Do employers reward physical attractiveness in transition countries?

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ABSTRACT:
This paper studies the labour market returns to physical attractiveness using data from three transition countries of the Caucasus: Armenia, Azerbaijan and Georgia. I estimate a large positive effect of attractive looks on males probability of employment. Results from the most comprehensive model suggest a marginal effect of 11.1 percentage points. Using a partial identification approach, I show that this relationship is likely to be causal. After accounting for covariates, particularly measures of human capital, there is no evidence for a statistically significant link between females' attractiveness and employment.

JEL classification: J21, J70, P23

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1. Introduction

Labour market return to physical attractiveness is the subject of a growing literature in economics. Most of the studies have shown that attractiveness matters for labour market outcomes in the context of various developed countries such as the US and Canada (Hamermesh and Biddle, 1994; Mocan and Tekin, 2010), United Kingdom (Harper, 2000), Germany (Gehrsitz, 2014; Oreffice and Quintana-Domeque, 2016), Australia (Borland and Leigh, 2014). A few studies have looked at the relationship in developing countries including Bangladesh (Islam and Smyth, 2012), China (Hamermesh et al., 2002), Ecuador and Mexico (Arunachalam and Shah, 2012).[1] This paper studies labour market returns to physical attractiveness in a previously unexplored setting: transition countries.

Egalitarianism was a central aspiration of the communist regime. Not only this was expressed in ideological terms, it was often formally institutionalised. Labour markets are one area where this phenomenon manifested itself. Achieving full employment for all able-bodied population was one of the central policies of the centralized planned economies of the Former Soviet Union (FSU) (Porket, 1989). Unemployment was not officially recognized. In some countries not having a job was even penalised criminally (Brainerd, 2000). Did the collapse of the communist regime undermine the equality in the labour market? This study explores the differences in labour market outcomes among observationally identical individuals with different endowments of physical attractiveness.

The literature on differences in labour market outcomes in transition countries has predominantly focused on the case of gender. The findings of this literature remain mixed as to whether transition has resulted in an improvement or deterioration of women's relative position (e.g., Brainerd, 2000; Gerber and Mayorova, 2006); several studies demonstrate actual improvements in women's labour market outcomes post-transition (e.g., Orazem and Vodopivec, 1995; Jolliffe and Campos, 2005). However, the case of gender has an important idioscyncrasy that limits the scope for generalized inferences on labour market inequalities in FSU countries: a form of gender discrimination was institutionalised in the Soviet Union. The labor legislation regarded women as a 'specific labor force' because of their maternity and childcare roles and imposed restrictions around their employment (Ogloblin, 1999). By focusing on physical looks as a basis of differences in labour market outcomes, this study overcomes that caveat.

[1] The literature has also considered the effect of attractiveness on other outcomes, including life satisfaction (Hamermesh and Abrevaya, 2013), electoral success in politics (King and Leigh, 2009; Berggren et al., 2010) and in professional organisations (Hamermesh, 2006), students' academic performance at high school (French et al., 2009) and at university (Cipriani and Zago, 2011), student's evaluations of instructors' performance (Hamermesh and Parker, 2005), criminal behaviour (Mocan and Tekin, 2010), etc.

Attractiveness may be rewarded in the labour market for several reasons. It may enhance productivity, especially in certain occupations such as sex work or sales (Hamermesh and Biddle, 1994). On the other hand, unattractive individuals may be discriminated against.[2] Under taste-based discrimination theory, employers or customers may consciously discriminate simply because they have a taste for attractive individuals (Becker, 1971). Under such scenario, attractive employees will be favoured over equally productive unattractive employees in the labour market. According to the statistical theory of discrimination, employers or customers may consciously discriminate because they lack information about the productivity of individuals and 'statistically discriminate' against them on the basis of easily observable characteristics such as looks (e.g., Phelps, 1972; Arrow, 1973). Furthermore, as Bertrand et al. (2005) argue, discrimination may be unintentional and outside of the discriminator's awareness, e.g. they may hold implicit associations between attractive individuals and desirable attributes.

A key challenge in studying the relationship between physical attractiveness and labour market outcomes is unobserved heterogeneity: physical looks may be correlated with a range of unobserved variables (e.g. cognitive or non-cognitive characteristics) that may have the potential to directly affect labour market outcomes. In the absence of experimental data, the conventional way to address the issue of potential bias is to find an instrumental variable for attractiveness. However, as Hamermesh and Abrevaya (2013) note, "it is difficult to impossible to construct instrument for beauty that would allow one to claim convincingly to have eliminated concerns about causality" (p. 362). In their study, Hamermesh and Abrevaya (2013) exploit information on lagged attractiveness measures as instruments for current attractiveness. This approach, however relies on the (rather strong) assumption that the error term is uncorrelated with the past values of the endogenous variable. It is perhaps due to the absence of persuasive instruments that attractiveness is treated as exogenously determined in most previous studies in this literature (see the review by Liu and Sierminska, 2014). Identification in these studies largely relies on controlling for potentially confounding influences. However, this approach clearly cannot fully account for all such influences. I apply a novel strategy to the estimation of attractiveness effect: I assess the extent of the bias based on measuring the ratio of selection on unobservables to selection on observables that would be required to explain away the entire causal effect of attractiveness following the approach proposed by Altonji et al. (2005).

[2] This extends to other physcial characteristics - see, e.g. the discussion by Brunello and D'Hombres (2007) on the sources of obesity penalty in the labour market.

This study uses unique dataset from three FSU countries of Armenia, Azerbaijan and Georgia that contains information on interviewer-assessed measures of attractiveness along with standard labour market outcomes and background characteristics of employers. I find a large positive effect of attractive looks on males' probability of employment. The results from a model with a comprehensive list of controls suggest a marginal effect of 11.1 percentage points; this is equivalent to a 16% increase in the probability of employment - an economically significant effect. Applying the Altonji et al. (2005) approach, I find that this effect is likely to be causal: selection on unobservables would need to be 3.4 times stronger than selection on observables to cancel out the attractiveness effect; this seems rather unlikely. Moreover, I find some indication that taste-based employer discrimination in favour of attractive males may be in place, without being able to exclude the possibility of other discrimination- and productivity-related mechanisms potentially underlying the results. Consistent with some previous studies (e.g., Biddle and Hamermesh, 1998; Borland and Leigh, 2014), I do not find evidence for attractiveness premium for females once their human capital is accounted for.

The rest of the paper proceeds as follows: the next section presents the data; in section 3, I describe the methodology; section 4 reports the estimation results; I discuss the implications of these results in section 5; section 6 concludes.

2. Data

Source and sample. The data source for this study is the annual Data Initiative (DI) survey conducted by the Caucasus Research Resource Centres (CRRC) in Armenia, Azerbaijan, and Georgia.[3] Introduced in 2004, the first wave of the survey was carried out in the three capital cities only while the second wave also included one region in each country. In 2006 the DI survey was expanded to cover all the regions controlled by central governments in the three countries. In 2007, CRRC introduced a unified sampling methodology in line with international best practices to ensure full comparability of data across the three countries (CRRC, 2007). Since then the surveys have been running annually in Armenia, Azerbaijan, and Georgia based on the same methodological approach (based on a stratified two stage sampling) and the same survey instruments (CRRC, 2008). The surveys provide reliable data

[3] DI was renamed into Caucasus Barometer (CB) in 2010.

on a wide range of demographic, social, economic and political variables, and have been already utilised in several recent published articles (e.g., Habibov and Afandi, 2011; Habibov, 2012; Duncan and Mavisakalyan, 2015; Antinyan, 2016; Mavisakalyan and Meinecke, 2016).

Cross-country comparability, representativeness, richness and relevance of the data make DI highly appropriate to study labour market returns to attractiveness in transition countries. Another key source of information on transition countries is Life in Transition Survey (LITS). Similar to DI, LITS is a collection of comparable representative surveys from transition countries. Over 30, mostly transition countries are included in the survey, including the three countries in the current study (the country sample sizes in LITS are smaller compared to DI). However, while LITS includes information on employment and background characteristics of survey individuals, unlike DI, it does not contain assessments of their physical attractiveness.[4]

I use the 2008 wave of DI survey which provides data on the respondents looks (not included in subsequent waves) along with usual labour market and demographic variables of interest. This wave comprises 5,869 observations of which 2,075 are from Armenia, 1,996 from Azerbaijan, and 1,798 from Georgia. I restrict the sample to those aged 26 to 50 to capture prime-age workers (for a similar approach see Oreffice and Quintana-Domeque, 2016).[5] This reduces the sample size to 2,763 observations. I further drop the small number of observations with missing outcome data.[6] This leads to the final sample size to 2,557 observations in total.

Measurement of attractiveness. Studies measure attractiveness based on subjective rankings of people's physical appearances (e.g., Hamermesh and Biddle, 1994; Mocan and Tekin, 2010; Hamermesh and Abrevaya, 2013). This approach is consistent with standard dictionary definitions of beauty as "the quality or aggregate of qualities in a person or thing that gives pleasure to the senses or pleasurably exalts the mind or spirit" (Hamermesh, 2011, p. 11). Many studies obtain this measure based on facial photographs (e.g., Biddle and Hamermesh, 1998; Mobius and Rosenblat, 2006; Scholz and Sicinski, 2015). However, as Biddle and Hamermesh (1998) note, "The ideal measure of beauty would account for all of a persons

[4] I am not aware of another source of data from transition countries that contains information on the respondents' attractiveness.

[5] The life expectancies in the three countries range from 67-71 (males) and 73-77 (females). The retirement age starts from 62-65 (males) and 60-63 (females). The results based on samples restricted by alternative age brackets are similar - available on request.

[6] The number of missing observations on key variables of interest is very small in DI. In the sample of 26 to 50 years olds, attractiveness is coded as missing only for 0.4% of respondents due to 'interviewer error'. Regarding employment status, information on 1.12% of respondents is missing. Over 77% of this is due to 'interviewer error'.

features that make a visual impact on others" (p. 178). Face-to-face, "full-body" assessments of attractiveness do so more accurately (Oreffice and Quintana-Domeque, 2016). Consistent with that view, this study employs interviewer rating of attractiveness based on face-to-face contact.

The measure of attractiveness used in this study is based on after-interview ratings of attractiveness. While this measure has been used in a number of previous studies (e.g., French et al., 2009; Mocan and Tekin, 2010), there is a concern that it may potentially be "contaminated by other information about the subject obtained during an interview (e.g. by socioeconomic status)" (Biddle and Hamermesh, 1998, pp. 178-179). Ratings of attractiveness obtained at the start of the interview used in some previous studies (e.g., Hamermesh and Abrevaya, 2013; Gehrsitz, 2014; Oreffice and Quintana-Domeque, 2016) are largely immune to such problem, however these are not available in the dataset. The empirical strategy in this paper exploits different approaches in an effort to mitigate the effect of some such contaminating factors in assessing the labour market returns to attractiveness.

