R&D are based on the conventional Cobb-Douglas production function. However, an alternative specification is also derived and applied that specifically adjusts for the effects of

double counting and expensing biases (Schankerman 1981). The biases in the estimates are the result of using the double-counted R&D expenditure data as well as using the output measures from national accounts in which the expenditure on R&D is treated as a current expense, rather than as an investment. The adjustments made in the alternative specification make novel use of known results on mis-specification biases in econometrics.

Using various model specifications, some evidence is found of a positive relationship between the industry's own R&D capital stock and its productivity growth. However, the estimated returns in some industries are very high and appear implausible. Also, the results are highly sensitive to the choice of the control variables. This may reflect the problems of small sample and the quality of the industry-level data used in the regressions. Future work may concentrate on obtaining a larger sample and improving the quality of the various variables used for the industry-level regressions.

While the main empirical results from the second major part of the thesis appear somewhat less encouraging, identifying and attempting to address these problems are also contributions to the evidence-based debate on the effectiveness of R&D at the industry level in Australia. Particularly, the conclusion from the study has direct policy implications. It cautions policy makers against using econometric estimates as 'hard evidence' to support R&D related policies without knowing the many limitations and qualifications associated with the results.

The last major part of the thesis investigates the main causes for the mining industry's poor productivity performance as measured by the conventional MFP index during the recent mining boom in Australia. It has long been known in the literature that the measure of productivity change in the extraction industry can be affected by the evolution of natural resource inputs. This has provided a useful clue to our investigation of the mining productivity paradox appeared recently in Australia. It points to some underlying issues associated with measured MFP in mining, which can only be addressed appropriately by correcting for the biases

arising from the missing resource inputs in the input measurement and from the simplifying assumptions used in deriving the MFP index.

To this end, a relationship is derived between the measured and 'true' MFP growth that separates the effects of returns to scale, market power, capacity utilisation and resource inputs from measured MFP. Also incorporated is the effect of the endogenously derived rental price for capital, a common practice by the national statistical agencies, in the derivation of the decomposition equation. A variable translog cost function is then estimated that provides the parameter estimates for the various components in the decomposition formula. Of course, the methodology developed here and in other parts of the thesis is quite general, and it can be applied to analyse similar issues in other industries and in other countries.

The results show that the average MFP growth in Australian mining based on the dual measure of technical change over the sample period is nearly 2%, rather than 0.01% from the published index. Also, the model-based MFP growth is quite stable, in contrast to the large positive and negative swings observed in the official mining MFP statistics. The results indicate that changes in resource inputs have subtracted the true MFP growth by 1.14 percentage points, while the effects of capacity utilisation and returns to scale also have sizable, but relatively less negative impact on the measured MFP growth in Australian mining.

5.2 Lessons and implications

Several lessons may be learnt from the thesis research and the resulting findings. First, measurement issues should be taken seriously. This point is demonstrated in many places throughout the thesis. Chapter 2 shows that economic statistics, including the MFP index published by the national statistical agencies, involve using data from various parts of the national accounts, which are closely linked to concepts and measures in economics. Also, the data from the national accounts rely on a complex process of compilation and imputation through various statistical surveys and sampling procedures. As discussed in Chapter 3, despite being the continuous

interests of economists for quite some time, the measures of R&D that are commonly constructed at the aggregate and industry levels still suffer from some major problems that can cause serious biases. Some of these can manifest themselves as the misspecification bias when the R&D measures are used in econometric estimation. As demonstrated in Chapter 4, the natural resource inputs, which are excluded in the measurement of mining inputs and MFP, are poignant reminder that our understanding of the mining production and productivity can be hampered by the use of imperfect measures.

Second, economic theory provides useful guide to economic measurement. The production of economic statistics is not merely a data collection and compilation process; it also involves establishing a conceptual and measurement framework in which economic theory plays a central role. The conceptual scope and requirements of many economic statistics can find their origin in economics. On the other hand, economic statistics facilitate the progress of empirical research in economics, which, in turn, provides evidence and catalyst to the evolution of economic theory.

The very concept of MFP is originated from production economics. R&D is part of capital stock used in production, while the natural resource inputs are crucial factors for mining production. Thus, these three economic measures have their conceptual counterparts in economics. The thesis uses various properties in production economics to gain some in-depth understanding of these measures and their relationships with other factors of production in an attempt to improve our knowledge of the productivity dynamics in Australian industries.

Another notable lesson from the thesis research is that robust econometric parameter estimates are hard, if not impossible, to obtain. The R&D-productivity regressions in Chapter 3 and the translog variable cost function estimation in Chapter 4 both encounter this problem. As pointed out previously, the fragile results could be due to the small sample and many proxy variables used in the estimation. This problem, again, highlights the importance of economic measurement.

Last, but not the least, it is worth emphasising that an appropriate understanding of the various aspects of the published, official economic statistics is not only useful for

academic economists in their empirical research, but also important to the analysts who advice policy makers to make decisions based on their assessment of the industry and economy using economic statistics.

5.3 Suggestions for future research

As indicated in many places throughout the thesis, the analysis that has been provided there may be further extended and refined. This includes both theoretical and empirical topics that may further advance and consolidate our knowledge of industry-level productivity dynamics in Australia.

In the discussion of the input-output based approach to estimating industry-level productivity growth, it has pointed out that the quality of the supply-use tables currently available in Australia is a major barrier to the adoption of this approach for statistical production purposes. The natural question that follows is: what is the minimum set of quality criteria that the supply-use tables should satisfy in order for them to be useful for constructing the productivity index? While this question is directed to the statistical agency that sets sample survey and data compilation frameworks and standards, there are issues that are related to the consistency between the MFP index from the input-output based approach and that based on the other non-parametric methods. These issues may be not only of interest to index number theorists and other productivity analysts, but also to national accountants who seek theoretical consistency and economic justifications in the published productivity index.

As discussed in Chapter 2, further work is needed to crystallise a generally accepted solution to the issue of open economy MFP estimates, particularly for the purposes of statistical production.

While there are many measurement issues in the data used in the R&D regressions as discussed in Chapter 3, the most important one is the R&D capital stock. Since the finalisation of the thesis, there has already been some progress in this area by the statistical agencies attempting to systematically capitalise R&D in the national

accounts. The impact of this new practice on the measures of outputs and inputs at the industry level and how it will affect the estimates of industry-level MFP and the rates of returns in Australia are yet to be investigated.

