How Skills and Parental Valuation of Education Influence Human Capital Acquisition and Early Labor Market Return to Human Capital in Canada

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Abstract

Using the Youth in Transition Survey we estimate a Roy model with a three dimensional latent factor structure to consider how parental valuation of education, cognitive skills and non-cognitive skills influence endogenous schooling decisions and subsequent labour market outcomes in Canada. We find the effect of cognitive skills on adult incomes arises by increasing the likelihood of obtaining further education. Further, we find that both non-cognitive skills and parental valuation for education play a larger role in determining income at age 25 than cognitive skills. Last, our analysis uncovers striking differences between men and women in several of the estimated relationships. Specifically, simulations of the estimated model illustrate that i) among the low skilled, women have much higher college graduation rates, ii) the age 25 earnings gradient by either skill measure is much flatter for women, and iii) parental valuation of education plays a larger role in influencing young women than men.

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1 Introduction

Over the last decade, research by economists documenting both declining economic mobility (e.g. Chetty et al., 2014, Corak et al., 2014) and rising economic inequality (e.g. Saez and Zucman, 2016, Autor et al., 2008) has captured the attention of policymakers and the popular press. Within each literature, studies have also documented significant time-varying gender differences in both how education influences labor market outcomes (e.g. Fortin et al., 2015, Goldin et al., 2006) as well as how the effects of family and neighborhood characteristics influence educational attainment and career prospects (e.g. Chetty and Hendren, 2018, Autor et al., forthcoming, Chetty et al., 2016). One of the primary challenges facing researchers in these areas is that many of the candidate explanations for the observed heterogeneity are variables that are difficult to reliably measure using surveys, such as individual skills or parental aspirations. In this paper, we use factor models as a means to flexibly but parsimoniously model several of these latent candidate variables. We then subsequently examine the role these candidate factors play in generating early adult outcomes, thereby allowing us to connect and contribute to these two literatures.

Bridging these literatures is important since many traits including skills and preferences are transmitted from parents to children. Parents not only make direct time and material resource investments into their child's human capital and skill production function, they also instill levels of educational expectations in their children. While economists first formally considered the role of parental investments in child development in Leibowitz (1974), there have been relatively few studies of the role played by parental beliefs and expectations, in part since they are difficult to reliably measure. Whether parental educational expectations influence a child's educational outcome has also attracted the attention of researchers in both sociology and psychology, who have developed large literatures documenting a strong positive association.[1] Parents' educational expectations serve as a major influence on children's expectations and in a review of the literature in psychology, Schneider and Stevenson (1999) concluded, "One of the most important early predictors of social mobility is how

[1] Recent contributions in psychology documenting how parents view education can influence their child's educational attainment include studies using a U.S. nationally representative sample (Jacob and Linkow, 2011) and is also found among high risk samples (Ou and Reynolds, 2008). Within the literature in sociology, there is evidence that parents' educational expectations matter for children's educational attainment (e.g. Teachman, 1987; Wood et al., 2007) and can have long-term influences on children's adult life outcomes (e.g. Jacobs et al. 2006; Flouri and Hawkes 2008).

much schooling an adolescent expects to obtain". One aim of this study is to isolate the contribution of parents' valuations of education at age 15—conditional on a child's level of skills at that age—on subsequent schooling decisions and early labor market outcomes.

While few studies in economics have explored the role of parental valuation of education, a growing body of research surveyed in Heckman and Mosso (2014) has developed that emphasizes the role of skills on life outcomes and the technology of skill formation. This body of research has clearly established that skill is not only multidimensional in nature (e.g. see Cunha and Heckman, 2008, Borghans et al., 2008) but also that skills develop in a heterogeneous manner over the lifecycle (e.g. Hansen et al., 2003; Cunha et al., 2010; Ding and Lehrer, 2014). Further, while a substantial body of research (e.g. Green and Riddell, 2003; Hartigan and Wigdor, 1989; Murnane, et al., 2000; Heckman et al., 2006) has shown that cognitive skills such as literacy and problem-solving matter, an emerging body of evidence (e.g. Cunha and Heckman, 2008; Borghans et al., 2008; and Almlund et. al., 2011, among others), suggests that social and emotional skills such as perseverance and self-control are equally as important as cognitive skills in enhancing an individuals' future education and career prospects.

Evidence in the latter studies is derived primarily from the estimation of economic models of skill development using longitudinal data collected in either the United States, South Korea or England. These studies do not additionally consider the effects of parental valuation of education on young adult outcomes. In this paper, using longitudinal data that tracks a cohort of Canadians from age 15 through to age 25, we present the first empirical evidence of the role of these three latent competencies that jointly influence schooling decisions and subsequent labor market outcomes in Canada.[2]

Our empirical analysis builds on the economic framework developed by Willis and Rosen (1979) who model self-selection into college and potential earnings within a traditional Roy model. Our empirical approach offers two major advantages. First, we treat parental valua-

[2] Foley et al. (2014) and Foley (forthcoming) also estimate a three-factor model to respectively understand high school dropout decision for males and the gender gap in university enrollment in Canada. Beyond the different outcomes considered, the second estimation step in these papers includes a single choice equation and does not consider potential outcomes. This distinction is important since these studies focus on understanding how observed and unobserved factors respectively relate to a specific decision, whereas our focus is to control for unobserved heterogeneity, thereby allowing for the simulation of accurate counterfactuals of schooling and labor market outcomes. As discussed in detail in section 3, our study also differs in how the distribution of factors are identified and estimated.

tions of education and the two skill dimensions as a vector of low dimensional factors, rather than using proxy variables to account for types of unobserved competencies. By using linear factor analysis methods to recover the distribution of three latent competencies, we can more accurately capture a single parental valuation and multiple skill dimensions as well as account for potential measurement errors in these latent competencies, while imposing weaker assumptions on the data. Second, we explicitly model two sequential selection processes,[3] allowing us to identify all of the channels through which each competency measured at earlier ages affects schooling and labor market outcomes in early adulthood. That is, by considering the timing of these choices, we can separate out how different competencies affect labor market outcomes into components explained by schooling and productivity.

We also contribute to the literature evaluating the labor market consequences of different measures of skills by following the suggestion in Prada and Urzúa (2017) and explore gender differences.[4] A growing literature not only documents gender differences in non-cognitive skills at early ages (e.g. Cornwell et al., 2013) but also differences in parental behaviors by child gender (e. g. Lundberg, 2005; Kottelenberg and Lehrer, 2018). Since gender employment patterns suggest that occupational differences between men and women are a persistent presence in North American labor markets, abilities may be rewarded differently and in a manner that is consistent with observed occupational choices. Our analysis will help develop an understanding of an economic mechanism behind the role of skills in the labor market.

The first set of results is obtained from variance decompositions of the models used to estimate the distribution of the latent factors. We find that cognitive skills explain between 60-75% of the PISA test scores across subject areas. More striking is that responses to questions related to the child's perception of parent attitudes appears to capture the lion's share of variation in parental valuation of education. This finding is consistent with evidence in psychology that children form their educational expectations largely in response to parental inputs (e.g. Jacobs and Eccles, 2000; Schneider et al., 2010).