Other measures of physical looks used in the literature include hair colour (e.g., Price, 2008; Johnston, 2010; Guguen, 2012), height (e.g., Steckel, 1995; Persico et al., 2004; Rashad, 2008), weight (e.g., Cawley, 2004; Rooth, 2009; Sabia and Rees, 2012). Furthermore, recent studies on labour market effects of body weight have distinguished between the effects of various indicators of body composition such as body fat, fat free mass and waist circumference (Johansson et al., 2009; Wada and Tekin, 2010; Bozoyan and Wolbring, 2011) in addition to body mass index (BMI) commonly used in the literature (e.g., Atella et al., 2008; Lindeboom et al., 2010; Caliendo and Lee, 2013). While these measures are less prone to measurement error, they are also less likely to capture the concept of attractiveness compared to the measure used in this study. They are also not available in the current dataset.

Fifty-nine survey interviewers in Armenia, 79 in Azerbaijan and 84 in Georgia were asked to rate how attractive they found the respondent on the five-point scale.[7] The distribution of attractiveness ratings is shown in Table 1. Among both males and females, many more are viewed as above-average than below-average. This is similar to patterns observed in other contexts such as the US (Mocan and Tekin, 2010; Hamermesh and Biddle, 1994), Canada (Hamermesh and Biddle, 1994) and Germany (Gehrsitz, 2014). In both samples, roughly half are rated as attractive, while around 9% of males and around 13 % of females are rated as 'very attractive'. The higher female attractiveness rating is consistent with other studies

[7]The dataset contains interviewer IDs, however there is no information on the characteristics of the interviewers. Based on the information received from CRRC, the interviewers are always the nationals of the respective country, with the majority of them being females.

in the literature (e.g., Hamermesh and Biddle, 1994; Gehrsitz, 2014; Oreffice and Quintana-Domeque, 2016). The share of those regarded as unattractive or very unattractive is close to 10 % among both males and females, with the rest being rated as 'neither attractive nor unattractive'.

To minimize misclassification errors and increase cell sizes, information on attractiveness is often reduced into broader categories of attractiveness in studying its effects (Hamermesh and Biddle, 1994; Mocan and Tekin, 2010; Doorley and Sierminska, 2015). To make my analysis comparable, I use a similar approach to defining the baseline measure of attractiveness in this study. Following Doorley and Sierminska (2015), I define a dummy variable to distinguish between two categories of attractiveness. ATTRACTIVE takes on the value 1 if the respondent was rated as attractive or very attractive by the interviewer, and 0 otherwise. Thus the reference category is everybody whose appearance is rated as neither attractive nor unattractive, unattractive, or very unattractive. To investigate the sensitivity of the results to the manner in which attractiveness is measured, in robustness checks I present results from employing continuous and more detailed categorical measures of attractiveness. The qualitative conclusions are very similar.

[Table 1 about here.]

Description of variables. Table 2 provides the definitions and descriptive statistics for all variables used in the baseline analysis by gender. Fifty-seven percent of males and 63% of females are classified as attractive. I split the samples of males and females into two further sub-samples divided by the level of attractiveness.

My analysis of economic returns to attractiveness focuses on employment.[8] The baseline models employ a binary employment status distinguishing between those employed and not employed (including those not in the labor force). This approach has been used to minimize the misclassification error in contexts where the distinction between unemployed and not being in the labour force is vague; individuals in both groups may be willing to take up employment if there was the opportunity, however individuals may be discouraged from actively searching for work or have little incentives to register as unemployed (e.g., Daly, 1993). This measure of employment has also been employed in previous studies on the region (e.g., Duncan and Mavisakalyan, 2015; Mavisakalyan and Meinecke, 2016).[9] As Table

[8] Although other labour market outcomes such as wages or promotions can be influenced by attractiveness, these are not available in the current dataset. In extended results I employ proxies for these measures as dependent variables.

[9] The results (available on request) are robust to applying a standard definition of employment that excludes those not in the labor force.

2 demonstrates, the employment rate is 74% among attractive males, and only 61% among unattractive males. This gap of 13 percentage points suggests a positive effect of attractive looks on employment. For females, the difference in raw employment rates of attractive and unattractive females is only 3 percentage points.

[Table 2 about here.]

My analysis of the link between attractiveness and employment probability controls for a range of observable characteristics of individuals. Three groups of covariates are included in baseline employment models. The first includes individual characteristics such as age group,[10] ethnic and linguistic majority background. I additionally control for family status and self-reported health. There is no apparent trend in the age distribution of males and females. Furthermore, no decrease in attractiveness levels by age is observed for males: e.g. the share of those of 41-50 years of age in the samples of both attractive and unattractive males is close to 40%. In the sample of females, 41% of attractive individuals and 46% of unattractive individuals are in the age group of 41-50. This is somewhat different to findings by others. For example, Gehrsitz (2014) reports that German respondents (in a pooled sample of males and females) who are more than 40 years old are significantly less likely to be categorised as above-average looking. However, it does not appear to be clear from his study, whether (and what) upper age limit is applied to the sample - in the case of this study it is as low as 50 years of age. The majority of males and females come from ethnic and linguistic majority background. Eighty-two percent of males and 77 percent of females report having a partner. Similar to Hamermesh and Biddle (1994), I find that attractiveness is not statistically significantly related to one's likelihood of having a partner. Around 44% of males and 36% of females report being of good or very good health. These relatively low health outcomes are consistent with the observations of health crisis in countries of the Former Soviet Union (Field, 1995; Shkolnikov et al., 1998). It has been argued that psychological stress caused by the shock of an abrupt and severe economic transition is likely to have played an important role in leading to such crisis (Shkolnikov et al., 1998) with females potentially more vulnerable to such stress relative to males (Matud, 2004). While attractiveness can be affected by adverse health conditions (e.g., Harper, 2000), this is not observed in the current sample to some extent owing to the fact that it has been restricted to those under 50 years of age.

[10] The approach to breaking age into categories is potentially less restrictive than an alternative specification using age and its squared term which may not accurately capture the actual age pattern.

The second group of covariates is educational attainment. Individuals invest in a level of education or a degree program, rather than in years of education. I therefore include dummies for school education and below, EDUC$\leq$ 10, secondary technical or incomplete university education, EDUC11-14, and first or higher university degree, EDUC$\geq$ 15 (omitted category).[11] EDUC$\leq$ 10 and EDUC11-14 comprise 38% and 37% of the male population and 41% and 35% of female population. Twenty-four percent of both males and females are university-educated. Levels of attractiveness increase in educational attainment. Thirty-one percent of attractive males have a university degree, while only 16% of unattractive males have. On the other hand, 43% of unattractive males have no more than 10 years of education compared to 35% among attractive males. Similarly, 28% of attractive females and only 18% of unattractive females have a university degree. Forty-nine percent of unattractive females have no more than 10 years of education compared to 36% among attractive females. These patterns have been observed in other studies (e.g. evidence in Mocan and Tekin (2010); Scholz and Sicinski (2015) from the US, Harper (2000) from the UK, Cipriani and Zago (2011) from Italy) and are consistent with research findings that suggest attractiveness at young age may contribute to subsequent human capital investment since attractive children apparently receive more attention from teachers and peers (e.g., Lerner et al., 1990; Langlois et al., 2000).

The final group of control variables are dummies for the location of residence. These include dummies for capital city (omitted), other urban and rural areas, as well as country dummies (with Azerbaijan omitted from the regressions). Forty-eight percent of male respondents and 40% of female respondents come from rural areas with the rest evenly split between capital and other cities in both samples. The largest country by population in the sample, Azerbaijan, makes up for 58% of the male sample and 53% of the female sample. Twenty-two percent of the male respondents and 26% of the female respondents come from Georgia. Finally, around 20% of the respondents in both samples are from Armenia.

3. METHOD

Baseline model. To establish a baseline effect of attractiveness, I start with a standard model of employment propensity Y_i^* for an individual i of the following form

$$Y_i^* = X_i\beta + \alpha A_i + \varepsilon_i \text{ for all } i = 1, ..., N. \quad (1)$$

[11] For similar approaches to using a set of educational qualifications instead of years of education in the context of transition countries see e.g. studies by Reilly (1999); Gerry et al. (2004).

where A_i is attractiveness, X_i is a vector of controls for age, ethnicity, marital status, health, education and location characteristics and ε_i is a disturbance term. Observed employment status Y_i is assumed to relate to latent propensity through the criterion $Y_i = 1(Y_i^* \geq 0)$, which under an assumption of normality for ε_i gives rise to the standard probit model of the form

$$Pr(Y_i = 1|X_i, A_i) = \Phi(X_i\beta + \alpha A_i) \tag{2}$$

where Φ is the cdf of the standard normal distribution.

Estimating the causal effect of attractiveness on employment requires that it is exogenously determined and uncorrelated with the error term in (1). However, this is unlikely to hold due to unobserved heterogeneity. First, attractiveness may be correlated with unobserved characteristics that are rewarded in the labour market, leading to an omitted variable bias in the estimates. Second, a non-classical measurement error may arise due to the fact that the information on respondent's attractiveness is elicited at the very end of the interview and the attractiveness ranking and the unobservable component of employment propensity may be correlated.[12] Thus, estimating this single equation probit model is likely to provide biased estimates of the impact of attractiveness on employment.

The standard approach to addressing the problem of unobserved heterogeneity is to estimate the joint likelihood of employment and attractiveness using a bivariate probit model. However this approach requires the exclusion of at least one reliable instrument. The absence of a reliable instrument in the data prevents the implementation of this approach. My strategy to mitigate the endogeneity problem instead relies on selecting a comprehensive set of controls and comparing the effects of selection on observables with selection on unobservables. These strategies provide useful robustness checks of the baseline results.

Comprehensive controls. As a first step to mitigate the influence of unobserved heterogeneity I include a comprehensive list of observables that remain correlated with the unobserved component of employment. In doing so, I also explore the ways that attractiveness might proxy for other attributes: I examine three potentially important mechanisms through which attractiveness might influence labour market outcomes - cognitive characteristics, non-cognitive characteristics and social connectedness (for similar approaches see Biddle and Hamermesh, 1998; Scholz and Sicinski, 2015). First, I test directly for a correlation between attractiveness and proxies for these characteristics. Second, I sequentially introduce

[12] It is unlikely that the reported employment propensity directly affects the attractiveness ranking, given the substantial space between the two questions.

these proxies into the estimations of employment equation. The intention in so doing is to reveal the extent to which the estimated effects of attractiveness on employment capture the correlation between attractiveness and these variables that have been omitted from employment equation, by comparing the estimated parameters from baseline and comprehensive specifications. Given the richness of information available in the dataset, this approach allows me to mitigate, although not eliminate entirely, the effect of important sources of unobserved heterogeneity.