As indicated in Chapter 3, the panel data estimation has been attempted on the industry-level R&D regressions, but without any success. It is not clear whether this is due to the small number of industries included in the sample, and whether using the data at a lower level of aggregation (i.e. below the current ANZSIC divisional level) would improve the results. However, more detailed, sub-industry level data often entail new measurement challenges and heightened quality issues. Thus, much more work needs to be done to resolve these issues as a prerequisite to generate credible results from empirical research using the sub-industry level data.

Apart from the measurement issues associated with using the sub-industry level data, the pure competition assumption underlying the theoretical and empirical specifications currently used in this thesis for estimating the effects of R&D would have to be replaced by one that takes into account market structures and non-competitive behaviours.

Another area that may need further work is the capital measurement in mining. Given the data constraint, the thesis separates the mineral and petroleum exploration expenditure from the total mining productive capital stock and uses the former as a proxy for natural resource inputs. Future work may explore the possibility of directly estimating natural resource inputs and incorporating the effect of long lead time of mining capital formation in a more systematic fashion.

As the probability distributions for the dual measure of MFP and the measure of returns to scale as currently derived in the thesis are generally unknown, future work may consider using Monte Carlo simulations to estimate the empirical distributions and produce alternative interval estimates for these variables.

Appendix A: A derivation of the relationship between the industry-level value added and gross output MFP growth

An industry's technology can be summarized in the following gross output production function incorporating all primary and intermediate inputs and time:

$$G = f(K_1, K_2, \dots, K_m; L_1, L_2, \dots, L_r; X_1, X_2, \dots, X_n; t) \quad (A1)$$

where

G : quantity of the industry's gross output;

K_k : k th capital input used in the industry;

L_l : ... l th labour input used in the industry;

X_i : i th intermediate input used in the industry.

It is emphasized from the outset that all the formulae are at the industry level; but the industry index j is omitted for notational simplicity.

Under the assumptions of constant returns to scale and competitive equilibrium, total differentiating equation (A1) logarithmically with respect to time and using factor income shares to replace the partial elasticities, the following gross output MFP growth is obtained,

$$\tau_G = \hat{G} - \sum_k \theta_k \hat{K}_k - \sum_l \theta_l \hat{L}_l - \sum_i \theta_i \hat{X}_i \quad (A2)$$

where

$$\tau_G = \frac{\partial \ln G}{\partial t}; \quad \hat{G} = \frac{d \ln G}{dt}; \quad \hat{K}_k = \frac{d \ln K_k}{dt}; \quad \hat{L}_l = \frac{d \ln L_l}{dt};$$

$$\hat{X}_i = \frac{d \ln X_i}{dt}; \quad \theta_k = \frac{p_k K_k}{p_G G}; \quad \theta_l = \frac{p_l L_l}{p_G G}; \quad \theta_i = \frac{p_i X_i}{p_G G};$$

$$k=1,2,\dots,m; \quad l=1,2,\dots,r; \quad i=1,2,\dots,n; \quad \sum_k \theta_k + \sum_l \theta_l + \sum_i \theta_i = 1.$$

p_z denotes the price corresponding to quantity z .

If the production function (A1) is restricted to maintain value added separability, the industry's technology can also be represented by the value added production function

$$V = h(K_1, K_2, \dots, K_m; L_1, L_2, \dots, L_r; t) \quad (\text{A3})$$

where V is the industry's quantity of value added.

Following the same assumptions and the derivation for the gross output MFP growth, the value added MFP growth can be obtained as

$$\tau_v = \hat{V} - \sum_k \theta_k^* \hat{K}_k - \sum_l \theta_l^* \hat{L}_l \quad (\text{A4})$$

where

$$\tau_v = \frac{\partial \ln V}{\partial t}; \quad \hat{V} = \frac{d \ln V}{dt}; \quad \theta_k^* = \frac{p_k K_k}{p_v V}; \quad \theta_l^* = \frac{p_l L_l}{p_v V};$$

$$\sum_k \theta_k^* + \sum_l \theta_l^* = 1.$$

Given equations (A2) and (A4), another relationship is needed to link gross output and value added so that the MFP growth based on these two measures can be related. The following identity says that the value of industry value added is defined as the industry gross output less the value of all intermediate inputs used.

$$p_v V \equiv p_G G - \sum_i p_i X_i \quad (\text{A5})$$

Holding prices constant and differentiating each variables with respect to time yield

$$\hat{V} = \left(\frac{p_G G}{p_v V} \right) \hat{G} - \sum_i \left(\frac{p_i X_i}{p_v V} \right) \hat{X}_i \quad (\text{A6})$$

Substituting \hat{V} of (A6) into (A4) yields

$$\tau_v = \left(\frac{p_G G}{p_v V} \right) \hat{G} - \sum_i \left(\frac{p_i X_i}{p_v V} \right) \hat{X}_i - \sum_k \theta_k^* \hat{K}_k - \sum_l \theta_l^* \hat{L}_l \quad (\text{A7})$$

Multiplying both sides of (A7) by $\left(\frac{p_V V}{p_G G}\right)$ and observing the definitions for the factor shares yields

$$\begin{aligned}\left(\frac{p_V V}{p_G G}\right) \tau_V &= \hat{G} - \sum_i \left(\frac{p_i X_i}{p_G G}\right) \hat{X}_i - \sum_k \left(\frac{p_k X_k}{p_G G}\right) \hat{K}_k - \sum_l \left(\frac{p_l X_l}{p_G G}\right) \hat{L}_l \\ &= \hat{G} - \sum_k \theta_k \hat{K}_k - \sum_l \theta_l \hat{L}_l - \sum_i \theta_i \hat{X}_i = \tau_G\end{aligned}$$

Thus

$$\tau_G = \left(\frac{p_V V}{p_G G}\right) \tau_V \quad (\text{A8})$$

To emphasize that this holds at the industry level, the industry index is put back and for the j th industry, this yields

$$\tau_G^j = \left(\frac{p_V^j V^j}{p_G^j G^j}\right) \tau_V^j \quad (\text{A9})$$

which is equation (2.13) of Chapter 2.