[3] This modeling follows Heckman et al., (2006) and Urzúa (2008), where individuals first decide whether to invest in higher education, considering their predetermined competencies, the influence of both parents and peers, as well as both skill and educational investments that may influence labor market outcomes. Second, workers select into jobs based on their competencies and their previous schooling choices.

[4] To the best of our knowledge, only Prada and Urzua (2017) have previously estimated a three factor model to understand how different dimensions of unobserved skills influence endogenous schooling and labor market outcomes. Their analysis used a sample of white males in the United States.

The second set of results, obtained from simulations of the model, indicate that heterogeneity in the effects of each competency on both education and labor market outcomes along gender lines is empirically important. Specifically, we observe that for girls, the probability of self-reported tertiary education completion at age 25 is above 25% in every cognitive skill decile. In addition, the gradient in college graduation across non-cognitive skill deciles is quite flat for Canadian women. We find that in comparison to men, the parental valuation for education has a larger influence on both women's college degree completion. Women with higher non-cognitive skills or parental valuation for education earn larger labor market premiums. In contrast, for young men cognitive skills are found to play the largest role on expected earnings, and their expected earnings decline with the parental factor. Given that we uncover significant heterogeneity in the effects of each competency by gender, our results highlight the trade-offs that policymakers face when developing policies that cultivate any of these competencies.

While these differences are striking, our four remaining principal findings in the full sample appear consistent with US evidence. First, we find that the average treatment effect of university education in the full sample is positive. Second, non-cognitive skills play a role in determining income at age 25 that is slightly larger than cognitive skills. Third, accounting for the education decision is crucial to understand how cognitive skills affect age 25 income. The channel of increasing the likelihood of obtaining further education accounts for roughly one-third of the effect of cognitive skills on income. In contrast, non-cognitive skills influence age 25 income levels not only through the educational choice channel, but they are additionally directly rewarded in the labor market. Fourth, simulations of the estimated model show the cumulative effect of these two channels of influence for non-cognitive skills are twice as large as that of cognitive skills. The effect of non-cognitive skills is slightly smaller than the parental factor on income, but cognitive skills do play the largest role on the decision to complete college.

This paper is structured as follows. Section 2 describes the data set we analyze. The economic framework that underlies the econometric analysis is sketched in section 3, where we additionally consider the conditions needed to identify the structural parameters of the model. Our empirical results are presented and discussed in section 4. Simulations of the model are undertaken to clearly illustrate the role played by the two dimensions of skill and parental valuation of education on educational attainment and early labor market outcomes. A final section draws the main conclusions.

2 Data

We use data from the Youth in Transition Survey (YITS-A) collected by Statistics Canada. This study used a two-stage sampling frame to follow a nationally representative cohort of 15-year olds. In the first stage, 1,187 schools were selected. From these schools, 29,867 students were randomly selected in the second stage. Among these students, 29,330 participants first completed both the OECD Performance for International Student Achievement (PISA) reading test and the separate YITS survey questionnaire. In the first cycle, students, the student's principal, and either a parent or guardian who identified him or herself as "most knowledgeable" about the child completed a survey, providing additional and likely more accurate measures of home and school inputs.[5] Follow-up surveys were conducted with only the students on a biennial basis until they reached 25 years of age.

This paper uses factor analysis methods to construct measures of different competencies that applied econometricians do not directly observe including cognitive skills, non-cognitive skills and parental valuation for education. Responses to three different questions in the YITS-A survey are used to measure the parental factor. The questions include responses on a four point scale of what is the highest level of education they hope their child completes. Parents are then asked to use a four point scale to attach the importance they place on their child getting education beyond high school. The scale runs from not important to very important and is also used by the child to give their perspective of how important they believe their parent(s) feel that they complete more education after high school.[6]

The YITS-A data contains measures of cognitive skills obtained from three domains of the PISA test. While every student within the sample completed the reading test, only half of them wrote either the math or science test and a smaller minority completed all three tests. In addition there are a battery of questions to measure multiple dimensions of non-

[5] Approximately, 13 percent of the parents did not complete the parental survey which was conducted over the phone.

[6] For children in two-parent households, we took the maximum of the child's response associated with each guardian.

cognitive skills. In this paper, we use information collected from three scales. Self-esteem is measured using the 10-item Rosenberg (1965) scale that measure's one general feelings of self-worth. A self-efficacy scale adapted from Pintrich and Groot (1990) measures perceived competence and confidence in academic performance. Last, a sense of mastery scale provides an appraisal of the individual's sense of broader control and consists of questions related to one's ability to do just about anything they set their minds to.

Since the YITS-A surveys the child, parent and school principal, a rich set of controls including demographics, parental education and family income are available. Besides standard conditioning variables, we use information on the expectation of one's peers at age 15, family structure, family income and wealth,[7] immigration status, and whether parent's have set money aside for future education. The definitions of these variables are provided in appendix A.

Throughout our analysis, we control for geographic differences since there is substantial regional heterogeneity in both labor markets and how higher education is delivered. In particular, the province of Quebec has a special system where students only attend secondary school to the equivalent of grade 11.[8] Canada has distinct regional labor markets (e.g., Atlantic Canada, Québec, Ontario, the Prairies, and British Columbia) that differ sharply by both policies of sub-national governments and industry compositions that can experience pronounced boom and bust cycles (e.g. Morrisette et al. 2015).[9]

As with many longitudinal studies, there is substantial attrition within the YITS-A. While Statistics Canada does provide sampling weights to accommodate several of these features, given that we focus on parental valuation of education, cognitive and non-cognitive skills, our primary analysis restricts the sample to include those individuals who completed all

[7] Income is derived from wages/salaries, self-employment, and governmental transfers and social assistance. In contrast wealth is a proxy calculated by the availability of a suite of material goods including dishwasher, cell-phones, television sets, cars, computers, number of bathrooms in the primary residence and whether the student has both her own bedroom and access to the internet at home.

[8] Following high schools students in Quebec can attend a two year Collège d'enseignement général et professionnel (CEGEP), which further prepares one for a university degree. As such, those attending university in Quebec normally can complete university in three years, compared to four years in the rest of Canada. Students interested in a technical degree in Quebec, generally register in a three year CEGEP program.