Selection on unobservables. My second strategy to assessing the role of unobserved heterogeneity in the absence of a reliable instrument is to use the amount of selection on the observables as a guide to the amount of selection on the unobservables proposed by Altonji et al. (2005).[13] The idea here is to assess how much selection on unobservables there must be, relative to the amount of selection on observables, to entirely account for the estimated association between attractiveness and employment.

Selection on unobservables is formalized by the ratio

$$S_{uo} := \frac{\mathbb{E}\left[\varepsilon_i | \mathrm{A}_i = 1\right] - \mathbb{E}\left[\varepsilon_i | \mathrm{A}_i = 0\right]}{\mathrm{Var}[\varepsilon_i]}, \tag{3}$$

Altonji et al. (2005) show that under the hypothesis that the effect of attractiveness is zero, i.e. $\alpha = 0$, the maximal amount of selection on unobservables can be estimated as

$$\hat{S}_{uo} := \hat{\pi}^{-1}\hat{\alpha}. \tag{4}$$

where $\hat{\alpha}$ is the estimate of α in equation (2) and π is given by

$$\pi := \mathrm{Var}[\mathrm{A}_i]/\mathrm{Var}[\widetilde{\mathrm{A}_i}]. \tag{5}$$

where $\widetilde{\mathrm{A}_i}$ is the residual in the regression of A_i on X_i.

Similarly, selection on observables is defined as

$$S_o := \frac{\mathbb{E}\left[X_i'\beta | \mathrm{A}_i = 1\right] - \mathbb{E}\left[X_i'\beta | \mathrm{A}_i = 0\right]}{\mathrm{Var}[X_i'\beta]}, \tag{6}$$

and can be consistently estimated by sample averages and plugging in the estimate $\hat{\beta}$ from the constrained estimation of equation (2) forcing $\alpha = 0$. I denote this estimate of selection on observables by $\hat{S}_o$.

[13] In a recent paper, Oster (2016) extends this methodology by linking the bias explicitly to coefficient stability. However it is appropriate only for a linear model.

The ratio of the estimate $\hat{S}_{uo}$ to the estimate $\hat{S}_o$ tells us the relative magnitude of the role of unobservables to observables in order to explain away the entire causal effect of attractiveness. I compute this ratio for the baseline model as well as for the comprehensive model with additional controls.

A note on classical measurement error. In the absence of objective information on beauty, asking interviewers to rate people's physical attractiveness (either during face-to-face contact or based on photos) is the main approach to measuring attractiveness in the literature. This approach is justified based on the observation that there is substantial agreement among observers on what constitutes human beauty (for a summary of existing evidence, see Chapter 2 of Hamermesh, 2011). This is the case "within a society at a point in time, including the worldwide society of developed nations" (Hamermesh, 2011, p. 13).

A measurement error may arise, however, if standards of beauty differ across interviewers. To the extent that interviewer standards are correlated with the respondents' employment propensities, this would lead to a downward bias in the estimates of attractiveness. To account for this issue, I include interviewer fixed effects in the estimations, following previous studies (e.g., Hamermesh and Biddle, 1994; Mocan and Tekin, 2010; Hamermesh and Abrevaya, 2013; Oreffice and Quintana-Domeque, 2016).

4. Results

Baseline results. Probit model estimates of the effect of attractiveness on the probability of employment given in equation (2) are reported in Table 3 for males and Table 4 for females. For ease of interpretation, marginal effects are reported throughout. The specifications reported in columns (1) exclude other controls (parsimonious specifications). Consistent with the descriptive statistics reported in Table 2, the estimates identify a positive relationship between attractiveness and the probability of employment. The marginal effect of attractiveness is 13.4 percentage points for males and 6.1 percentage points for females.

Next, I examine the relationship between attractiveness and employment probability, controlling for standard individual characteristics of respondents. I find very similar results for attractiveness in both male and female samples (columns (2)). There are no systematic differences in employment probabilities of males of different age groups. However, in the sample of females those in all older age cohorts are more likely to be employed relative to women in the age group of 26-30. The largest difference in employment probabilities is observed with the age group of 41-45: moving a person of 26-30 years of age to this group would result in an increase in the employment probability of 18.2 percentage points. These results appear

to be consistent with usual patterns of fertility and child-rearing roles in the three countries. Being part of an ethnic and linguistic majority status does not bear statistically significant implications for employment probabilities of males and females.

In columns (3) and (4), I augment the parsimonious specifications with measures of having a partner and being in good health respectively. The estimates on attractiveness are largely unaffected by the presence of these variables. Having a partner is associated with an increase in males' employment probability but with a decrease in females' employment probability. These results are broadly consistent with other findings on labour market returns to marriage where a premium is documented for males (e.g., Korenman and Neumark, 1991; Kermit, 1995) and a penalty for females (e.g., Anderson et al., 2003; Loughran and Zissimopoulos, 2009). Proposed explanations include employer discrimination and productivity differences due to specialization afforded by marriage. As expected, healthier males and females are more likely to be employed although the magnitude of the effect for males is the double of that for females.

Next, in columns (5), I extend the parsimonious specification to include measures of educational attainment of respondents. Consistent with patterns of sorting into educational attainment based on attractiveness endowment reported in Table 2, I observe a significant decline in the size of the estimated marginal effect on attractiveness for males. Not only the size of the estimated effect of attractiveness is significantly smaller in the sample of females, it is no longer significant once measures of educational attainment are controlled for. Educational attainment itself is associated with a significant increase in the probability of employment for both males and females. Furthermore, returns to education appear to be higher for females than for males, consistent with previous findings from the region (Duncan and Mavisakalyan, 2015; Mavisakalyan and Meinecke, 2016).

Next, in the specifications reported in columns (6), I include dummies for location of residence, in addition to controlling for the respondents' attractiveness. The estimated marginal effect on ATTRACTIVE is robust to inclusion of these variables; moreover in the sample of males, the size of the marginal effect is larger compared to that obtained from the parsimonious model. Capital-city-based males have a higher probability of employment relative to those in other urban and rural residences. Azerbaijani males are more likely to be employed compared to their Armenian but not Georgian counterparts. Location does not appear to be a significant correlate of females' employment.

Finally, in columns (7) I report the estimation results of baseline model that include all the controls jointly. The marginal effect of changing the dummy ATTRACTIVE from 0 to 1

is 0.136 in the sample of males. This is an economically substantial effect; it is larger, for example, than the effect of moving from single to partnered status, or from poor to good health condition.

Like this study, a number of previous studies on the link between physical looks and labour market outcomes have been based on pooled country datasets (e.g., Sousa, 2005; Lundborg et al., 2006; Brunello and D'Hombres, 2007). However, Garcia and Quintana-Domeque (2006) highlight the presence of heterogeneity across countries in their sample of European countries due to differences in labour market institutions. To assess whether such heterogeneity is observed in the case of the three countries in my sample, in columns (8)-(10) I re-estimate the baseline model separately for each country. Reassuringly, the estimated male attractiveness premiums in all three countries are similar in size and significance. This is perhaps unsurprising, given the similarities in the historical economic structures and cultures in the three countries.

In pooled and country-based models with full set of baseline controls (as well as in all subsequent estimations in this paper), no statistically significant effect of females' attractiveness on employment is found. To some extent, gender differences in labour market returns to attractiveness documented here are consistent with other findings in the literature. Several previous studies find stronger evidence of attractiveness premium in the labour market for males than for females (e.g., Hamermesh and Biddle, 1994; Mocan and Tekin, 2010; Gehrsitz, 2014; Doorley and Sierminska, 2015). Moreover, like this study, some do not find any evidence for attractiveness premium for females (e.g., Biddle and Hamermesh, 1998; Borland and Leigh, 2014). Yet in other cases, the analysis on females is deliberately omitted in view of more complicated female labour force decisions (Kreisman and Rangel, 2015; Scholz and Sicinski, 2015).

As it appears, levels of attractiveness increase in educational attainment; however there are some differences by gender, particularly at intermediate levels of education. Sixty-five percent of females with 10-14 years of education are rated as attractive compared to only 52% attractiveness among males (differences in prevalence of attractiveness are only marginally in favour of females at other levels of educational attainment). Consistent with these patterns of selectivity, the entire attractiveness effect of females but only a portion of attractiveness effect for males is accounted for by its effects on educational attainment. Moreover, attractiveness (as well as educational attainment) may alter women's labour market outcomes by altering their opportunities for marriage. In our sample, attractiveness is unrelated to women's probability of having a partner. However, as a body of evidence suggests, it may

be related to the quality of the partner with more attractive women often marrying more successful men (e.g., Hamermesh and Biddle, 1994; Averett and Korenman, 1996). The literature has also highlighted the existence of trade-offs across physical attributes and socio-economic status in marriage markets (Oreffice and Quintana-Domeque, 2010; Chiappori et al., 2012; Sohn, 2015). Furthermore, Oreffice and Quintana-Domeque (2012) demonstrate, in a collective labour supply framework, that heavier spouses may compensate with more hours of work. Unfortunately it is not possible to explore these possibilities within the scope of the current dataset since no information on partners' characteristics was collected.

[Table 3 about here.]

[Table 4 about here.]

Robustness checks.

Comprehensive controls. A key concern with the findings presented in the previous section is whether attractiveness itself is rewarded in the labour market or whether it is simply a proxy for unobserved characteristics that offer a comparative advantage in the labour market. Here I address the issue of possible omitted variable bias in the estimates of attractiveness by including proxy variables that could be correlated with hitherto unexplained part of employment. I evaluate the importance of omitted cognitive characteristics, non-cognitive characteristics and social connectedness. I, first, directly test for correlations between attractiveness and available proxies for these characteristics (with and without baseline controls). In doing so, I am able to directly evaluate whether attractiveness might influence employment through its effect on cognitive characteristics, non-cognitive characteristics and social connectedness of individuals. Furthermore, by considering correlations between attractiveness and indicators of these characteristics I can measure, I get some indication of whether attractiveness is correlated with similar characteristics of individuals that remain unobservable. Second, I sequentially introduce the proxies for cognitive characteristics, non-cognitive characteristics and social connectedness into the estimations of employment equation with the view of evaluating the extent to which the estimated effects of attractiveness on employment capture the correlation between attractiveness and these variables that have been omitted from employment equation.

Omitted cognitive skills may lead to upward bias in estimates of attractiveness if cognitive skills and attractiveness are positively correlated. This may be the case, for example, if attractive individuals invest more into their human capital since they receive more attention from teachers (e.g., Lerner et al., 1990). As the descriptive statistics in Table 2 suggests,

attractiveness increases in level of education. Moreover, the baseline results reported in Tables 3 and 4 demonstrate that controlling for educational attainment reduces the size of the estimated marginal effect on attractiveness for males and eliminates the entire effect for females. In columns (1) and (2) of Tables 5 and 6, I directly examine the links between attractiveness and education by estimating ordered probit models of educational attainment for males and females. In both bivariate (columns (1)) and multivariate (columns (2)) regressions, I estimate highly significant positive attractiveness effects. Attractiveness increases the probability of 11-14 years' educational attainment by 1.8 percentage points for males and 3.2 percentage points for females.[14] These differences are consistent with earlier discussion on more prevalent patterns of selection into education based on attractiveness for females compared to males.