Appendix B: Comparing the components of industry-level and aggregate MFP estimates

In Chapter 2, the industry-level MFP estimates are aggregated by applying the aggregation formula of equation (2.14). The resulting estimates of aggregate MFP are quite close to those from the aggregate approach used for the published MFP, with the largest difference being less than one percentage point in 1992-93. This comparison exercise seems to validate the plausibility of the industry-level MFP estimates. However, the question of what explains and causes these differences, however small, between the two sets of aggregate MFP estimates still remains.

This appendix compares the components used in the two MFP indices so that part of the difference caused by the measurement issues can be identified. The next appendix discusses the causes of the difference as a result of methodological distinctions between industry-level and aggregate approaches.

Output measures

One source of discrepancy between the estimates based on the two approaches is caused by the fact that gross value added (GVA) is used for the market-sector industries, whereas the published aggregate MFP uses GDP as the measure of output. The following accounting identity shows the difference between the two output measures:

$$\text{GDP} = \text{GVA at basic prices} + \text{net taxes on products} \quad (\text{B1})$$

In the published aggregate MFP, the total market-sector GDP volume measure is defined by

$$\text{GDP}^{\text{MKT}} = \sum_{i \in \text{MKT}} V^i + \text{net taxes on products}^{\text{e-wide}} \quad (\text{B2})$$

where all measures in the above equation are in volume terms, V^i is the volume measure of gross value added (GVA) for industry i , MKT is a shorthand for the market-sector and e-wide stands for the economy-wide, which includes all the industries in the economy, both market and non-market-sectors. Equation (B2)

indicates that the volume measure of GDP for the market-sector is equal to the volume measure of GVA summing across all the market-sector industries, plus the volume measure of the *economy-wide* net taxes on products. Thus the method used for deriving the MFP estimates in 5204.0 assumes that all net taxes on products are produced by the market-sector industries, or in other words, the non-market-sector industries do not contribute to any of these net taxes.

The GDP volume measures, as shown in equation (B2), in the two periods, t and t-1, can then be used to derive the rate of growth in volume GDP, which forms the first component of the aggregate MFP growth index of equation (2.4) of Chapter 2. This is essentially the method used in the estimation of aggregate output growth for the published MFP estimates. To compare the output estimates with those based on our industry-level approach, calculate the aggregate output growth using the industry-

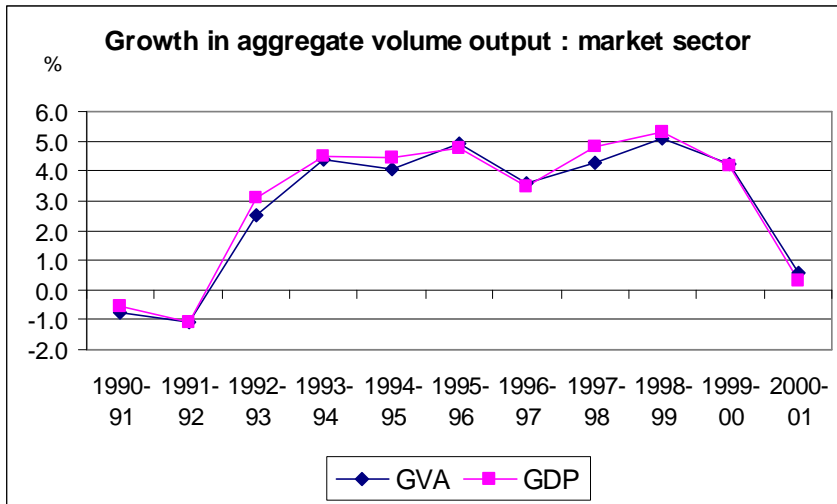
level volume measures of GVA and $\hat{V} = \sum_{i \in MKT} \left(\frac{p_{V^i} V^i}{\sum_{i \in MKT} p_{V^i} V^i} \right) \hat{V}_i$. The following table

and graph contain the results of the comparison.

Table B1: Different measures of aggregate output volume growth (%)

| | GVA | GDP | differ (% pts) |
|---------|------|------|----------------|
| 1990-91 | -0.8 | -0.6 | -0.2 |
| 1991-92 | -1.1 | -1.1 | 0.0 |
| 1992-93 | 2.5 | 3.1 | -0.6 |
| 1993-94 | 4.4 | 4.5 | -0.1 |
| 1994-95 | 4.1 | 4.4 | -0.4 |
| 1995-96 | 4.9 | 4.7 | 0.2 |
| 1996-97 | 3.6 | 3.5 | 0.1 |
| 1997-98 | 4.3 | 4.8 | -0.6 |
| 1998-99 | 5.1 | 5.3 | -0.2 |
| 1999-00 | 4.2 | 4.2 | 0.0 |
| 2000-01 | 0.6 | 0.3 | 0.3 |

Figure B1: Different measures of aggregate output volume growth (%)



Note that the market-sector GDP volume growth is directly obtained from the spreadsheet associated with Cat. 5204.0 (2001-02). As can be seen from the above table and graph, despite the different measures of output used, the differences (GVA column minus GDP column) in the growth rates between the two sets of measures are small, with the average GDP volume growth rate being 0.13 percentage point greater than its GVA counterpart. In addition, the directions of acceleration for the two series are identical.

Capital services

To compare the estimates for the capital component, $\hat{K} = \sum_{i \in MKT} \left(\frac{GVA_K^i}{\sum_{i \in MKT} GVA_K^i} \right) \hat{K}^i$ is

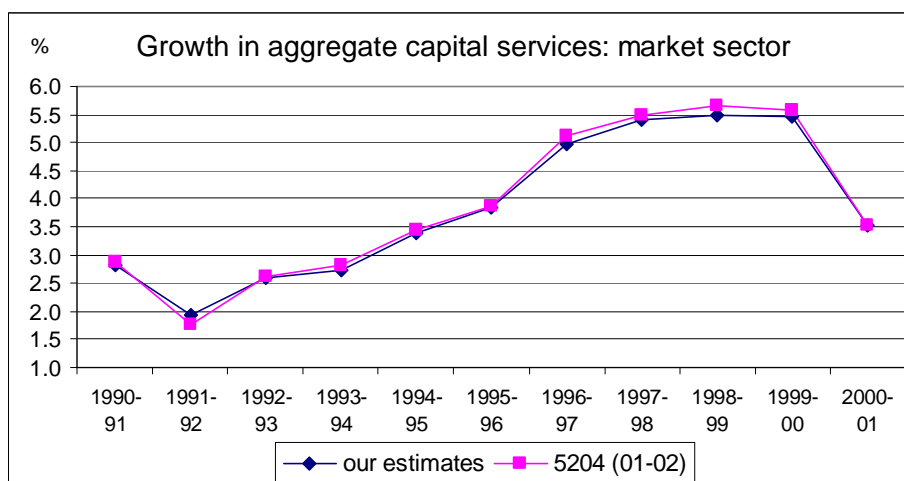
used to calculate the growth rate of aggregate capital services, where GVA_K^i is the adjusted capital income for industry i as defined in Section 2.3.4 of Chapter 2.