[9] Since we have data for a single cohort and the geographic identifiers in the data are coarse, there is very little within geographic unit variation that can be exploited to shed light on the differences in labor market conditions within regions. In appendix E, however, we do examine the impact of including provincial level data on unemployment and labour force participation rates in our model and find no significant differences in our main results.

three PISA tests, have complete income and education data until age 25 and have a parental survey. In addition, we dropped a handful of subjects that were either i) home-schooled or ii) attending a school on an Indian reserve at age 15, or iii) that are no longer residing in Canada at age 25. All of these restrictions combine to substantially reduce the number of observations available and the final sample consists of 1607 individuals. To examine the robustness of our findings, we used imputation methods to fill some of the missing covariates allowing us to conduct additional analyses with a sample of 6,181 individuals.[10]

Table 1 presents summary statistics for different samples of the YITS data. The first column presents information on all individuals measured in the first wave. The second column presents information on the subsample that completed two of the PISA tests. The third column presents information on our imputation sample and last column provides summary statistics on those with complete records. The first two panels of the table present the standardized test scores which show that this estimation sample is more skilled than the full sample with non-cognitive scores roughly .15 standard deviation higher and cognitive scores averaging between .3 and .5 standard deviations above the reference group.[11] Notice that individuals who completed at least two PISA tests outperform the reference group, indicating that there is likely some sample selection in who completes the tests.

Further, the estimation sample is relatively affluent as indicated by the wealth index in the third panel of Table 1. Nearly 75% of parents in this sample have set some money aside for their child's post-secondary education. Last by age 25, the last panel shows that over 50% of this sample has received a university degree. In summary, this sample selection leads to a group of young Canadians that are both more skilled and better-supported than the general population.

3 Model

In an important paper, Willis and Rosen (1979) develop and estimate a model of the demand for schooling that take account of heterogeneity in ability levels, tastes and the capacity to

[10] The imputation procedure is described in appendix D. The findings in the main text are re-conducted with this sample. We note the sample restrictions also lead to many observations being dropped in studies using U.S. data. For example, Prada and Urzua (2017) end up with 1022 individuals from an original sample of 12,686.

[11] Following Statistics Canada guidelines we report our summary statistics using the YITS-A survey weights.

finance schooling investments. The model assumes that high school or college education prepares an individual for a position in one of two occupations and allows for the possibility of comparative advantage. Similar to the Roy (1951) and Heckman and Sedlacek (1985) models, the notion that individuals may have latent talents that are not directly applied on their job is considered. The main challenge that empiricists face in this area is that the latent factors are unobserved to the econometrician. We will follow an emerging body of research that uses factor analysis methods to identify these factors and their distribution; as an alternative to employing (noisy) proxy variables.

Briefly, this model closely follows Heckman et al. (2006) and involves three steps that are important for the empirical strategy. First, we need to estimate the predetermined dimensions of ability as well as the existing parental valuation of education when the child reaches age 15. We assume that each child is endowed with a three dimensional competency vector θ at conception. Competency may subsequently develop due to parental investments and other environmental interactions that may interact with the child's invariant genetic characteristics. We use factor analysis methods to estimate a system of test score and parental valuation equations designed to identify and recover the distribution of latent competencies. With latent predetermined competencies we next consider estimating equations that integrate over these distributions to focus on how skills and parental valuation of education affect two decisions the child makes after age 15: whether to complete a university degree and subsequently which sector of the economy to work in.

This timing of decision making is important since we will decompose the importance of latent competencies in determining labor market outcomes in early adulthood, into components explained by schooling and productivity. The structural parameters from these estimated equations are then used to simulate outcomes given different levels of the three competencies. Below, we expand on the three steps of the model, focusing on how identification is obtained in each step and then outline the estimation strategy.[12]

[12] This framework is similar to studies using US data including Urzúa (2008) and Prada and Urzua (2017), which also build off identification results from Carneiro et al. (2003).

3.1 Latent Competencies

Since ability is multidimensional and difficult to measure precisely, a range of statistical and psychometric techniques have been developed to measure these latent characteristics. Intuitively, the idea underlying these techniques is that many test scores and questionnaires in surveys are designed to measure a concept and as such can be viewed as noisy proxies for domains of ability. For example, performance on either a reading or a math exam may be a noisy proxy for latent intelligence. Since these proxies of latent ability are imperfect and based on a noisy signal of an individual's underlying abilities, and thus are subject to measurement error. Similarly, proxies for parental beliefs about the value of education are also challenging to reliably measure. A growing number of studies by economists have built on insights in Kotlarski (1967) to develop methods to identify the underlying distribution of latent competencies requiring at least three measures of noisy proxies.[13]

In the first step, we must assume the number of domains of latent competencies we wish to identify and which elements of the YITS-A data provide a noisy signal of the competency in question. We consider cognitive skills that will be identified by the latent factor associated with three standardized tests (reading (T_0^c), mathematics (T_1^c), and science (T_2^c) from the PISA test, as well as non-cognitive ability is governed by the latent factor associated with the scales associated with self-efficacy (T_0^{nc}), a sense of mastery (T_1^{nc}), and self-esteem (T_2^{nc}).[14] This factor can loosely be interpreted as confidence: confidence in one's ability to influence outcomes, in one's ability to master material, and in one's self-image. The final factor that we interpret as parental valuation for education is associated with ordered responses to parental questions related to the highest educational attainment they hope for their child (T_0^p), importance of the child getting more education after high school (T_1^p), and the child's perspective of how much education after high school their parents wishes they compete (T_2^p).

Equations (1) - (3) describes a measurement system linking the test measures found in the data, T, to both the unobserved competencies (or factors), θ^s, and the individual context,

[13] See Carneiro et al. (2003) for further details. but in actually to identify f factors we only need $2f + 1$ test scores. In our analysis, we have an additional test score and noisy measure for parental valuation of education.

[14] Non-cognitive abilities are heterogeneous and difficult to reduce to one factor. While we could consider additional domains of non-cognitive skills using other variables measured in the YITS-A, we focus on a single non-cognitive factor to facilitate comparisions with the majority of U.S. studies that considered only a single non-cognitive domain.

Q. We use the subscript $_i$ to refer to the test of interest and the superscript ^{s} to the related skill, ^{c} for cognitive, ^{nc} for non-cognitive and ^{p} for parental valuation. Our interest is to first identify and estimate both the factor loadings (ψ_i^s) and factors' distributions from the following linear measurement system

$$T_j^c = \pi_j + \phi_j^c Q^c + \psi_j^c \theta^c + u_j^c \quad (1)$$

$$T_j^{nc} = \pi_j + \phi_j^{nc} Q^{nc} + \psi_j^{nc} \theta^{nc} + u_j^{nc} \quad (2)$$

$$T_j^p = \pi_j + \phi_j^c Q^p + \psi_j^p \theta^p + u_j^c \quad (3)$$

for j $= \{0, 1, 2\}$.The matrices Q^c, Q^{nc} and Q^p each include socio-economic status, family composition and background, and parental inputs specific to the competency in question. The parameter estimates in the vector ϕ_i^s include the effect of family context, learning environment, and personal characteristics on the given test score. The vector of the error terms (u_i^s) are assumed independent of the observed characteristics, their associated factors as well as being mutually independent with an associated distribution $f_i^s(\cdot)$. This independence implies that all the correlation in observed choices and measurements is captured by latent unobserved factors.[15] For identification, we normalize one of the loadings for each factor and set $\psi_2^c = 1, \psi_2^{nc} = 1$ and $\psi_2^p = 1$. By making this normalization and using insights from Kotlarski (1967) we identify the distribution of θ for each competency; $F_\theta^c(\cdot), F_\theta^{nc}(\cdot)$ and $F_\theta^p(\cdot)$.[16] Specifically, as described in further detail in the Estimation subsection 3,4 below, we use the result of Ferguson (1983) that a mixture of normal distributions can approximate any distribution. For each of the three competencies, we assume that the given competency is a mixture of two Normal distributions and estimate the standard deviation of each distribution