I additionally consider information on the respondents' language and computer proficiency. Presumably these would be correlated with unobserved skills productive in the labour market. I include: RUSSIAN PROFICIENCY, a dummy equal to 1 if the person has an advanced or intermediate self-reported proficiency of the language and 0 otherwise; COMPUTER PROFICIENCY, a dummy equal to 1 if the person has an advanced or intermediate self-reported computer proficiency (specified to include Microsoft Office programs, excluding games) and 0 otherwise; and INTERNET USER, a dummy equal to 1 if the person has experience of accessing internet, and 0 otherwise. In columns (3)-(8) of Tables 5 and 6, I report the results of bivariate and multivariate regressions of these variables on ATTRACTIVE. In the sample of males, I find that attractiveness is highly correlated with all three measures of cognitive skills. As Table 5 demonstrates, after controlling for background characteristics of individuals, attractiveness is associated with 16.8 percentage points increase in males' probability of being proficient in Russian (column (4)), 7 percentage points increase in their probability of having computer proficiency (column (6)), and 5.6 percentage points increase in the probability of being internet user (column (8)). In the results for females reported in Table 6, I observe significant positive marginal effects on attractiveness in parsimonious specifications; however attractiveness is no longer significantly correlated with the three measures of cognitive skills once background characteristics of females are accounted for.

Tables 7 and 8 repeat the estimates from baseline specifications in Tables 3 and 4 (columns 1). Further, in columns (2), the measures of cognitive skills are additionally controlled for.

[14] To conserve space, I report the marginal effects for 11-14 years' educational attainment only. The marginal effects on the lowest educational attainment category (less than 10 years of education) always has the opposite sign to that of the highest outcome (15 or more years of education). Because the outcomes are ordered, the marginal effects for 15 or more years of education are larger relative to the marginal effects for the middle category reported in Tables 5 and 6; they are also highly statistically significant.

As expected, the size of the marginal effect on attractiveness for males is smaller; however it remains significant. No statistically significant effect of cognitive skill proxies is found. These are, however, significant in the sample of females: Having computer proficiency and being internet user both lead to an increase in employment probability of around 11 percentage points. Employment probability is 9.7 percentage points higher for Russian-speaking females. This effect is consistent with other findings from the three countries (Duncan and Mavisakalyan, 2015).

[Table 5 about here.]

[Table 6 about here.]

Attractiveness may also be correlated with non-cognitive skills correlated with employment. For example, there is evidence to suggest that attractiveness is positively correlated with confidence (Mobius and Rosenblat, 2006) as well as sense of self-acceptance, purpose in life and personality traits (Scholz and Sicinski, 2015). To proxy for unobserved non-cognitive characteristics of respondents, I include HIGH LOCUS OF CONTROL in the analysis. This variable is defined based on the question eliciting the respondents' level of control over their economic situation on a scale from 1 (no control at all) to 10 (complete control), and re-defined as a categorical variable representing low, intermediate and high loci of control. With conceptual links to both motivation and self-control, locus of control is one of the most important constructs for understanding a wide range of economic decisions (Cobb-Clark, 2015). Previous studies have linked internal locus of control with labor market success (e.g., Heineck and Anger, 2010; Caliendo et al., 2015). It may also be positively correlated with attractiveness, leading to upward bias in estimates. In addition to HIGH LOCUS OF CONTROL, I control for a behavioural characteristic of individuals: a dummy that takes 1 for positive number of cigarettes smoked on a daily basis and 0 otherwise. This variable arguably proxies for a range of non-cognitive characteristics in the absence of direct measures for such characteristics (e.g. risk-averseness, time-preference) potentially correlated with attractiveness. To the extent smoking behaviour proxies for risk-taking or high rates of time preference, it may be positively associated with employment (e.g., Mavisakalyan and Meinecke, 2016).

Furthermore, the observed effect of attractiveness may operate through favourable experiences of socialisation. Langlois et al. (2000), for example, find that attractive adults are treated more positively than unattractive adults, even by those who know them. It is possible, that the effect of attractiveness on employment is over-estimated, given the evidence on positive implications of social capital for employment outcomes (e.g., Mouw, 2003;

Yakubovich, 2005). To address this issue, I introduce three measures of social connectedness available in the dataset. First, I consider two measures to capture the respondents' perception of their own social connectedness. I include a dummy, FEELS REJECTED, that equals 1 if the respondents agree that the statement 'I often feel rejected' describes or more or less describes their feelings, and 0 otherwise. Similarly, the dummy FEELS EMPTINESS included in the regressions equals 1 if the respondents agree that the statement 'I experience a general sense of emptiness' describes or more or less describes their feelings, and 0 otherwise. Additionally, I include the objective NUMBER OF FRIENDS. [15]

Columns (3)-(5) of Tables 7 and 8 repeat the baseline specifications in Tables 3 and 4 but additionally include the measures of non-cognitive skills and social connectedness (sequentially). In both male and female samples, high locus of control is associated with increased probability of employment with the size of the effect larger for males relative to females (columns (3)). The marginal effects on feelings of rejection and emptiness have negative signs in both samples (columns (4)); however only the marginal effect on FEELS REJECTED for males is statistically significant. Number of friends are positively significantly associated with the employment probabilities of males and females (columns (5)).

Finally, columns (6) report the results after including the entire list of comprehensive controls. The estimated marginal effect on attractiveness for males is smaller compared to the baseline estimate. Thus a portion of the male attractiveness premium can be accounted for by its correlation with their cognitive characteristics, non-cognitive characteristics and social connectedness. However, even after accounting for such a comprehensive list of controls, attractiveness remains positively correlated with the employment probability of males with a marginal effect equal to 11.1. This is equivalent to over a 16% increase in employment probability. The attractiveness effects in the sample of females remain insignificant throughout these specifications.[16]

[Table 7 about here.]

[15] Tables 12 and 13 in the Appendix present the correlations between attractiveness and non-cognitive and social connectedness attributes discussed above in the samples of males and females. In bivariate regressions in the sample of males reported in Table 12, I find that attractiveness is significantly positively correlated with high locus of controls (column (1)). However this result is not robust to accounting for background characteristics of males in column (2). Attractive individuals are also less likely to feel rejected (columns (5)-(6)) or experience a feeling of emptiness (columns (6)-(7)). Correlations with other measures included in this analysis are not significant. Interestingly in the sample of females, I find highly significant correlations between attractiveness and number of friends but not other non-cognitive and social connectedness measures (Table 13).

[16] As a further robustness test, I applied propensity score matching method proposed by Rosenbaum and Rubin (1983) to assess the effect of attractiveness on employment. Reassuringly, the estimated average treatment effect for males was positive and statistically significant while the effect for females was indistinguishable from zero. The results of this exercise are available on request.

[Table 8 about here.]

Selection on unobservables. The analysis performed in the preceding section can at the best mitigate the problem of unobserved heterogeneity; however it cannot eliminate it. The later would require having a convincing instrumental variable, which is not available in the dataset. Here I take a different approach to addressing the issue of unobserved heterogeneity: I identify the relative role of unobservables required in order for the attractiveness premium to be zero. This approach provides further guidance in assessing the reliability of estimates of the attractiveness effect.

I compare the amount of selection on unobservables to the amount of selection on observables for two probit specifications: the baseline specification with the full set of controls (as per columns (7) of Tables 3 and 4), and the comprehensive specification with the full set of comprehensive controls, including the baseline controls (as per columns (6) of Tables 7 and 8). Table 9 reports the results.

Based on the baseline specification, the amount of selection on observables under the hypothesis of no causal effect of attractiveness is equal to 0.131. The estimate of α at 0.397, adjusted for the value of $\hat{\pi}$ of 1.076 implies a maximum amount of selection on unobservables of 0.369. The resulting ratio of 2.805 means that the maximum amount of selection on unobservables would have to be 2.805 times as large as the amount of selection on the observables to explain away the entire male attractiveness effect. Performing similar calculations for the comprehensive specification yields a ratio of 3.406. That is, the maximum amount of selection on unobservables would have to be 3.406 times as large as the amount of selection on the observables to cancel out the attractiveness effect. This is rather improbable, given the comprehensive set of explanatory variables included in the models (pseudo R^2=0.161). In assessing the effectiveness of Catholic schools, Altonji et al. (2005) report selection ratios of 1.43 (for college attendance) and 3.55 (for high school graduation), and suggest these to be "unlikely". Numbers in similar range are reported and declared as unlikely in other studies having applied this approach in different contexts (e.g., Fletcher and Frisvold, 2011; Chintrakarn et al., 2013; Mavisakalyan and Meinecke, 2016).

[Table 9 about here.]

Measurement of attractiveness. The fact that attractiveness can be defined in a number of ways may bear implications for the results. In Table 10, I test the sensitivity of the results to measurement of attractiveness. To allow for comparisons, in columns (1) and (6) I repeat the specifications with comprehensive list of controls reported in columns (6) of Tables 7 and 8.

My baseline measure of attractiveness is generated based on interviewers' assessment on how attractive they found the respondents on the five-point scale. I reduced this information to a dummy variable coded 1 if the respondent was rated as attractive or very attractive by the interviewer, and 0 if the rating was 'neither attractive nor not attractive', 'unattractive' or 'very unattractive'. This approach minimizes the probability of misclassification of attractiveness. However, a drawback associated with it is that it does not distinguish across those with plain and unattractive looks, something that has been done in previous studies (e.g., Hamermesh and Biddle, 1994; French, 2002). Here I introduce more nuance to the measurement of looks by merging the bottom two (instead of three) categories into one, 'unattractive'. I then compare the employment outcomes for attractive and unattractive individuals to those who are neither attractive nor not attractive (excluded category). In columns (2) and (7) of Table 10, I report the results of this exercise. The results suggest that attractive males have significantly higher probability of being employed compared to males with plain looks; however there is no significant difference in employment probabilities of males with plain and unattractive looks.[17]

In an effort to introduce further nuance in the relationship between attractiveness and employment, I next introduce a distinction between individuals rated as 'very attractive' or just 'attractive' by interviewers (at the cost of having noisier measures of attractiveness). I then compare the employment probability of these two groups relative to those with plain or unattractive looks. Columns (3) and (8) present the results. Interestingly, the positive relationship between attractiveness and employment propensity is more pronounced for males with just attractive looks. The estimated marginal effect on JUST ATTRACTIVE is 11.3 percentage points while that on VERY ATTRACTIVE is 9.8 percentage points. One explanation behind this finding is that most people may apparently prefer the company of those close to the statistical norm, and similar to themselves (Huebler, 2009).