The same set of indices of capital services by industry is used in the two approaches. However, instead of using the weights of adjusted capital income as shown in the above aggregation formula for the growth of capital services, the shares of the industry's gross operating surplus (GOS) in the aggregate GOS for the market-sector, including the net indirect taxes attributed to capital, are employed as weights for the aggregate capital services of the published MFP estimates. As before, the growth rates for the aggregate capital services in the published MFP are obtained using the indices that are available from the spreadsheet associated with Cat. 5204.0 (2001-02). The results of comparison are shown in the following table and graph.

Table B2: Growth in the aggregate capital services (%)

| | our estimates | 5204 (01-02) | differ (% pts) |
|---------|---------------|--------------|----------------|
| 1990-91 | 2.8 | 2.9 | -0.1 |
| 1991-92 | 1.9 | 1.8 | 0.2 |
| 1992-93 | 2.6 | 2.6 | 0.0 |
| 1993-94 | 2.7 | 2.8 | -0.1 |
| 1994-95 | 3.4 | 3.4 | 0.0 |
| 1995-96 | 3.8 | 3.9 | 0.0 |
| 1996-97 | 5.0 | 5.1 | -0.1 |
| 1997-98 | 5.4 | 5.5 | -0.1 |
| 1998-99 | 5.5 | 5.7 | -0.2 |
| 1999-00 | 5.5 | 5.6 | -0.1 |
| 2000-01 | 3.5 | 3.5 | 0.0 |

Figure B2: Growth in the aggregate capital services (%)



As can be seen, the differences between the two sets of estimates are very small. On average, the growth in aggregate capital services in the published MFP is marginally higher than that based on our estimates by 0.05 percentage point, and in majority of the years, the differences are negligible. This is not surprising because in both sets of the estimates, the same industry-level capital services indices are used for aggregation. The very small differences are caused only by the different definitions of the weights used for aggregation, which seem to have very little impact on the growth of aggregate capital services.

Labour input

The aggregate labour input growth is calculated using the indices of hours worked by

market-sector industry and applying $\hat{L} = \sum_{i \in MKT} \left(\frac{GVA_L^i}{\sum_{i \in MKT} GVA_L^i} \right) \hat{L}^i$, where GVA_L^i is the

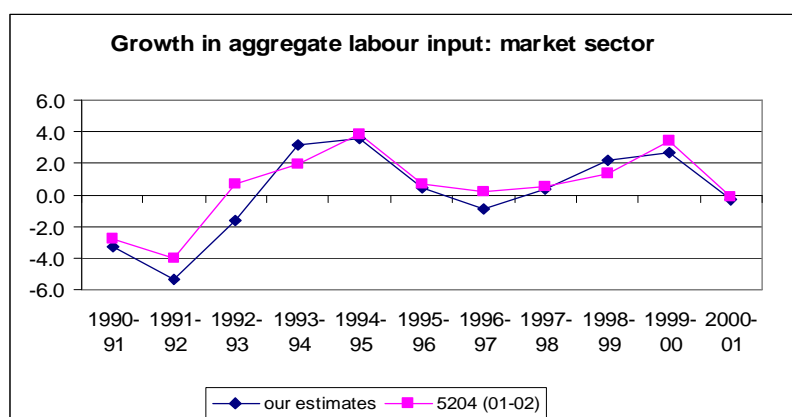
adjusted labour income for industry i as defined in Section 2.3.4 of Chapter 2. In discrete approximation, this is equivalent to the Tornqvist index shown in equation (2.22) in Chapter 2. In the published MFP estimates, the aggregate (market-sector) labour input is derived by adding up hours worked of all the market-sector industries and then it is indexed to some base year value. The corresponding proportional

growth rate for the aggregate labour input is calculated using two years indices, and hence there are no weights being used in this procedure. This is essentially a fixed weight Laspeyres type quantity index as shown in equation (2.21) in Chapter 2. Thus, the estimates derived from this method can be expected to be different from those based on the approach that uses the Tornqvist index formula. The following table and graph show these differences.

Table B3: Aggregate labour input growth (%)

| | our estimates | 5204 (01-02) | differ (% pts) |
|---------|---------------|--------------|----------------|
| 1990-91 | -3.30 | -2.75 | -0.55 |
| 1991-92 | -5.32 | -4.02 | -1.30 |
| 1992-93 | -1.62 | 0.68 | -2.30 |
| 1993-94 | 3.20 | 1.91 | 1.29 |
| 1994-95 | 3.64 | 3.86 | -0.22 |
| 1995-96 | 0.47 | 0.74 | -0.27 |
| 1996-97 | -0.90 | 0.21 | -1.11 |
| 1997-98 | 0.36 | 0.53 | -0.17 |
| 1998-99 | 2.20 | 1.36 | 0.84 |
| 1999-00 | 2.72 | 3.41 | -0.69 |
| 2000-01 | -0.31 | -0.10 | -0.21 |

Figure B3: Aggregate labour input growth (%)



Clearly, the differences between the two sets of estimates of the labour input growth are now much larger than those for the aggregate output and capital services. For the two periods 1992-93 and 1996-97, even the signs of the growth rates are opposite in the two sets of estimates.

Concluding comments

To identify the causes of the difference between the estimate of the market-sector MFP growth based on the industry-level MFP approach and those using the aggregate approach as published in Catalogue 5204.0, each component of the MFP growth indices is examined in detail. The causes of the differences can partly be attributed to the methods of aggregation as well as to the definitions of output used in the two approaches. Despite the fact that the different definitions of output are used, the size of the differences is small in the two sets of the estimates of aggregate output growth. Small differences are found in the aggregate capital services growth estimates. Compared with output and capital services, the labour input growth seems a larger contributing factor in the discrepancy observed in the aggregate MFP growth estimates. Although the same definition of labour input is used, the differences in the estimates of labour input growth are the result of different methods of aggregation used in the two approaches.