[15] Our measurement equations differ sharply from Foley et al. (2014) and Foley (forthcoming) who are just identified, and we overlap with using the PISA reading score, parental question on highest educational attainment and question on the child's perspective of the amount of education their parent hopes they complete. While Foley et al. (2014) and Foley (forthcoming) allow for more correlations between the factors across the measurement equation, this relaxation comes at the cost of imposing additional strong covariance restrictions between the residuals in the system of measurement equations for identification. For completeness, the variables used as outcomes in the measurement equation system that differ from our own study include self-reported high school GPA, parental savings for child education, and responses to different questions related to effort spent on homework for non-cognitive skills. Note, we prefer the use of PISA scores rather than GPA since grading standards are common in the former, whereas the latter differences may capture neighborhood influences that can not be controlled for within the data.

[16] Kotlarski (1967) shows these distributions are nonparametrically identified and the remaining loadings in equation (1) are interpreted relative to ψ_2^c, ψ_2^{nc} and ψ_2^p. There are no natural units for these competencies. These distributions are found through identifying the parameters for a mixture of two normal distributions.

as well as both the mean shift for one of these distributions and the mixture probability.

In the above linear measurement system, we follow Prada and Urzúa (2017), Heckman et al. (2006), among others and treat each skill and parental valuation for education independently. We are imposing an upper triangular assumption on the measurement system, that requires each of the factors to be mutually independent. This assumption may appear strong since one could postulate that performance on the PISA tests is a function of both cognitive and non-cognitive skills or vice versa. We investigate the sensitivity of our conclusions to relaxing the assumption of mutual independence in appendix D. Specifically, we no longer assume that each test measure is a "pure" measure of specific competency, but do maintain the assumption for a small subset of test measures. The results are quite similar to results obtained when mutual independence is assumed.[17] As such, we are comfortable with a measurement system where each measure has a dedicated factor which ensures the factor loadings can be interpreted to scale.[18]

3.2 The Education Decision

We now model the impact of skills and parental valuation for education at age 15 on a subsequent educational investment decision: whether to complete a university degree or not. This decision is based on expected returns given their levels of latent competencies that has been accumulated by age 15 and their potential earnings for each education level. We assume that latent competencies are unobserved by the econometrician but the individual has full information about his/her competencies, as well as knowledge of their returns. We do not consider the exact timing of the decisions and assume that individuals make optimal educa-

[17] This robustness exercise uses a two factor set-up and relaxes assumptions made in the formulation of equation (1). We considered a variant that allowed the scales to reflect both cognitive and non-cognitive skill factor but the non-cognitive skill factor was excluded in the equations used to measure the PISA subject test scores. While the main results appear robust to a two factor model that treats each test measure to be a "pure" measure of a specific factor, there were large computational costs associated with relaxing these assumptions. As such, we follow Prada and Urzúa (2017) and exclude the cognitive skill factor as a determinant of any non-cognitive test score and vice versa.

[18] This interpretation comes from normalizing one loading per factor to equal 1. As discussed in Appendix D, relaxing mutual independence does allow for a richer interpretation of variance decompositions of test measures, but the factor loading themselves become more challenging to interpret. It should also be pointed out that the assumption of independence among the idiosyncratic errors in the measurement system is equally strong as restricting test measures to be a function of a single factor. While Williams (2018) provides new identification results involving reduced rank restrictions for the setting of correlated errors across test measures for a single factor, we did not consider this extension.

tional choices when deciding between completing and not completing a university degree by the age of 25. Each individual chooses the education level and sector of employment that provides the highest payoff among the feasible choice set.

Define $D = 1$ to be a binary indicator of whether an individual completes university and model this choice that reflects the alternative yielding the highest net benefit as

$$D = 1[\gamma^D Z + \lambda_c \theta^c + \lambda_{nc} \theta^{nc} + \lambda_p \theta^p + \upsilon > 0] \tag{4}$$

where Z is a vector of personal, family and peer characteristic, θ^c, θ^{nc} and θ^p are the unobserved competencies, and υ is an idiosyncratic error term with a standard Normal distribution. The estimated parameters, λ_c, λ_{nc}, λ_p and γ^D, estimate the influence of the corresponding covariates on the decision to complete university.

It can be expected that while cognitive skills (or a proxy of them) may govern the decision to apply, attend, and complete university, parents may also influence these decisions. For example, beyond the parents' valuation for education, one's parents may have prepared financially to support a youth's university education. We additionally control for this measures of parental savings towards education, since they may be correlated with cognitive and non-cognitive skills.[19] Additionally, since a large literature has shown that measures of one's peers can influence decision making and academic performance in adolescence (e.g. Ding and Lehrer, 2007, Sacerdote, 2011), we control for the influence of one's peer group. This control is obtained from responses to a question of the youth's perception of the number of her friends that are planning to attend higher education.

[19] We treat them as separate from the parental factor since a large body of literature following Dynan et al. (2004) has documented that the marginal propensity to save increases with income. Since there is a possibility that the true factor-to-indicator relationship in the measurement system is nonlinear and invariant, by applying a linear factor model with parental savings as a test measure can lead to the factor loadings and indicator intercepts of the linear model to diverge across income groups as the factor mean difference increases. Thus, we include this as a separate regressor and estimate a linear measurement system rather than treat it as another test measure for parental valuations and apply nonlinear factor analysis.

3.3 The Labor Market at Age 25

We model early labor market outcomes using a pair of equations that correspond to the specific education decision described above.[20] Let Y_{1i} and Y_{0i} denote the outcome of interest if person i completed university or did not, respectively. The system of outcome equations is given by

$$Y_1 = \left\{ \begin{array}{c} \gamma^{Y_1} X + \lambda_c^{Y_1} \theta^c + \lambda_{nc}^{Y_1} \theta^{nc} + \lambda_p^{Y_1} \theta^p + v_1 \; if \; D = 1 \\ 0 \; if \; D = 0 \end{array} \right\} \tag{5}$$

$$Y_0 = \left\{ \begin{array}{c} 0 \; if \; D = 1 \\ \gamma^{Y0} X + \lambda_c^{Y0} \theta^c + \lambda_{nc}^{Y0} \theta^{nc} + \lambda_p^{Y_0} \theta^p + v_0 \; if \; D = 0 \end{array} \right\} \tag{6}$$

where X is a vector of personal and family characteristics and v_1 and v_0 are idiosyncratic error terms from a standard Normal distribution. Note, the setup involving equations (4) – (6) parallels the model underlying the literature exploring whether there are sheepskin effects in education on wages.