An alternative to defining attractiveness as a categorical variable would be to treat it as continuous - an approach that has been used in some previous studies (e.g., Gehrsitz, 2014; Oreffice and Quintana-Domeque, 2016).[18] Columns (4) and (9) present the estimates of employment equation where a continuous measure of attractiveness used. Males' probability of employment increases by 5.9 percentage points in response to one unit increase in attractiveness ranking. The magnitude of this effect is remarkably similar to that from the

[17]The results for females remain significant throughout. They are reported however not discussed in the remainder of this subsection.

[18]It should be noted that both studies used attractiveness data defined on a scale from 1 to 11 instead of more standard 5-categorical definition (Sierminska, 2015).

German study by Gehrsitz (2014) - a somewhat comparable study to this study, given its focus on employment.

An important justification behind using interviewer ranking-based measures of looks in economic analysis is the absence of large disagreement about looks. In fact, as Langlois et al. (2000) suggest, raters agree on a universal beauty standard, not just within cultures, but also between cultures. To allow for the fact that interviewers may use different scales in assessing the looks of respondents, interviewer fixed effects are controlled for in columns (5) and (1). The results are robust to this change; as expected, the marginal effect on attractiveness is larger compared to the baseline estimate.

[Table 10 about here.]

Implications for other labour market outcomes. Other labour markets such as wages and promotions can be influenced by attractiveness. Information on these outcomes, however, is not available in the current dataset. To get some indication of whether attractiveness affects wages and promotions, I employ proxy measures for these outcomes and analyse these in relation to attractiveness, accounting for baseline characteristics of individuals. The results are presented in Table 11.

While there is no information on wages in the dataset, it includes information on 'personal income' in the preceding month reported in 8 categories. It should be noted that this is a highly imperfect measure of wages, especially since no information on the hours of work is available. I apply the simple procedure of treating the midpoint of a group as if it is the observed value of that variable to construct a proxy for pay.[19] The results of OLS regressions using (the log of) this proxy as the dependent variable separately are reported in columns (1) and (4). The relationship between attractiveness and wages is significant in the sample of males but not in the sample of females. These results exhibit a similar pattern to those obtained from parametric interval regressions that take into account the interval nature of personal income data (columns (2) and (5)).

Data on promotions is also unavailable in the data. What it does contain is information on change in the respondents' 'employment status' over the preceding 12 months. Based on this information, I construct a dummy that equals 1 if the respondent reports having experienced positive change in employment status and 0 otherwise. To ensure that the initial offer of employment is not counted as a positive change in employment status, the estimations are limited to those with at least two years of employment with the current employer. As the

[19] Applying this approach to construct a dependent variable in a linear regression model should not create serious issues (e.g. Fryer and Pethybridge, 1972).

results reported in columns (3) and (6) of Table 11 demonstrate, there is a positive association between attractiveness and the incidence of positive employment change of males but not females.

[Table 11 about here.]

5. Discussion

The results establish a robust link between attractiveness and employment probability of males. An important question is whether these results suggest discrimination on the basis of looks. Theories of discrimination predict that employers or customers may simply have a taste for attractive employees (Becker, 1971). Under such taste-based discrimination scenario, attractive individuals will be favoured over equally productive unattractive individuals. It is also possible, under statistical theory of discrimination, that employers or customers consciously discriminate because they lack information about the productivity of individuals and 'statistically discriminate' against them on the basis of easily observable characteristics such as looks (e.g., Phelps, 1972; Arrow, 1973). Yet it is also possible that the results are not an evidence of discrimination but instead of productivity associated with attractiveness itself. This may be the case in certain occupations, such as sex work or sales, where looks are likely to enhance productivity (Hamermesh and Biddle, 1994). Empirically distinguishing between these scenarios is extremely challenging if not 'impossible' (Hamermesh and Parker, 2005, p. 369).

An implication of taste-based theories of employer discrimination is that competition among employers should limit such discrimination since it is costly. However, this is less likely to hold for public sector employers for whom profit maximization is not a key objective, and who are therefore more able to follow taste for discrimination. This may be particularly true for settings with poor-quality and corrupt public institutions as in the case of the three countries of this study. One way to determine whether the results are consistent with the taste-based theory of discrimination is therefore to consider the relationship between attractiveness and labour market outcomes by public/private sector.

Ehrenberg and Schwarz (1987) posit that discrimination in the public sector primarily takes the form of unequal access to initial jobs and promotion opportunities and not of unequal pay given the structured nature of employment in the public sector that often requires equal pay for all individuals with the same seniority and qualifications. Indeed, analysing the relationship between attractiveness and wages yields insignificant results in sub-samples

of public as well as private employees (the results are available on request). I do not find evidence of sorting into public/private sector based on attractiveness; however I do find a positive association between attractiveness and the incidence of positive employment change of public but not private sector employees.[20]

These results are broadly consistent with the scenario of tasted-based discrimination limited to the public sector given that there is no reason to believe that attractiveness is particularly productive in the public sector (indeed if anything, it may be more productive in private sector for certain occupations - for evidence on job market for lawyers see Biddle and Hamermesh, 1998). Furthermore, the fact that there is an effect of attractiveness on the probability of experiencing a positive employment status change two years along the employment path suggests limited scope for statistical theory of discrimination under which employers lack information about the productivity of new employees and 'statistically discriminate' among them in their hiring decisions on the basis of easily observable characteristics such as looks (e.g., Phelps, 1972; Arrow, 1973).

It cannot be entirely ruled out, of course, that the observed positive significant effect of attractiveness on labour market outcomes is attributable to its productive value. Such value, however, would be highly occupation-specific, and testing for it would require detailed data on occupations which is not available in the current dataset. The analysis in Hamermesh and Biddle (1994) exploits information on productivity-enhancing values of occupations. That analysis, however, finds only weak support for a productivity-related mechanism. Hamermesh and Biddle (1994) conclude that employer discrimination is likely to underlie their findings on positive labour market returns to attractiveness. This is likely to also hold in the context at hand. The scenario of employer discrimination in favour of attractive individuals is also supported by findings from field experiments. Recent studies document lower callbacks for unattractive individuals after submitting a resume (e.g., Boo et al., 2013; Ruffle and Shtudiner, 2015) even though attractiveness is not correlated with labor productivity (Mobius and Rosenblat, 2006).

6. Conclusion

This study provides the first evidence on labour market return to physical attractiveness in transition countries. Based on data from three post-Soviet countries of the Caucasus, I document large positive effect of attractiveness on the employment probability of males. This result is robust to conditioning on an extensive set of characteristics. Moreover, following

[20] It should be noted that the analysis by sector faces a problem of small sample size.

an approach proposed by Altonji et al. (2005), I show that the degree of selection on the unobservables would have to be much stronger than the degree of selection on the observables to overturn this result. I therefore conclude that at least part of the effect of attractiveness on employment probability of males is likely to be causal. Applying this approach to assessing the selection bias is novel to the economics literature on attractiveness and strengthens the evidence base for causal inferences on its labour market returns.

While I am not able to precisely identify the mechanism that accounts for the attractiveness effect, my results suggest a role for taste-based employer discrimination. That there is scope for such discrimination in transition countries is not surprising given the absence of truly competitive markets and fair employment laws to prevent discrimination following the breakdown of institutions of full employment after the collapse of the Soviet Union. A policy implication that follows from this study is therefore to adopt formal (e.g. anti-discrimination laws) and informal (e.g. social norms) institutions to prevent refusing employment on the basis of physical characteristics (along with other characteristics not bearing direct relation to productivity such as gender or race).

After accounting for covariates, there is no evidence for a statistically significant link between females' attractiveness and employment - something that warrants further attention in future research. Understanding the marriage market returns to attractiveness in transition countries, subject to data availability, is one promising approach in that direction. Further investigation of the relationship between attractiveness and labour market outcomes in the context of other transition countries, particularly those with relatively more evolved labour market institutions, would be beneficial. Whether discrimination vs productivity-related mechanisms mediate the observed relationship between attractiveness and labour market outcomes of males is another area with high potential returns to further analysis, since existing findings are far from being conclusive. Finally, assessment of discrimination on the basis of other characteristics such as race, weight, or age in transition countries is another important area of future research.

REFERENCES

Altonji, J. G., T. E. Elder, and C. R. Taber (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy 113*(1), 151–184.

Anderson, D. J., M. Binder, and K. Krause (2003). The motherhood wage penalty revisited: Experience, heterogeneity, work effort, and work-schedule flexibility. *ILR Review 56*(2), 273–294.

Antinyan, A. (2016). Reference group income and subjective well-being: Empirical evidence from low-income transition economies. *Social Indicators Research 127*(3), 1333–1348.

Arrow, K. J. (1973). The theory of discrimination. In O. Ashenfelter and A. Rees (Eds.), *Discrimination in Labor Markets*, pp. 3–33. Princeton University Press.

Arunachalam, R. and M. Shah (2012). The prostitute's allure: The return to beauty in commercial sex work. *The BE Journal of Economic Analysis & Policy 12*(1), 1–25.

Atella, V., N. Pace, and D. Vuri (2008). Are employers discriminating with respect to weight?: European evidence using quantile regression. *Economics & Human Biology 6*(3), 305 – 329. Symposium on the Economics of Obesity.

Averett, S. and S. Korenman (1996). The economic reality of the beauty myth. *Journal of Human Resources 31*(2), 304–330.

Becker, G. S. (1971). *The Economics of Discrimination*. Chicago, IL: University of Chicago Press.

Berggren, N., H. Jordahl, and P. Poutvaara (2010). The looks of a winner: Beauty and electoral success. *Journal of Public Economics 94*(12), 8 – 15.

Bertrand, M., D. Chugh, and S. Mullainathan (2005). Implicit discrimination. *The American Economic Review 95*(2), 94–98.

Biddle, J. E. and D. S. Hamermesh (1998). Beauty, productivity, and discrimination: Lawyers' looks and lucre. *Journal of Labor Economics 16*(1), 172–201.

Boo, F. L., M. A. Rossi, and S. S. Urzua (2013). The labor market return to an attractive face: Evidence from a field experiment. *Economics Letters 118*(1), 170 – 172.

Borland, J. and A. Leigh (2014). Unpacking the beauty premium: What channels does it operate through, and has it changed over time? *Economic Record 90*(288), 17–32.

Bozoyan, C. and T. Wolbring (2011). Fat, muscles, and wages. *Economics & Human Biology 9*(4), 356 – 363.

Brainerd, E. (2000). Women in transition: Changes in gender wage differentials in Eastern Europe and the Former Soviet Union. *Industrial and Labor Relations Review 54*(1), 138–162.

Brunello, G. and B. D'Hombres (2007). Does body weight affect wages?: Evidence from Europe. *Economics & Human Biology 5*(1), 1 – 19.

Caliendo, M., D. A. Cobb-Clark, and A. Uhlendorff (2015). Locus of control and job search strategies. *Review of Economics and Statistics 97*(1), 88–103.