The differences identified in this appendix are directly related to the measurement issues associated with the components of the MFP indices used in industry-level and aggregate approaches. There is, however, an inherent, methodological difference which also contributes to the observed discrepancies between the estimates derived from the two approaches. This is discussed in details in Section 2.6 of Chapter 2.

Appendix C: Data description and analysis for Chapter 3⁴⁷

MFP index

The estimates of MFP index for the four market-sector industries are obtained from the Productivity Commission's MFP database, which contains a much longer series than the industry-level MFP estimates presented in Chapter 2. These estimates are also derived from the non-parametric, growth accounting approach in which constant returns to scale and competitive equilibrium are assumed to hold in each industry. The industry-level MFP estimates from the PC's database are based on value added.⁴⁸

Given that the MFP index measures inter-temporal changes in productivity, it is also informative to express the index in terms of rate of growth. The growth rates across different industries can then be meaningfully compared. Following the convention in the empirical literature, all growth rates are calculated as the natural log difference, $\ln X(t) - \ln X(t-1)$, where X is any variable. The rate of growth calculated this way will be approximately equal to the growth rate that is based on the proportional change.

The summary statistics of the MFP growth rates for the four industries are shown in Table C1. Together with the information in Figure C1, they reveal some major characteristics of MFP changes in the four industries.

⁴⁷ For details on data sources and variable construction, see Shanks and Zheng (2006).

⁴⁸ See Chapter 2 for further details on the various properties and issues associated the value added MFP measure.

**Figure C1: MFP index for the four market-sector industries, 1974-75 to 2002-03
(2000-01 = 100)**

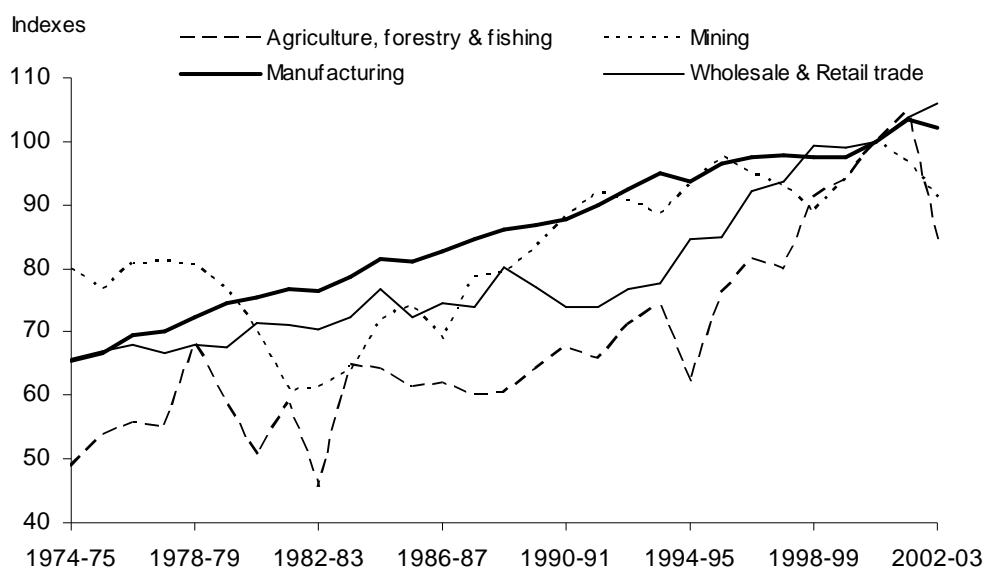


Table C1: Summary statistics for MFP growth

| | <i>Agriculture</i> | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade</i> |
|--------------------|--------------------|----------------------|---------------|-------------------------------------|
| Mean (%) | 1.9 | 1.6 | 0.5 | 1.7 |
| Standard Deviation | 0.132 | 0.015 | 0.061 | 0.037 |
| Maximum (%) | 35 | 4 | 12.9 | 8.6 |
| Minimum (%) | -25 | -1.5 | -14.8 | -5.9 |

As expected, MFP growth in agriculture tends to be the most volatile compared with the other three industries. This is mainly due to the impact of weather condition on the industry's output. The part of the volatility that is directly caused by changes in weather conditions can be controlled for by introducing a weather index variable in

the agriculture regressions. Despite this volatility, the industry records the highest average rate of growth over the period 1974-75 to 2002-03. This is also considerably stronger than that achieved in Australia's total market sector (about 1% in terms of proportional rate of growth during the same period). For a detailed discussion of the main drivers of productivity growth at the industry-level, see PC (2005) for agriculture and its sub-sectors, Productivity Commission (2003) for manufacturing and its sub-sectors, and Johnston et al. (2000) for the wholesale and retail trade industries.

Industry's own R&D capital stock

The next important variable used in the regression analysis is the industry's own R&D capital stock. This measure is constructed using the perpetual inventory method and assuming a certain percentage for the rate of depreciation. Throughout the industry level analysis in this report, measures of R&D capital stock, whether domestic or foreign, are based on a 15% depreciation rate, but for the non-business R&D stock, the measure is derived from a zero depreciation rate. Since the latter measure approximates the stock of knowledge at a more basic or fundamental level in the economy, it is expected that this type of knowledge stock depreciates at a rate that is much slower than those resulting directly from business expenditure on R&D.

The ABS business enterprise R&D survey excludes enterprises mainly engaged in Agriculture, forestry & fishing (AFF). This is largely because such enterprises are believed to have very low levels of R&D activity, as R&D activity for this industry is generally carried out by specialised research institutions, such as state departments of agriculture, CSIRO and the agricultural faculties of universities (Mullen et al. 2000).

A partial measure of Agriculture's 'own-industry' R&D capital can be constructed based on a decomposition of the Scientific research industry's (ANZSIC 781) R&D expenditure by socio-economic objective (SEO). Expenditures classified by SEOs related to AFF are used to form the stock. The stock peaks in 1994 and then declines until 2000, when it recovers to its 1989 level (Figure C2).