3.4 Estimation

Equation sets (1) – (6) constitute a system in which the education decision is specified jointly with the measurement equations. To estimate the parameters of the model, factor loadings and characteristics of the distributions of the factor loadings, we rely on the assumption that conditional on these unobserved skills all of the idiosyncratic errors are mutually independent. This assumption allows us to use maximum likelihood estimation. Since the true underlying distribution for the competencies may take many forms, we are flexible and approximate it using a mixture of normals.[21] Define β to be the vector of all the parameters of the model

[20] We present and discuss results related to income at age 25 as the labor market outcome in the main text. Additional results that separately consider employment at age 25, voluntary work (once a month) and the use of employment insurance in the past year as alternative outcomes are presented in the online appendix.

[21] To the best of our knowledge, Ferguson (1983) was the first to prove that a mixture of normals can approximate any distribution. By being flexible we mean that we wish to impose as few restrictions as possible on the factor distributions.

and $W = \{Q, Z, X\}$, the likelihood is

$$L(\beta|W) = \prod_{i=1}^{n} \iiint f(D_i, Y_i, T_i|Q_i, Z_i, X_i, \theta^c, \theta^{nc}, \theta^p) dF_\theta^c(\cdot) dF_\theta^{nc}(\cdot) dF_\theta^p(\cdot). \tag{7}$$

To estimate equation (7) we integrate over the distribution of the three factors using Gauss-Hermite quadrature for numerical integration.[22] In the next section, we present and discuss estimates of this model to consider the impact of unobserved competencies on educational choices and income at age 25.[23]

This estimation treats the model as static and it should be explicitly stated does make strong assumptions on how much adolescents know about their skill levels and parental valuation for education. The education decision is evaluated only when the individual is 25 years old and does not consider the exact timing of the schooling decision. Since this modeling does not either impose strict guidelines on either preferences or what is the full content of the information set, Heckman et al. (2016b) point out thereby ensuring that agents may not be aware of all factors that could influence how they value more schooling when they make this decision. This modeling does provide a clear advantage by allowing individuals to regret their earlier irreversible decision to attend college, a feature consistent with evidence from post-graduation surveys.[24]

4 Results

We begin by discussing the parameter estimates, factor loadings and factor distributions obtained from maximum likelihood estimation of equation (7). For space considerations, Table 2 presents estimates of how each of the unobserved latent competencies (θ^c, θ^{nc} and θ^p) and other covariates influence each of the test measures in the model described in equations (1)–(3). For space considerations we only include analysis from the full sample.[25] Recall, for

[22] The distributions of the underlying factors are estimated separately from equation (7).

[23] Note, for estimation of the analysis presented in the online appendix which considers alternative outcomes that are all given by discrete indicators, an individual's contribution to the likelihood function is simply the product of normal CDF evaluations when we condition on the factors.

[24] Similarly, behavioral models where individuals have self-serving beliefs or are over-confident about their abilities will also generate individuals continuing their education despite the ex-post benefiit being negative.

[25] We observe differences between the genders in the effect of parental valuation on educational aspiration for children, where the estimated magnitude for young women is roughly 50% larger in magnitude. Similarly,

identification purposes, one loading for each unobserved competency is set to one and the remaining loadings must be interpreted in relation to the loading set as the numeraire. In examining the role of the covariates from equations (1)-(3) we find several interesting gender differences in the estimated relationships, where perhaps unsurprisingly girls score higher on the PISA reading test, whereas boys score higher in math. While we do not find a significant gender difference in science,[26] females perform significantly worse than the males on two of the non-cognitive test measures.[27]

The estimates in Table 2 reveal striking regional differences in each cognitive measure. Ontario, the base group, has ceteris parabus lower cognitive test scores than both the western Canadian provinces and Quebec. On non-cognitive measures, the Atlantic provinces have significantly lower sense of mastery and self-esteem scores than Ontario. Further, family wealth rather than income wealth plays a larger role on performance in math and on both parental aspirations and on parental importance of post-secondary education. Parental education levels are highly correlated to the cognitive test scores measures, even when controlling for the cognitive skill.

Holding the cognitive skill factor constant, youth from non-traditional families perform significantly better on the science tests. Not surprisingly those from non-traditional families fare worse on measures of their non-cognitive ability and this is likely related to changes in their self-perception relating to their experiences in transitioning between different family structures.[28] Perhaps, these children face similar parental aspirations and parents rank the importance of future education similarly. As a whole, these results suggest that the situation

we observe a slightly smaller effect of the non-cognitive factor on both self-efficacy and sense of mastery for girls relative to boys.

[26] Using a novel assessment based on the PISA that was administered in different regions of urban China, Ding et al (2018) demonstrate that gender gaps in scientific performance depend heavily on which domains of scientific intelligence are being tested. The PISA science score is obtained by asking questions related to the concept of scientific literacy from four domains -across context, knowledge, attitude and competencies.

[27] We are referring to a non-cognitive skill that could be capturing conscientiousness, which matters for a wider spectrum of job complexity (Barrick and Mount 1991). We would expect that higher levels of socio-emotional abilities are more important for some occupations requiring low-order cognitive skills, especially in the service sector (Bowles et al. 2001). Occupational choices are driven by personality competencies such as being a caring or a direct person in adolescence (Borghans et al. 2008). Individuals partly select occupations that correspond to their orientations. competencies related to grit (persistence and motivation for long-term goals) seems to be essential for success no matter the occupation through their effect on education achievements (Duckworth et al. 2007).

[28] Note that this does not indicate lower levels of non-cognitive skill for those in non-traditional families, though this may be the case, but rather lower scores on the non-cognitive tests given a level of the latent non-cognitive skill.

at home can be important to determining measures such as grades and thus educational pathways.

To shed further light on the relative importance of each dimension of unobserved competency in explaining test measures used as outcomes (T), Figure 1 presents the variance decomposition of the measurement system. The results present the contribution of observed covariates, latent competencies and and unobservables as determinants of the variance of each test measure. The contribution of observed variables to the variance of any of the nine test measures never exceed 8% and not surprisingly play virtually no role for the child's impression of the importance their parents place on post secondary education. Interestingly between 60-80% of the variance in PISA test scores can be explained by our cognitive factor.[29] The cognitive skill factor appears to explain more of the variation on the reading test, the subject where performance in the underlying data exhibits less variation than underlying either the PISA math or science test score.

Perhaps, the most striking result in Figure 1 is that much of the variance in parental valuation for education arises from the single measure of the child's perception of the parent's valuation. This result implies that at age 15, the child's perception of their parents importance is a fairly accurate predictor for the true parental valuation for education. The variance decomposition illustrates the large size of the unexplained component for the additional two test measures used to obtain the parental factor.