Caliendo, M. and W.-S. Lee (2013). Fat chance! Obesity and the transition from unemployment to employment. *Economics & Human Biology 11*(2), 121 – 133.

Cawley, J. (2004). The impact of obesity on wages. *Journal of Human Resources 39*(2), 451–474.

Chiappori, P.-A., S. Oreffice, and C. Quintana-Domeque (2012). Fatter attraction: Anthropometric and socioeconomic matching on the marriage market. *Journal of Political Economy 120*(4), 659–695.

Chintrakarn, P., N. Jiraporn, and P. Jiraporn (2013). The effect of entrenched boards on corporate risk-taking: Testing the quiet life hypothesis. *Applied Economics Letters 20*(11), 1067–1070.

Cipriani, G. P. and A. Zago (2011). Productivity or discrimination? Beauty and the exams. *Oxford Bulletin of Economics and Statistics 73*(3), 428–447.

Cobb-Clark, D. A. (2015). Locus of control and the labor market. *IZA Journal of Labor Economics 4*(1), 1–19.

CRRC (2007). Data initiative 2007 - unified sampling methodology. Technical report, Caucasus Research Resource Centres.

CRRC (2008). Data initiative - 2008. Fieldwork report, Caucasus Research Resource Centres.

Daly, A. (1993). The determinants of employment for aboriginal people. *Australian Economic Papers 32*(60), 134–151.

Doorley, K. and E. Sierminska (2015). Myth or fact? The beauty premium across the wage distribution in Germany. *Economics Letters 129*, 29–34.

Duncan, A. and A. Mavisakalyan (2015). Russian language skills and employment in the Former Soviet Union. *Economics of Transition 23*(3), 625–656.

Ehrenberg, R. G. and J. L. Schwarz (1987). Public-sector labor markets. In O. Ashenfelter and R. Layard (Eds.), *Handbook of Labor Economics*, Volume 2, Chapter 22, pp. 1219–1260. Elsevier.

Field, M. G. (1995). The health crisis in the Former Soviet Union: A report from the 'post-war' zone. *Social Science & Medicine 41*(11), 1469 – 1478.

Fletcher, J. M. and D. E. Frisvold (2011). College selectivity and young adult health behaviors. *Economics of Education Review 30*(5), 826 – 837. Special Issue on Education and Health.

French, M. T. (2002). Physical appearance and earnings: Further evidence. *Applied Economics 34*(5), 569–572.

French, M. T., P. K. Robins, J. F. Homer, and L. M. Tapsell (2009). Effects of physical attractiveness, personality, and grooming on academic performance in high school. *Labour Economics 16*(4), 373 – 382.

Fryer, J. G. and R. J. Pethybridge (1972). Maximum likelihood estimation of a linear regression function with grouped data. *Journal of the Royal Statistical Society. Series C (Applied Statistics) 21*(2), 142–154.

Garcia, J. and C. Quintana-Domeque (2006). Obesity, employment and wages in europe. In K. Bolin and J. Cawley (Eds.), *The Economics of Obesity*, pp. 187–217. Emerald Group Publishing Limited.

Gehrsitz, M. (2014). Looks and labor: Do attractive people work more? *Labour 28*(3), 269–287.

Gerber, T. P. and O. Mayorova (2006). Dynamic gender differences in a post-socialist labor market: Russia, 1991-1997. *Social Forces 84*(4), 2047–2075.

Gerry, C. J., B.-Y. Kim, and C. A. Li (2004, Jun). The gender wage gap and wage arrears in russia: Evidence from the rlms. *Journal of Population Economics 17*(2), 267–288.

Guguen, N. (2012). Hair color and wages: Waitresses with blond hair have more fun. *The Journal of Socio-Economics 41*(4), 370 – 372.

Habibov, N. (2012). Income inequality and its driving forces in transitional countries: Evidence from Armenia, Azerbaijan and Georgia. *Journal of Comparative Social Welfare 28*(3), 209–221.

Habibov, N. N. and E. N. Afandi (2011). Self-rated health and social capital in transitional countries: Multilevel analysis of comparative surveys in Armenia, Azerbaijan, and Georgia. *Social Science and Medicine 72*(7), 1193 – 1204.

Hamermesh, D. S. (2006). Changing looks and changing discrimination: The beauty of economists. *Economics Letters 93*(3), 405 – 412.

Hamermesh, D. S. (2011). *Beauty Pays*. Princeton, NJ: Princeton University Press.

Hamermesh, D. S. and J. Abrevaya (2013). Beauty is the promise of happiness? *European Economic Review 64*, 351 – 368.

Hamermesh, D. S. and J. E. Biddle (1994). Beauty and the labor market. *The American Economic Review 84*(5), 1174–1194.

Hamermesh, D. S., X. Meng, and J. Zhang (2002). Dress for success? Does primping pay? *Labour Economics 9*(3), 361–373.

Hamermesh, D. S. and A. Parker (2005). Beauty in the classroom: Instructors pulchritude and putative pedagogical productivity. *Economics of Education Review 24*(4), 369–376.

Harper, B. (2000). Beauty, stature and the labour market: A British cohort study. *Oxford Bulletin of Economics and Statistics 62*, 771–800.

Heineck, G. and S. Anger (2010). The returns to cognitive abilities and personality traits in Germany. *Labour Economics 17*(3), 535 – 546.

Huebler, O. (2009). The nonlinear link between height and wages in Germany, 1985-2004. *Economics & Human Biology 7*(2), 191 – 199.

Islam, A. and R. Smyth (2012). The economic returns to good looks and risky sex in the Bangladesh commercial sex market. *The BE Journal of Economic Analysis & Policy 12*(1), 1–25.

Johansson, E., P. Böckerman, U. Kiiskinen, and M. Heliövaara (2009). Obesity and labour market success in Finland: The difference between having a high BMI and being fat. *Economics & Human Biology 7*(1), 36 – 45.

Johnston, D. W. (2010). Physical appearance and wages: Do blondes have more fun? *Economics Letters 108*(1), 10 – 12.

Jolliffe, D. and N. F. Campos (2005). Does market liberalisation reduce gender discrimination? Econometric evidence from Hungary, 1986–1998. *Labour Economics 12*(1), 1–22.

Kermit, D. (1995). The marriage premium. In M. Tommasi and K. Ierulli (Eds.), *The new economics of human behavior*, pp. 113–25. Cambridge University Press.

King, A. and A. Leigh (2009). Beautiful politicians. *Kyklos 62*(4), 579–593.

Korenman, S. and D. Neumark (1991). Does marriage really make men more productive? *The Journal of Human Resources 26*(2), 282–307.

Kreisman, D. and M. A. Rangel (2015). On the blurring of the color line: Wages and employment for black males of different skin tones. *Review of Economics and Statistics 97*(1), 1–13.

Langlois, J. H., L. Kalakanis, A. J. Rubenstein, A. Larson, M. Hallam, and M. Smoot (2000). Maxims or myths of beauty? A meta-analytic and theoretical review. *Psychological bulletin 126*(3), 390.

Lerner, R. M., M. Delaney, L. E. Hess, J. Jovanovic, and A. von Eye (1990). Early adolescent physical attractiveness and academic competence. *The Journal of Early Adolescence 10*(1), 4–20.

Lindeboom, M., P. Lundborg, and B. van der Klaauw (2010). Assessing the impact of obesity on labor market outcomes. *Economics & Human Biology 8*(3), 309 – 319.

Liu, X. and E. Sierminska (2014). Evaluating the effect of beauty on labor market outcomes: A review of the literature. *Luxembourg Institute of Socio-Economic Research (LISER) Working Paper Series 11*.

Loughran, D. S. and J. M. Zissimopoulos (2009). Why wait?: The effect of marriage and childbearing on the wages of men and women. *Journal of Human Resources 44*(2), 326–349.

Lundborg, P., K. Bolin, S. Höjgård, and B. Lindgren (2006). Obesity and occupational attainment among the 50+ of europe. In *The Economics of Obesity*.

Matud, M. (2004). Gender differences in stress and coping styles. *Personality and Individual Differences 37*(7), 1401 – 1415.

Mavisakalyan, A. and J. Meinecke (2016). The labor market return to academic fraud. *European Economic Review 82*, 212 – 230.

Mobius, M. M. and T. S. Rosenblat (2006). Why beauty matters. *The American Economic Review*, 222–235.

Mocan, N. and E. Tekin (2010). Ugly criminals. *Review of Economics and Statistics 92*(1), 15–30.

Mouw, T. (2003). Social capital and finding a job: Do contacts matter? *American Sociological Review 68*(6), 868–898.

Ogloblin, C. G. (1999). The gender earnings differential in the Russian transition economy. *Industrial and Labor Relations Review 52*(4), 602–627.

Orazem, P. F. and M. Vodopivec (1995). Winners and losers in transition: Returns to education, experience, and gender in Slovenia. *The World Bank Economic Review 9*(2), 201–230.

Oreffice, S. and C. Quintana-Domeque (2010). Anthropometry and socioeconomics among couples: Evidence in the United States. *Economics & Human Biology 8*(3), 373 – 384.

Oreffice, S. and C. Quintana-Domeque (2012). Fat spouses and hours of work: Are body and pareto weights correlated? *IZA Journal of Labor Economics 1*(1), 6.

Oreffice, S. and C. Quintana-Domeque (2016). Beauty, body size and wages: Evidence from a unique data set. *Economics & Human Biology 22*, 24–34.

Oster, E. (2016). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics 0*(ja), 0–0.

Persico, N., A. Postlewaite, and D. Silverman (2004). The effect of adolescent experience on labor market outcomes: The case of height. *Journal of Political Economy 112*(5), 1019–1053.

Phelps, E. S. (1972). The statistical theory of racism and sexism. *The American Economic Review 62*(4), 659–661.

Porket, J. L. (1989). Full employment in Soviet theory and practice. *British Journal of Industrial Relations 27*(2), 264–279.

Price, M. K. (2008). Fund-raising success and a solicitor's beauty capital: Do blondes raise more funds? *Economics Letters 100*(3), 351 – 354.

Rashad, I. (2008). Height, health, and income in the US, 1984-2005. *Economics & Human Biology 6*(1), 108 – 126.

Reilly, B. (1999). The gender pay gap in russia during the transition, 1992-96. *Economics of Transition 7*(1), 245–264.

Rooth, D.-O. (2009). Obesity, attractiveness, and differential treatment in hiring: A field experiment. *Journal of Human Resources 44*(3), 710–735.

Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*(1), 41.

Ruffle, B. J. and Z. Shtudiner (2015). Are good-looking people more employable? *Management Science 61*(8), 1760–1776.

Sabia, J. J. and D. I. Rees (2012). Body weight and wages: Evidence from add health. *Economics & Human Biology 10*(1), 14 – 19.

Scholz, J. K. and K. Sicinski (2015). Facial attractiveness and lifetime earnings: Evidence from a cohort study. *Review of Economics and Statistics 97*(1), 14–28.