Figure C2: Industry's own R&D capital stocks, 1974-75 to 2002-03
(2000-01 = 100)

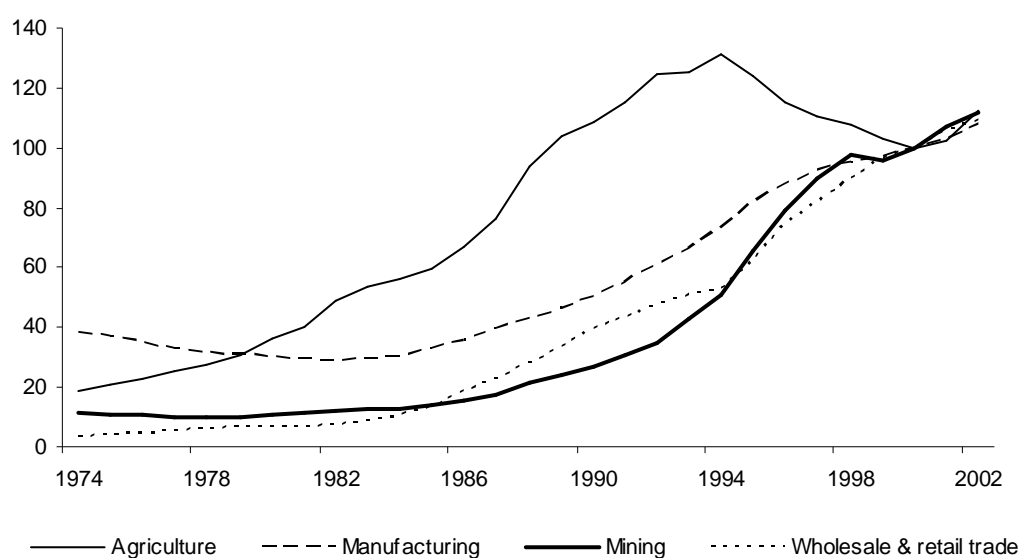


Table C2: Summary statistics for the growth in industry's own R&D stock

| | <i>Agriculture</i> | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade</i> |
|--------------------|--------------------|----------------------|---------------|-------------------------------------|
| Mean (%) | 6.4 | 3.7 | 8.2 | 12.4 |
| Standard Deviation | 0.074 | 0.054 | 0.077 | 0.074 |
| Maximum (%) | 20.1 | 11.5 | 25.9 | 33.2 |
| Minimum (%) | -7.4 | -5.6 | -4.1 | 2.5 |

As can be seen, the level of volatility in the industry's own R&D capital stock growth in agriculture is similar to that in mining and wholesale and retail trade, but it is much less than the volatility in its rate of growth in MFP. This may be due to the fact that there is no relationship between agriculture's own R&D capital stock and weather conditions. Another notable feature in agriculture is that its own R&D

capital stock peaks in 1994 and then declines until 2000, when it recovers back to its 1989 level. As will be seen below, because of the decline in agriculture's own R&D stock during this 6 year period, it reverses the relationship between the industry's own R&D stock and its MFP from being positive to negative. This raises some questions about the assumptions used to construct the R&D capital stock in this industry.

Usage of public infrastructure

The construction of the variable 'usage of public infrastructure' is documented in Shanks and Zheng 2006. There are several measures of public infrastructure usage. At the industry-level, the one that is used reflects the general level of government infrastructure and the industry's importance in the market-sector. Specifically, the variable used is derived from a measure of government infrastructure in the market sector multiplied by the industry's share of value added. The graph and summary statistics for the variable of usage of public infrastructure are presented below (Figure C3 and Table C3).

Figure C3: Industry's usage of public infrastructure, 1974-75 to 2002-03 (2000-01 = 100)

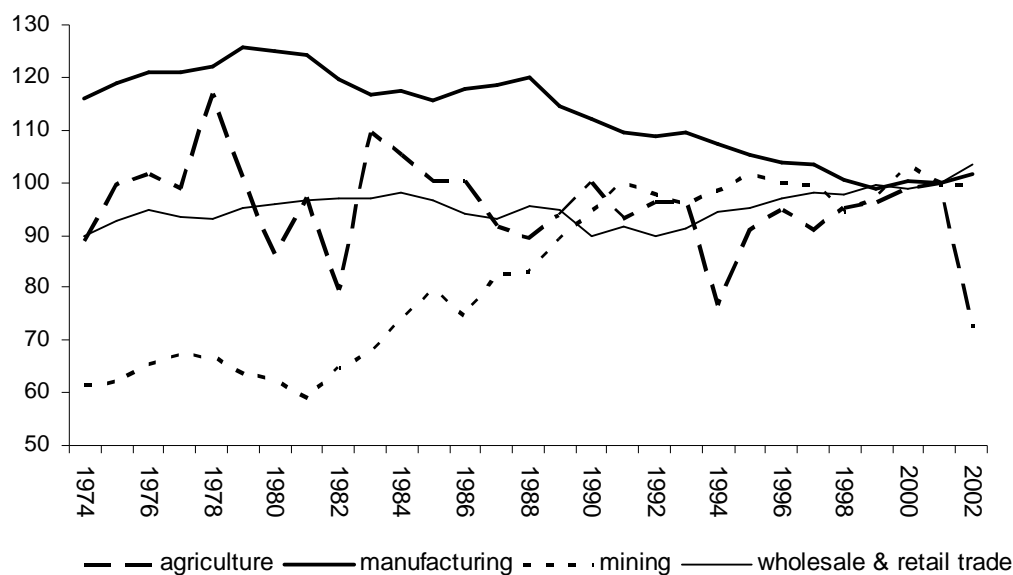


Table C3: Summary Statistics for the growth in industry's usage of public infrastructure

| | <i>Agriculture</i> | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade</i> |
|--------------------|--------------------|----------------------|---------------|-------------------------------------|
| Mean (%) | -0.7 | -0.5 | 17.1 | 0.5 |
| Standard Deviation | 0.131 | 0.019 | 0.049 | 0.020 |
| Maximum (%) | 32.1 | 2.7 | 10.1 | 3.7 |
| Minimum (%) | -32.6 | -4.4 | -6.5 | -5.3 |

As with MFP, the usage of public infrastructure is more volatile in agriculture compared to other industries. Since the changes in general government infrastructure and aggregate market-sector value added are relatively stable, the volatility in this variable is then largely determined by the fluctuation in the industry's value added.