Figure 2 presents estimates of the distribution of each competency for each group by educational decision and they appear to be quite different from the distribution of the underlying test measures. For each competency, there is substantial overlap in the distribution across education groups and Kolmogrov-Smirnov tests reject the assumption of the distribution of skills being equal across these groups. The distribution of both the cognitive skill and parental factor exhibits more variation for college graduates than the corresponding distribution of non-graduates.

Table 3 presents the estimates of λ_v^c, λ_v^{nc}, λ_v^p and γ from equation (4), providing evidence on the importance of cognitive and non-cognitive skills as well as the parental valuation

[29] We are grateful to an anonymous reviewer for suggesting this analysis. In appendix D, we estimate richer models for the measurement system that allow for some correlation and test measures to be a function of two competencies such as the self-esteem score being a function of cognitive and non-cognitive skills. Even with richer models, we still find the explanatory power of the non-cognitive factor remains similar to estimates presented in figure 1.

factor on the decision to complete university. In the first column, we present results for the full sample and the gender subsamples appear in the third and fourth column. The second column presents results for the larger imputed sample. There are few differences in the magnitude and statistical significance of estimates the full and imputed sample and each competency enters the decision in a highly significant manner. There are several prominent gender differences where we observe that the effect of non-cognitive skills is more than twice as large for boys and the effect of the parental valuation for education competency is roughly 47% larger in magnitude for girls. In section 4.1, we provide a more intuitive understanding of the role of each competency using a simulation of the model.

Several other results in Table 3 are consistent with the North American literature on attending higher education. Females are much more likely than males to complete university, holding other factors constant. Consistent with Belley et al. (2014), in the non-imputed samples, family income and wealth are found to not significantly influence the completion of university in Canada. We find that a measure of whether parents have put money aside for post-secondary education plays a large role, even after conditioning on the parental valuation for education factor. These savings reflect a reduction of the opportunity cost of education and the results are suggestive of being more influential than current levels of family income or wealth.

Our results also suggest that peers play a significant role in determining educational attainment that is approximately twice as large for young men. While this variable is statistically significant, additional analyses presented in Appendix E shows that it has a very small influence and that all of the results are robust to the exclusion of the peer measure. There are also interesting gender differences in the effects of immigrant status and geographic variables. Holding all else constant, women from the Atlantic provinces are much more likely to go to university than men. In contrast, we find a significant reduction of females completing universities in Quebec relative to Ontario. Last, we find that the negative impact of immigrant status on university completion is driven by men.

Tables 4 and 5 respectively present estimates of the parameters λ_0^s, $\lambda_1^s, \beta_0, and\ \beta_1$ from Equations 5 and 6 for income and employment at age 25 conditional on educational attainment. We continue to present results for four samples and the column headings of $D = 1$ and $D = 0$ refer to those who have completed and not completed a university degree respectively. While each competency played a large role on the decision to complete university, the majority of the effects of each competency on labor market outcomes are statistically insignificant.

The results in this table show that cognitive skills significantly improve employment rates amongst non-university graduates. The benefits of earning a higher income or higher likelihood of having a job from possessing higher cognitive skills operate mainly through the educational channel. This effect of cognitive skills on labor market outcomes is driven by young men, who are penalized by employers for not having this credential. While university graduates of both genders observe a positive gradient of the non-cognitive skill measure on income, it is not statistically significant when we also control for the parental valuation of education.[30] The parental valuation for education factor significantly boosts salaries and employment at age 25, an effect that is driven by the subsample of women. Last, a puzzling finding that non-cognitive skills significantly decrease the odds of employment for women with a college degree are employed at age 25. When contrasting these estimates to those presented in the appendix C and D for a two factor model of cognitive and non-cognitive skills, we can conclude that ignoring the parental valuation for education suggests a much larger role for non-cognitive skills.

4.1 Evidence from Simulation of the Model

Simulation methods facilitate our understanding of the size and significance of the estimated parameters discussed above. To conduct simulations, we first randomly draw an individual and use their full set of regressors from the population. These individuals are paired with random draws from each of the three distributions of the latent competencies, and the distribution of each parametrized error term. Using the parameter estimates for the appropriate sample, we can then explore the effects of both skills and parental valuation of education on the outcomes of interest that are traced across individual contexts and through university completion decisions. These simulations are presented in figures 3 and 4, which examine how the university completion and income vary across levels of competency respectively. The rows of each figure focus on a single competency and the columns of each figure present

[30] Note, for those without a university degree, we find a gender difference in the sign of the estimated effect of non-cognitive skills on income, but the effects are statistically insignificant.

results for the full sample and each gender subsample. Throughout, this section, we ensure that within subgroup, the deciles of skills are placed on a comparable scale.

The top row of figure 3 presents the probability of completing a university degree for each decile of the cognitive skill distribution. Not surprisingly, for each sample the probability of completing a degree increases dramatically with cognitive ability. At almost every skill decile, college completion rates for men are roughly 10% lower than for women. In the lowest deciles of the cognitive skill distribution, college completion rates for women always exceed 25%, whereas graduation rates are very low for young men with low cognitive skills.

The second row of figure 3 documents a positive gradient between non-cognitive skills and the likelihood of university completion. The gradient for non-cognitive skills has a more gradual incline than the gradient for cognitive skills. We continue to find gender differences in the gradient and college completion rates for young men fall below rates for young women. Last, there is limited heterogeneity in the completion rates across deciles of non-cognitive skills for women.

While the gradient for college completion in either cognitive or non-cognitive skill is steeper for men then women, the reverse occurs across the distribution of parental valuation for education. The bottom row of figure 3 illustrates a positive gradient only among young women. Further, at every decile of parental valuation for education, the college completion rate for women is higher than at any and all deciles of the distribution for men. In contrast, figure 4 shows a positive gradient for women at every decile of parental valuation for education on income and a corresponding flat gradient for men. Income for females moves from roughly \$20,000 to \$32,000 across the full distribution of the factor, whereas men's income remains effectively unchanged. However, the labor market income for women at any decile of this competency is lower than at any and all deciles of the corresponding distribution for men.

Examining the panels in the top two rows of figure 4, we obverse a steep gradient for non-cognitive skills on earnings for young women. Earnings climb from \$22,000 to nearly \$31,000 across the deciles. However, even at the highest decile of non-cognitive skills, women on average earn less than a man at any decile of the non-cognitive skill distribution. Similarly, young women on average earn similar amounts at each decile of the cognitive skill distribution. The gender gap appears quite large at roughly \$12,000 at each decile of the cognitive factor.

The interpretation of many of these gender gaps diminish once we condition on university completion. Figure 5 illustrates the simulation results corresponding to two incomes at age 25 and estimated confidence intervals graphed across deciles of each competency.[31] The dashed line and dark blue shaded line respectively represent individual who did not complete college and graduates. Across the panels presented in the first column of Figure 5, we observe fairly flat gradients on income for the full sample for each competency. Across each competency, we observe positive gradients for the full sample among university graduates. The positive slopes for the cognitive and parental valuations are driven by a single gender. We observe that only earnings among university graduated males increase across deciles of the cognitive skill distribution moving from \$27,000 to \$40,000. There is a similarly large impact on female graduates from the parental valuation factor; earnings nearly double moving from \$20,000 at the lowest decile to \$35,000 at the highest decile. Both the male and female income gradients are positive across the non-cognitive skill deciles with more moderate changes in earnings.