Shkolnikov, V. M., G. A. Cornia, D. A. Leon, and F. Mesl (1998). Causes of the Russian mortality crisis: Evidence and interpretations. *World Development 26*(11), 1995 – 2011.

Sierminska, E. (2015). Does it pay to be beautiful? *IZA World of Labor 161*.

Sohn, K. (2015). The value of male height in the marriage market. *Economics & Human Biology 18*, 110 – 124.

Sousa, S. (2005). Does size matter? a propensity score approach to the effect of bmi on labour market outcomes. *Unpublished manuscript, University of Minho, Portugal*.

Steckel, R. H. (1995). Stature and the standard of living. *Journal of Economic Literature 33*(4), 1903–1940.

Wada, R. and E. Tekin (2010). Body composition and wages. *Economics & Human Biology 8*(2), 242 – 254. Special Issue Section: Latin American Anthropometrics.

Yakubovich, V. (2005). Weak ties, information, and influence: How workers find jobs in a local Russian labor market. *American Sociological Review 70*(3), 408–421.

APPENDIX

[Table 12 about here.]

[Table 13 about here.]

List of Tables

Table 1: Distribution of attractiveness ratings

Category	Males	Females
VERY UNATTRACTIVE	2.21	2.44
JUST UNATTRACTIVE	8.48	7.12
NEITHER ATTRACTIVE NOR UNATTRACTIVE	32.79	27.56
JUST ATTRACTIVE	47.55	50.07
VERY ATTRACTIVE	8.97	12.81
N	1006	1551

Note.—Percentage distributions representative of the population.

Table 2: Descriptive statistics: sample means and standard deviations

Variables	Definition	Males			Females		
		Unattractive	Attractive	All	Unattractive	Attractive	All
ATTRACTIVE	0-1 binary variable; equals 1 if rated 'attractive' or 'very attractive'	0	1	0.57 (0.50)	0	1	0.63 (0.48)
EMPLOYED	0-1 binary variable; equals 1 if respondent reported having a job	0.61 (0.49)	0.74 (0.44)	0.69 (0.46)	0.31 (0.46)	0.34 (0.47)	0.33 (0.47)
AGE 26-30	0-1 binary variable; equals 1 if respondent is aged 26 to 30	0.25 (0.43)	0.22 (0.41)	0.23 (0.42)	0.22 (0.41)	0.24 (0.43)	0.23 (0.42)
AGE 31-35	0-1 binary variable; equals 1 if respondent is aged 31 to 35	0.19 (0.39)	0.18 (0.38)	0.18 (0.39)	0.17 (0.37)	0.18 (0.39)	0.18 (0.38)
AGE 36-40	0-1 binary variable; equals 1 if respondent is aged 36 to 40	0.18 (0.39)	0.20 (0.40)	0.19 (0.39)	0.16 (0.37)	0.17 (0.38)	0.17 (0.37)
AGE 41-45	0-1 binary variable; equals 1 if respondent is aged 41 to 45	0.19 (0.39)	0.18 (0.39)	0.19 (0.39)	0.22 (0.41)	0.18 (0.38)	0.19 (0.39)
AGE 46-50	0-1 binary variable; equals 1 if respondent is aged 46 to 50	0.19 (0.39)	0.22 (0.42)	0.21 (0.41)	0.24 (0.43)	0.23 (0.42)	0.24 (0.42)
ETHNIC MAJORITY	0-1 binary variable; equals 1 if respondent is from ethnic majority	0.90 (0.30)	0.96 (0.19)	0.94 (0.24)	0.85 (0.35)	0.93 (0.26)	0.90 (0.30)
LINGUISTIC MAJORITY	0-1 binary variable; equals 1 if respondent is from linguistic majority	0.92 (0.27)	0.98 (0.15)	0.95 (0.21)	0.90 (0.30)	0.96 (0.20)	0.94 (0.24)
PARTNERED	0-1 binary variable; equals 1 if respondent has a partner	0.82 (0.39)	0.81 (0.39)	0.82 (0.39)	0.74 (0.44)	0.79 (0.41)	0.77 (0.42)
GOOD HEALTH	0-1 binary variable; equals 1 if respondent has good/very good health	0.47 (0.50)	0.48 (0.50)	0.47 (0.50)	0.36 (0.48)	0.36 (0.48)	0.36 (0.48)

Note.—Means representative of the population; standard deviations in parentheses.

Table 2: Descriptive statistics: sample means and standard deviations (continued)

Variables	Definition	Males			Females		
		Unattractive	Attractive	All	Unattractive	Attractive	All
EDUC$\leq$ 10	0-1 binary variable; equals 1 if	0.43	0.35	0.38	0.49	0.36	0.41
	at most 10 years of education	(0.50)	(0.48)	(0.49)	(0.50)	(0.48)	(0.49)
EDUC11-14	0-1 binary variable; equals 1 if	0.41	0.34	0.37	0.33	0.36	0.35
	between 11 and 14 years of education	(0.49)	(0.48)	(0.48)	(0.47)	(0.48)	(0.48)
EDUC$\geq$ 15	0-1 binary variable; equals 1 if	0.16	0.31	0.24	0.18	0.28	0.24
	15 or more years of education	(0.36)	(0.46)	(0.43)	(0.38)	(0.45)	(0.43)
CAPITAL CITY	0-1 binary variable; equals 1 if	0.27	0.25	0.26	0.27	0.31	0.30
	respondent lives in capital city	(0.45)	(0.43)	(0.44)	(0.45)	(0.46)	(0.46)
OTHER URBAN	0-1 binary variable; equals 1 if	0.24	0.27	0.26	0.35	0.27	0.30
	respondent lives in urban area	(0.43)	(0.44)	(0.44)	(0.48)	(0.45)	(0.46)
RURAL	0-1 binary variable; equals 1 if	0.48	0.48	0.48	0.37	0.41	0.40
	respondent lives in rural area	(0.50)	(0.50)	(0.50)	(0.48)	(0.49)	(0.49)
ARMENIA	0-1 binary variable; equals 1 if	0.17	0.24	0.20	0.13	0.26	0.21
	respondent lives in Armenia	(0.37)	(0.42)	(0.40)	(0.34)	(0.44)	(0.41)
AZERBAIJAN	0-1 binary variable; equals 1 if	0.66	0.51	0.58	0.70	0.43	0.53
	respondent lives in Azerbaijan	(0.47)	(0.50)	(0.49)	(0.46)	(0.50)	(0.50)
GEORGIA	0-1 binary variable; equals 1 if	0.17	0.25	0.22	0.18	0.31	0.26
	respondent lives in Georgia	(0.38)	(0.43)	(0.41)	(0.38)	(0.46)	(0.44)
N		444	562	1006	533	1018	1551

Note.—Means representative of the population; standard deviations in parentheses.

Table 3: Baseline model—probit marginal effects: males

Control variables	All	All	All	All	All	All	All	Armenia	Azerbaijan	Georgia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATTRACTIVE	0.134***	0.129***	0.132***	0.136***	0.110***	0.160***	0.136***	0.134**	0.138***	0.129*
	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.061)	(0.041)	(0.072)
AGE 31-35		0.079					0.100*	0.042	0.170**	-0.048
		(0.049)					(0.051)	(0.098)	(0.069)	(0.116)
AGE 36-40		-0.054					-0.076	-0.013	-0.070	-0.196*
		(0.050)					(0.055)	(0.112)	(0.078)	(0.107)
AGE 41-45		0.059					0.085	0.139	0.052	0.039
		(0.050)					(0.053)	(0.101)	(0.076)	(0.106)
AGE 46-50		-0.046					-0.038	-0.009	-0.037	-0.153
		(0.050)					(0.055)	(0.109)	(0.079)	(0.113)
ETHNIC MAJORITY		0.136					0.091	-0.405***	0.201	-0.023
		(0.094)					(0.101)	(0.052)	(0.138)	(0.157)
LINGUISTIC MAJORITY		0.097					0.046	0.621***	0.070	0.150
		(0.112)					(0.119)	(0.051)	(0.183)	(0.166)
PARTNERED			0.103**				0.116**	0.083	0.106	0.142*
			(0.042)				(0.047)	(0.098)	(0.074)	(0.081)
GOOD HEALTH				0.132***			0.121***	0.183***	0.132***	0.002
				(0.032)			(0.033)	(0.062)	(0.047)	(0.073)
EDUC11-14					0.088**		0.067*	0.060	-0.006	0.229**
					(0.037)		(0.039)	(0.074)	(0.055)	(0.090)
EDUC$\geq$ 15					0.244***		0.214***	0.205***	0.222***	0.252**
					(0.038)		(0.041)	(0.075)	(0.056)	(0.100)
OTHER URBAN						-0.193***	-0.187***	-0.274***	-0.134**	-0.222**
						(0.039)	(0.040)	(0.074)	(0.056)	(0.107)
RURAL						-0.246***	-0.184***	-0.353***	-0.071	-0.187*
						(0.039)	(0.041)	(0.070)	(0.061)	(0.112)
ARMENIA						-0.074*	-0.080**			
						(0.038)	(0.039)			
GEORGIA						-0.047	-0.068			
						(0.043)	(0.045)			
Pseudo R^2	0.017	0.031	0.022	0.031	0.046	0.057	0.108	0.150	0.122	0.111
N	1006	1006	1006	1006	1006	1006	1006	310	467	229

Note.—Dependent variable is EMPLOYED. Marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 4: Baseline model—probit marginal effects: females

Control variables	All	All	All	All	All	All	All	Armenia	Azerbaijan	Georgia
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATTRACTIVE	0.061**	0.061**	0.066***	0.062**	0.015	0.062**	0.027	0.044	-0.007	0.088
	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)	(0.028)	(0.052)	(0.041)	(0.056)
AGE 31-35		0.096***					0.107***	0.113	0.065	0.127**
		(0.037)					(0.038)	(0.070)	(0.061)	(0.063)
AGE 36-40		0.112***					0.153***	0.115*	0.173***	0.144**
		(0.035)					(0.036)	(0.065)	(0.061)	(0.059)
AGE 41-45		0.182***					0.231***	0.182**	0.224***	0.248***
		(0.036)					(0.038)	(0.071)	(0.060)	(0.069)
AGE 46-50		0.131***					0.184***	0.101	0.193***	0.246***
		(0.034)					(0.036)	(0.063)	(0.062)	(0.063)
ETHNIC MAJORITY		0.057					0.034	0.338***	-0.008	0.091
		(0.062)					(0.072)	(0.047)	(0.101)	(0.099)
LINGUISTIC MAJORITY		0.046					-0.014	-0.704***	0.075	-0.021
		(0.079)					(0.093)	(0.045)	(0.124)	(0.139)
PARTNERED			-0.175***				-0.185***	-0.094*	-0.200***	-0.248***
			(0.029)				(0.031)	(0.052)	(0.052)	(0.060)
GOOD HEALTH				0.061**			0.052*	0.098*	-0.030	0.113**
				(0.025)			(0.028)	(0.051)	(0.043)	(0.053)
EDUC11-14					0.139***		0.161***	0.137***	0.167***	0.194***
					(0.026)		(0.027)	(0.044)	(0.044)	(0.051)
EDUC$\geq$ 15					0.359***		0.408***	0.418***	0.492***	0.297***
					(0.032)		(0.034)	(0.059)	(0.053)	(0.066)
OTHER URBAN						0.043	0.066**	0.017	0.107**	0.066
						(0.029)	(0.029)	(0.052)	(0.045)	(0.052)
RURAL						-0.041	0.091***	0.029	0.120*	0.092
						(0.029)	(0.033)	(0.053)	(0.063)	(0.062)
ARMENIA						0.015	0.003			
						(0.029)	(0.032)			
GEORGIA						-0.010	-0.098***			
						(0.030)	(0.031)			
Pseudo R^2	0.003	0.017	0.022	0.006	0.068	0.008	0.116	0.106	0.142	0.152
N	1551	1551	1551	1551	1551	1551	1551	545	597	409