Other control variables

The summary statistics for the other control variables (in growth rates) used in the regression equations are shown in Table C4. The farmer's terms of trade variable is the ratio of prices received by farmers to index of prices paid by farmers. It specifically takes account of the changes in prices of inputs and outputs that are only relevant to farmers in their production process. For the details of how this variable is derived, see ABARE (2003).

One common feature of these variables (in log level) is that they are all highly trending. Thus, they are likely to be non-stationary. This is confirmed by the standard unit-root tests applied to these variables (Table C5).

Table C4: Summary Statistics for other control variables in rate of growth

| | <i>Mean</i> | <i>Standard Deviation</i> | <i>Maximum</i> | <i>Minimum</i> |
|--|-------------|-------------------------------|----------------|----------------|
| | % | | % | % |
| Foreign R&D capital stock | 4.0 | 0.015 | 7.0 | 1.9 |
| Public R&D capital stock | 2.8 | 0.003 | 3.2 | 2.5 |
| Trade openness | 1.1 | 0.047 | 12.5 | -7.8 |
| Oil price index | 3.0 | 0.240 | 64.0 | -30.1 |
| CPI | 5.9 | 0.037 | 13.0 | 0.0 |
| Farmers terms of trade | -1.4 | 0.074 | 14.2 | -16.4 |
| IT capital in wholesale & retail | 28 | 0.089 | 45 | 16 |
| Use of communication infrastructure in wholesale & retail | 4.3 | 0.028 | 10.3 | -0.7 |

Table C5: Unit root test^a

| | <i>Manufacturing</i> | <i>Mining</i> | <i>Wholesale & retail trade</i> | <i>Agriculture, forestry & fishing</i> |
|---------------------------------------|----------------------|---------------|-------------------------------------|--|
| MFP | I(1) | I(1) | I(1) | I(1) |
| Industry BRD stock | I(2) | I(2) | I(2) | I(2) |
| Inter-industry BRD stock ^b | I(2) | I(2) | I(2) | I(2) |

^a Assumed decay rate of 15 per cent for the stock variables, and all variables are based on the data from 1974-75 to 2002-03. The unit root tests are based on the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test. The selection of the lag length was undertaken using a combination of inspection of the correlogram and a testing down procedure. ^b Weighted by inter-industry trade using input-output tables.

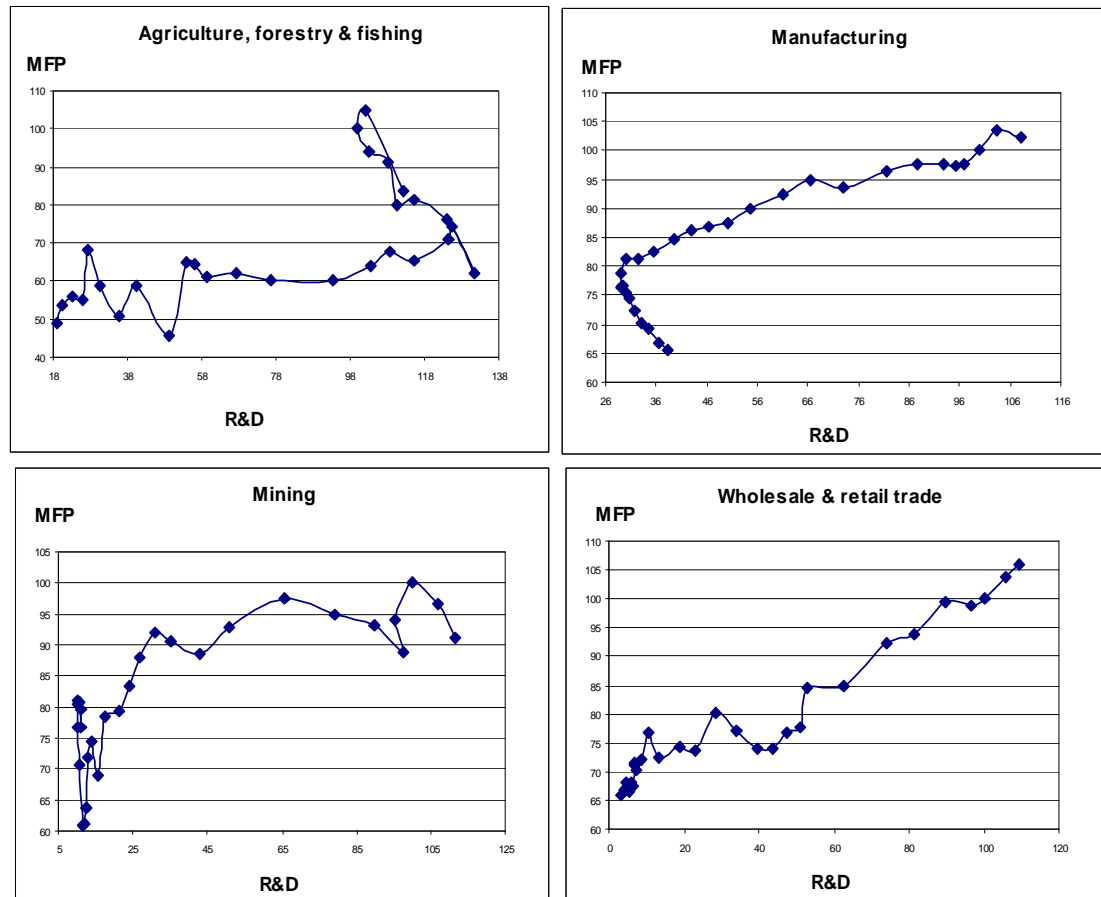
While the presence of non-stationary variables in the regression calls for caution against spurious regression results, the linear combination of these non-stationary variables can still yield non-spurious estimates, provided that the residuals from the linear regressions using these variables are stationary. This implies that these variables are co-integrated. Consequently, the residuals from the following regression equations have all been tested for non-stationarity.