In contrast, we observe that annual earnings of young men who did not complete college fall at higher levels of both cognitive and non-cognitive skills. These drops are more mild at roughly \$3,500 from 1st to 10th decile. Surprisingly, we also find that female college graduates earn lower incomes at higher deciles of the cognitive skill distribution. For men, the confidence intervals for income of men between graduates and non-graduates do not overlap at the bottom and top deciles. For women, we observe that the 95% confidence intervals do not overlap for all three competencies at virtually every decile, highlighting a greater role for education.

Due to their multidimensional nature, cognitive and non-cognitive skills are rewarded in the labor market according to their combinations (e.g. Urzúa (2008), Prada and Urzúa (2017)). Figure 6 presents a new set of panels containing three dimensional graphs that explores how the average simulated outcome varies across the two competency distributions when evaluated. The most striking results appear in the third column for young women. The top row of figure 6 presents combinations of the cognitive and non-cognitive factor, where

[31] For completeness, we conduct the same analysis corresponding to other outcomes measured at age 25. In appendix figures B.1 and B.2 we observe that both being employed and use of employment insurance do not appear to be affected by either skills. In appendix figure C.4d, we find that as the levels of both skills increase so too does the likelihood that an individual engages in volunteering. We find that the slope across the cognitive skill dimension is steeper, which is somewhat surprising given the dimension of non-cognitive skill that we are likely capturing. However, the role of skills on volunteering are small in magnitude and likely lack economic significance.

we observe a positive gradient for the non-cognitive factor at every decile of the cognitive factor for young women.[32] Similarly, in the middle row of figure 6 we observe the incline of the gradient in the parental factor exists at each cognitive skill decile. This gradient steepens across the deciles of the cognitive skills; the effect moving across the parenting factor distribution is $4,000 at the lowest decile and $15,000 at the highest. The bottom row of figure 6 illustrates the relationship between the non-cognitive and parental factor and suggests that young womens' earnings increase across both dimensions and at similar rates. Taken together, these results illustrate that earnings rise at all higher combinations of the non-cognitive skill and parental factors, but are generally flat across the cognitive skill dimension for Canadian women.[33]

The second column of figure 6 presents the corresponding results for boys. For boys, the picture is quite flat indicating absences of gradients in one competency, conditional on another. The results suggest that only among boys in the very top cognitive skill deciles, do earnings rise across the non-cognitive skill deciles. Similarly, we find a positive gradient for cognitive skills at fewer higher deciles of the non-cognitive distribution. Last, we observe that the size of the cognitive skill gradient declines across the parental factor deciles. As a whole, the majority of the relationships observed in the full sample arise from the subsample of women.

The results of the simulation exercise are summarized in table 7. The panels summarizes how a one standard deviation change in each competency affects outcomes in the model and through which pathway. The estimates indicate that each competency increases employment and income in the full sample. Non-cognitive skills play a substantially larger role on university completion for boys, whereas the parental factor has a 50% larger effect for women. Both non-cognitive skills and the parental factor play a large role in influencing early adult earnings, but the gender differences in the magnitude of these effects exhibit a different pattern compared to employment. Women receive a much larger gain in expected earnings from increases in both the parental factor and non-cognitive factor then men. Last, cognitive skills only significantly increase age 25 income for young men.

[32] We should note that the returns to skills differ across type of work and different reward of set of skills across occupational activities. For example, see Levine and Rubinstein (2013) and Hartog et al. (2010) for evidence on the skills necessary for success as an entrepreneur.

[33] The sole exception is there being a slight rise in gradient of cognitive skills conditional on a woman also being in the highest deciles of the parental factor.

The pathway through which each of these skills are rewarded in the labor market differ sharply by gender. Women benefit from a small indirect effect of cognitive skills that operates through their schooling decision on labor market income. This effect is completely offset by a direct labor market reward to cognitive skills. Young men face a significant negative gradient to their cognitive skills through the indirect channel, but do receive large direct rewards. These results suggest that employers can more accurately ascertain cognitive skills of boys and that they directly value increased confidence of girls that may arise either from their non-cognitive or parental factor.

In the full sample, we find that on average, attending four-year college is associated with higher average earnings. However, there is an important gender difference in the sign of the average treatment effect (ATE). We find a negative effect for boys, which suggests that they are correctly sorting to higher education. Whereas, consistent with the less steep gradient of college completion by cognitive skills for young women, we find a positive ATE. As a whole, the results suggest that the labor market return to each competency increases only for women who complete university, explaining why the average treatment effect for the untreated is only positive for young Canadian women. In summary, the simulations provide strong evidence of the multiple, heterogeneous ways each competency influences education and labor market outcomes in Canada.

4.2 Discussion of similarities and differences to evidence in US Studies

Since our approach builds off studies using US data, we briefly contrast our findings to these, recognizing the importance of the suggestion in Card and Freeman (1993) that "small differences" in policies and institutions including the market for higher education, have led to differences in economic outcomes between Canada and the US. Results from empirical studies are not only conditional to their methodology but also of their context including the time period of data collection and make-up of the population covered by the sampling frame. A number of studies use data from the NLSY-79 (e.g. Heckman et al. 2006, 2016a; Prada and Urzúa, 2017; and Urzúa, 2008) to measure cognitive skills and dimensions of non-cognitive through proxy variables and make use of a similar framework to explore the impact of these skills. The NLSY-79 and YITS-A ask different questions which explains why the metrics used in the factor model to capture the two latent cognitive skills differ across studies.[34] Further, as Humphires and Kosse (2017) point out the term non-cognitive skills is used broadly in the labor economics literature and how this factor is constructed influences what conclusions are reached about the role of non-cognitive skills in life outcomes.[35]

Despite these caveats certain commonalities exist in our findings and the US literature. First, both cognitive and non-cognitive skills are found to influence education and early labor market outcomes. Second, the effects of these skills on earnings is mediated by educational attainment. However, we identify important gender differences in these relationships.

Several of the relative differences in our findings between our study and work using United States data appear consistent with other pieces of evidence in the labor economics literature.[36] The labor market returns to different dimensions of skills appear higher in the United States relative to Canada is respectively consistent with the returns to a university degree and comparable workplace skill reported in Bowlus and Robinson (2012) and Hanushek et al. (2015). We also speculate that the finding of a higher university completion rate for Canadian women with low cognitive skills may provide an explanation for why the wage gap between male and female workers reported in Finnie et al. (2016) widens each year after graduation at a larger rate in Canada than the United States.