Note.—Dependent variable is EMPLOYED. Marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Heteroskedasticity-consistent standard errors in parentheses.. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 5: Attractiveness and human capital—probit marginal effects: males

Control variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATTRACTIVE	0.015***	0.018***	0.212***	0.168***	0.109***	0.070***	0.080***	0.056*
	(0.005)	(0.006)	(0.028)	(0.029)	(0.024)	(0.019)	(0.031)	(0.031)
Baseline controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.010	0.058	0.047	0.224	0.024	0.267	0.007	0.263
N	1006	1006	996	996	953	953	828	828

Note.—Dependent variables are: EDUC CATEGORICAL in columns (1) and (2); RUSSIAN PROFICIENCY in columns (3) and (4); COMPUTER PROFICIENCY in columns (5) and (6) and INTERNET USER in columns (7) and (8). Probit marginal effects (ordered probit marginal effects for 11-14 years of education in columns (1) and (2)) for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Baseline controls in column (2) exclude EDUC11-14 and EDUC$\geq$ 15. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 6: Attractiveness and human capital—probit marginal effects: females

Control variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATTRACTIVE	0.033***	0.032***	0.152***	0.030	0.073***	0.015	0.057***	0.019
	(0.007)	(0.008)	(0.025)	(0.026)	(0.016)	(0.014)	(0.022)	(0.021)
Baseline controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.013	0.085	0.020	0.253	0.016	0.259	0.005	0.198
N	1551	1551	1538	1538	1483	1483	1290	1290

Note.—Dependent variables are: EDUC CATEGORICAL in columns (1) and (2); RUSSIAN PROFICIENCY in columns (3) and (4); COMPUTER PROFICIENCY in columns (5) and (6) and INTERNET USER in columns (7) and (8). Probit marginal effects (ordered probit marginal effects for for 11-14 years of education in columns (1) and (2)) for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Baseline controls in column (2) exclude EDUC11-14 and EDUC$\geq$ 15. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 7: Model with comprehensive controls — probit marginal effects: males

Control variables	(1)	(2)	(3)	(4)	(5)	(6)
ATTRACTIVE	0.136***	0.103***	0.137***	0.126***	0.136***	0.111***
	(0.041)	(0.034)	(0.031)	(0.032)	(0.031)	(0.035)
RUSSIAN PROFICIENCY		0.063				0.049
		(0.047)				(0.049)
COMPUTER PROFICIENCY		0.091				0.101*
		(0.057)				(0.060)
INTERNET USER		-0.015				-0.029
		(0.054)				(0.059)
HIGH LOCUS OF CONTROL			0.207***			0.201***
			(0.036)			(0.040)
SMOKER			0.038			0.016
			(0.039)			(0.044)
FEELS REJECTED				-0.152***		-0.105**
				(0.043)		(0.047)
FEELS EMPTINESS				-0.005		-0.004
				(0.039)		(0.043)
NUMBER OF FRIENDS					0.006**	0.007*
					(0.003)	(0.003)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.108	0.111	0.138	0.122	0.111	0.161
N	1006	807	953	948	974	732

Note.— Dependent variable is EMPLOYED. Marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 8: Model with comprehensive controls — probit marginal effects: females

Control variables	(1)	(2)	(3)	(4)	(5)	(6)
ATTRACTIVE	0.027	0.001	0.040	0.028	0.022	-0.015
	(0.028)	(0.032)	(0.029)	(0.029)	(0.028)	(0.035)
RUSSIAN PROFICIENCY		0.097***				0.106***
		(0.036)				(0.039)
COMPUTER PROFICIENCY		0.107**				0.107*
		(0.053)				(0.056)
INTERNET USER		0.113**				0.113**
		(0.047)				(0.049)
HIGH LOCUS OF CONTROL			0.073**			0.035
			(0.031)			(0.036)
SMOKER			0.068			0.068
			(0.055)			(0.063)
FEELS REJECTED				-0.019		0.023
				(0.034)		(0.041)
FEELS EMPTINESS				-0.013		-0.030
				(0.030)		(0.036)
NUMBER OF FRIENDS					0.004*	0.002
					(0.002)	(0.003)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.116	0.131	0.121	0.116	0.117	0.138
N	1551	1259	1452	1457	1501	1127

Note.— Dependent variable is EMPLOYED. Marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 9: Amount of selection on unobservables relative to selection on observables

Control variables	Males					Females				
	$\hat{S}_0$	$\hat{\alpha}$	$\hat{\pi}$	$\hat{S}_{uo}$	$\frac{\hat{S}_{uo}}{\hat{S}_o}$	$\hat{S}_0$	$\hat{\alpha}$	$\hat{\pi}$	$\hat{S}_{uo}$	$\frac{\hat{S}_{uo}}{\hat{S}_o}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Baseline controls	0.131	0.397	1.076	0.369	2.805	0.441	0.075	1.082	0.069	0.157
Comprehensive controls	0.095	0.355	1.101	0.323	3.406	0.362	-0.040	1.120	-0.036	-0.099

Note.—Columns (1) and (6) report amount of selection on observables based on equation 6. Columns (2) and (7) report the probit estimate of α in equation 2. Columns (3) and (8) report the variance ratio defined in equation 5. Columns (4) and (9) report the maximum amount of selection on unobservables based on equation 4. Columns (5) and (10) report the amount of selection on unobservables relative to selection on observables. $N = 1006$ (baseline model) and $N = 732$ (comprehensive model) for males; $N = 1551$ (baseline model) and $N = 1127$ (comprehensive model) for females;.

Table 10: Robustness checks of measurement of attractiveness — probit marginal effects

Control variables	Males					Females				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATTRACTIVE	0.111***	0.108***			0.164***	-0.015	-0.011			0.059
	(0.035)	(0.038)			(0.058)	(0.035)	(0.038)			(0.044)
UNATTRACTIVE		-0.014					0.020			
		(0.073)					(0.066)			
VERY ATTRACTIVE			0.098*					-0.003		
			(0.055)					(0.047)		
JUST ATTRACTIVE			0.113***					-0.018		
			(0.037)					(0.036)		
ATTRACTIVE CONT				0.059***					-0.007	
				(0.021)					(0.018)	
Comprehensive controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer effects	No	No	No	No	Yes	No	No	NO	No	Yes
Pseudo R^2	0.161	0.161	0.161	0.158	0.271	0.138	0.138	0.138	0.138	0.241
N	732	732	732	732	501	1127	1127	1127	1127	1003

Note.— Dependent variable is EMPLOYED. Marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0 (ATTRACTIVE=0 and UNATTRACTIVE=0 in columns (2) and (7); VERY ATTRACTIVE=0 and JUST ATTRACTIVE=0 in columns (3) and (8) and ATTRACTIVE CONT at sample means in columns (4) and (9)); controls are fixed at sample means. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 11: Models with alternative dependent variables - probit marginal effects and OLS coefficients

Control variables	Males			Females		
	(1)	(2)	(3)	(4)	(5)	(6)
ATTRACTIVE	0.137**	0.197**	0.081***	0.126	0.163	0.010
	(0.060)	(0.086)	(0.029)	(0.079)	(0.107)	(0.036)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
(Pseudo) R^2	0.217	0.216	0.066	0.162	0.155	0.062
N	642	642	593	509	509	454

Note.— Dependent variable is: log personal income based on the mid-point of the stated income interval (columns (1) and (4)) or treated as an interval (columns (2) and (5)); incidence of positive change in employment status in the last 12 months (columns (3) and (6)). Columns (1) and (3) report OLS regression coefficients; columns (2) and (4) report interval regression coefficients; columns (3) and (6) report probit marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 12: Attractiveness, personality and social capital—probit marginal effects and OLS coefficients: males

Control variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATTRACTIVE	0.073**	0.045	-0.010	-0.014	-0.055*	-0.055*	-0.059*	-0.055*	0.627	0.198
	(0.029)	(0.031)	(0.029)	(0.031)	(0.029)	(0.030)	(0.032)	(0.033)	(0.385)	(0.366)
Baseline controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
(Pseudo) R^2	0.005	0.041	0.000	0.044	0.003	0.068	0.003	0.043	0.003	0.071
N	963	963	995	995	970	970	965	965	974	974

Note.—Dependent variables are: HIGH LOCUS OF CONTROL in columns (1) and (2); SMOKER in columns (3) and (4); FEELS REJECTED in columns (5) and (6); FEELS EMPTINESS in columns (7) and (8) and NUMBER OF FRIENDS in columns (9) and (10). Columns (1)-(8) report probit marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Columns (9)-(10) report OLS coefficients. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.

Table 13: Attractiveness, personality and social capital—probit marginal effects and OLS coefficients: females

Control variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ATTRACTIVE	0.032	-0.018	0.000	-0.012	-0.010	-0.044	0.007	-0.034	1.219***	0.767***
	(0.024)	(0.026)	(0.014)	(0.013)	(0.025)	(0.028)	(0.027)	(0.030)	(0.256)	(0.255)
Baseline controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.001	0.069	0.000	0.083	0.000	0.101	0.000	0.079	0.013	0.074
N	1466	1466	1536	1536	1490	1490	1487	1487	1501	1501

Note.—Dependent variables are: HIGH LOCUS OF CONTROL in columns (1) and (2); SMOKER in columns (3) and (4); FEELS REJECTED in columns (5) and (6); FEELS EMPTINESS in columns (7) and (8) and NUMBER OF FRIENDS in columns (9) and (10). Columns (1)-(8) report probit marginal effects for a discrete change of a variable from 0 to 1 for a person with ATTRACTIVE=0; controls are fixed at sample means. Columns (9)-(10) report OLS coefficients. Heteroskedasticity-consistent standard errors in parentheses. *Denotes significance at 10 percent; **at 5 percent; ***at 1 percent levels.