It must be noted that the standard unit root tests have notoriously low power against the trend stationary alternatives, and the size of our sample is relatively small. Thus, it is very difficult to reject the unit root hypothesis for the relatively short annual data under examination. Some researchers, for example, Connolly and Fox (2006), Rogers (1995) and Otto and Voss (1994), prefer not to use the unit root tests, and thus they do not consider the non-stationarity issue in their work using small sample time-series data. In this study, the residuals are tested for non-stationarity in each industry-level regression model, but no error-correction model is estimated because it critically depends on the results from unit-root tests.

Bivariate relationship between R&D and productivity

As part of preliminary data analysis, here the bivariate relationship is examined between R&D and productivity in the four market-sector industries. In Figure C4, the MFP index is plotted against the industry's own R&D index in each industry.

Figure C4: MFP versus industry's own R&D



As can be seen, the bivariate relationship between MFP and industry's own R&D stock is most unusual in agriculture. This may be due to the way in which the R&D stock is constructed for this industry. As discussed above, the R&D expenditure by agriculture underlying its stock measure is obtained by allocating the proportion of R&D performed by the Scientific research industry with socio-economic objectives related to Agriculture, forestry and fishing. Thus, only a very small amount is distributed to the agriculture industry, while the 'true' industry's own expenditure on

R&D in agriculture remains unknown. This is the main reason for replacing the industry's own R&D variable with public R&D in the regressions for Agriculture.

MFP in the manufacturing industry increases continuously since 1974 with only a small decline in 1994 and 2002. However, the industry's own R&D capital stock declines every year between the second half of the 1970s and early 1980s and reaches its trough in 1983, then exhibits a steady increase since then. This causes a negative correlation between R&D and MFP in manufacturing in the early years, and it is followed by a positive one.

The bivariate relationship between industry's own R&D stock and MFP in mining is clearly non-linear. While a positive trend can still be seen to dominate the whole period, several negatively correlated segments are quite visible. This may be partly due to the fluctuations in the rate of MFP growth in the industry, although the magnitude of the fluctuations is much less than that in agriculture.

As shown in Figure C4, a positive linear line can be easily fitted through the points in the plot of MFP against R&D in the wholesale and retail trade industry. However, between the period 1988 and 1990, the two variables are negatively correlated.

It is clear from Figure C4 that the relationship between R&D and productivity at the industry-level is not clear-cut just by examining the co-movements of the two indices. However, there is some evidence of a positive correlation between them.

Appendix D: Detailed estimation output for Chapter 4

SURE estimation output from EViews6 for the restricted translog variable cost function and the inverse share equation

Estimation Method: Iterative Seemingly Unrelated Regression

Sample: 1976 2007

Included observations: 32

Total system (balanced) observations 64

Simultaneous weighting matrix & coefficient iteration

Convergence achieved after: 10 weight matrices, 11 total coef iterations

| | Coefficient | Std. Error | t-Statistic | Prob. |
|---------------------------------|-------------|------------|-------------|--------|
| C(1) | 0.155506 | 0.182164 | 0.853662 | 0.3973 |
| C(2) | -4.279550 | 3.139617 | -1.363080 | 0.1788 |
| C(3) | 6.579840 | 2.007992 | 3.276825 | 0.0019 |
| C(4) | 4.302417 | 0.301083 | 14.28980 | 0.0000 |
| C(5) | 1.836257 | 3.143013 | 0.584235 | 0.5616 |
| C(6) | -5.091374 | 7.277388 | -0.699616 | 0.4873 |
| C(7) | -6.113895 | 4.717264 | -1.296068 | 0.2008 |
| C(8) | 8.834283 | 1.835730 | 4.812409 | 0.0000 |
| C(9) | -3.810102 | 0.585049 | -6.512455 | 0.0000 |
| C(10) | -0.091435 | 0.064030 | -1.427993 | 0.1594 |
| C(11) | 0.010028 | 0.004870 | 2.059173 | 0.0446 |
| C(12) | -0.267652 | 0.082118 | -3.259375 | 0.0020 |
| C(13) | 0.313820 | 0.615890 | 0.509540 | 0.6126 |
| Determinant residual covariance | | 0.000986 | | |

Equation: $\text{LOG}(\text{COE}) = \text{C}(1) + \text{LOG}(\text{AWE}) + \text{C}(2) * \text{LOG}(\text{K_NO_EXPLOR}(-1))$
 $+ \text{C}(3) * \text{LOG}(\text{EXPLORATION}(-1)) + \text{C}(4) * \text{LOG}(\text{VA_PC}) + \text{C}(5) * 0.5$
 $* (\text{LOG}(\text{K_NO_EXPLOR}(-1)))^2 + \text{C}(6) * 0.5 * (\text{LOG}(\text{EXPLORATION}(-1)))^2$
 $+ \text{C}(7) * (\text{LOG}(\text{K_NO_EXPLOR}(-1))) * (\text{LOG}(\text{EXPLORATION}(-1))) + \text{C}(8)$
 $* (\text{LOG}(\text{K_NO_EXPLOR}(-1))) * (\text{LOG}(\text{VA_PC})) + \text{C}(9) * (\text{LOG}(\text{EXPLORATI}$
 $\text{ON}(-1))) * (\text{LOG}(\text{VA_PC})) + \text{C}(10) * \text{T} + \text{C}(11) * 0.5 * \text{T}^2 + \text{C}(12) * \text{T}$
 $* \text{LOG}(\text{VA_PC}) + \text{C}(13) * 0.5 * (\text{LOG}(\text{VA_PC}))^2$

Observations: 32

| | | | |
|--------------------|----------|--------------------|----------|
| R-squared | 0.954253 | Mean dependent var | 1.530385 |
| Adjusted R-squared | 0.925360 | S.D. dependent var | 0.629888 |
| S.E. of regression | 0.172087 | Sum squared resid | 0.562667 |
| Durbin-Watson stat | 2.165157 | | |

Equation: $SW1_INV = C(4) + C(8) * LOG(K_NO_EXPLOR(-1)) + C(9) * LOG(EXPLORATION(-1)) + C(12) * T + C(13) * LOG(VA_PC)$

Observations: 32

| | | | |
|--------------------|----------|--------------------|----------|
| R-squared | 0.831167 | Mean dependent var | 3.928018 |
| Adjusted R-squared | 0.806155 | S.D. dependent var | 0.705685 |
| S.E. of regression | 0.310698 | Sum squared resid | 2.606401 |
| Durbin-Watson stat | 1.186321 | | |

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