One of the main contributions of this study is to estimate a model that allows for three dimensions of unobserved heterogeneity including a factor that captures the parents' perception of education as an investment in future income earning capacity. Economists dating

[34] For example, our Canadian evidence used PISA scores when estimating the cognitive skill factor, the US evidence estimates the latent cognitive skill factor from measures of mathematical knowledge, numerical operations and coding speed that were collected before children left high school. In our analysis, we can condition on variables such as number of siblings and immigrant status; whereas this information is to the best of our knowledge not available in the NLSY-79; in which researchers control for disability status and religion. This provides other reasons why caution must be taken when comparing results across studies using this framework.

[35] As Heckman et al. (2006) state the selection of variables is motivated by what is available in the data. Specifically, they (on p. 429) write "we choose these measures because of their availability in the NLSY79. Ideally, it would be better to use a wider array of psychological measurements and ... to connect them with more conventional measures of preference parameters in economics.".

[36] Cohort differences due to the timing of the data collection may also account for some of the differences in the estimated patterns from the simulations. For example, simulations using the NLSY-79 report a much larger effect of cognitive skills on income then we found. This result may arise since the Canadian data was collected on a later cohort that may have experienced the reversal in the demand for skills documented in Beaudry et al. (2014, 2016).

back to Becker (1962) have developed models of investment in human capital that postulates that the demand for education is driven by a measure capturing parental valuation for education. As the variance decomposition of these parental valuations illustrate that they are known to the child at age 15, it is not surprising to see that they are correlated to the two other dimensions of unobserved skills. By comparing estimates of both a two-factor and correlated two factor model which are presented in Appendices C and D, with those presented in the main text, allows us to understand how omitting the parental factor influences our estimates.

Assuming the two skills factors in the model are a sufficient statistic for the stock of all latent competencies at age 15, then how much parents value education beyond skill investment. In each specification of the two factor models presented in Appendix D, we do include the noisy test measures used to construct the parental factor. At first glance, the set of results seem similar. However, differences emerge in the effect of cognitive ability on the decision to attend a four-year college and earnings associated with the scenario of not attending a four-year college. Specifically, a one unit increase in cognitive ability increases the probability of attending college by 26.8 and 24.1 percent points in a three-factor model and a two factor model respectively. In earnings regressions that include the parental factor, the effect of non-cognitive ability for those not attending four-year college is less than one-sixth of the effect estimated in a two-ability model. These results illustrate the differences between our three-competency model and an alternative two-competency framework. While many of the results are robust to the setup, for young women conclusions on the role of non-cognitive ability and lack of steepness of the gradient of college attendance by cognitive skill, mask the importance of omitting a dimension of parental heterogeneity.

Given the importance of the role of parents, we undertook additional analyses in Appendix D, where we reestimate the two-factor skill model for samples defined on the basis of parental education. Motivating this investigation is that for policy audiences there is a need to not just determine if there are potential deficits in skills for those who are disadvantaged, but also to understand what are the potential benefits of any intervention that could foster cognitive or non-cognitive skills. The results of the simulations reveal that at every skill decile, children of less educated parents on average earn less than the corresponding children of high educated parents; where a child of high educated parents has at least one parent with some college education.[37] Further, the results suggest that among young adults in the YITS, completing a university degree does not significantly reduce the intergenerational effects of family disadvantage.

5 Conclusion

Using the Youth in Transition Survey (YITS-A) we estimate a Roy model with a three dimensional latent factor structure to consider how both cognitive and non-cognitive skills as well as parental valuation for education influence endogenous schooling decisions and subsequent labor market outcomes in Canada. Our analysis demonstrates that one third of the effect of cognitive skills on adult incomes arises by increasing the likelihood of obtaining further education. Conditional on the choice to complete a university degree, cognitive skills are found to play a very small additional role in determining earnings at age 25. This finding is driven by young women who do not achieve any benefit. In contrast, non-cognitive skills not only indirectly influence adult income through the channel of educational choice, they are directly rewarded in the labor market for both men and women. Young women also achieve large benefits from parents having a higher value of education that operates through both channels. Last, evidence from policy simulations suggest that there are trade-offs by gender from developing policies that cultivate either different dimensions of non-cognitive skills or the parental factor, relative to those that focus solely on cognitive skills.

Several of our findings differ from the existing evidence using data from the UK and the US. First, the gradient in college completion among young Canadian women is less steep and we speculate that the structure of the higher education markets likely play a large role in ensuring access. Indeed, our additional analyses in the appendix find differences in college completion rates across skill deciles for individuals raised in household that differ on the basis of parental education. However, we find that at every skill decile individuals who have at least one parent that is college educated earn $10,000 more a year on average than young adults from families where neither parent persisted beyond high school.

Future work using Canadian data can follow Heckman et al. (2016a) by considering richer

[37] Perhaps, most surprising is that on average the age 25 earnings of those with high skills and less educated parents are not significantly different from the earnings of young adults in the lowest skill decile from households where one parent has a higher level of education.

models of individual decision making and potentially examining how the type of higher education people acquire influences career paths. In addition, Statistics Canada has now linked participants in the YITS-A with federal tax records providing data that is unique in its depth and containing more accurate data on annual income.[38] This data can be used to not only reduce measurement error in self-reported labor market earnings as well as errors in any imputation procedure, but in combination with richer models should generate new insights on the role of competencies influencing transitions of youth during this stage of the life-cycle.

In summary, our analysis extends prior work that examined the role of multiple dimensions of latent skills on schooling and labor market outcomes, by additionally incorporating parental valuation for education in the set of an individual's latent competencies. We find that all three included factors influence the decision to complete college and each have additional multiple, heterogeneous, and independent effects on early labor market outcomes. We identify striking gender differences in the main channels through which unobserved initial competencies affect outcomes. We conclude by suggesting that this heterogeneity highlights the challenges that policymakers face and cast doubt that one size fits all education policies will be more effective than targeted policies in reducing economic inequality in the future.

[38] Specifically, 18 years of the T1 Family File as well as other administrative databases have been linked by Statistics Canada to the majority of the YITS-A study participants.

References

Almlund, Mathilde, Angela L. Duckworth, James J. Heckman, and Tim D. Kautz. 2011. Personality psychology and economics. In *The Handbook of The Economics of Education*, ed. E. A. Hanushek, S. Machin and L. Woessmann, Amsterdam: Elsevier.

Autor, David H., David Figlio, Krzysztof Karbownik, Jeffrey Roth, and Melanie Wasserman. Forthcoming. Family disadvantage and the gender gap in behavioral and educational outcomes. *American Economic Journal: Applied Economics.*

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. Trends in U.S. wage inequality: Re-assessing the revisionists, *Review of Economics and Statistics* 90 (2):300-323.

Barrick, Murray R., and Michael K. Mount. 1991. The big five personality dimensions and job performance: A meta-analysis. *Personnel Psychology* 44 (1):1-26.

Beaudry, Paul, David A.Green, and Ben M. Sand. 2014. The declining fortunes of the young since 2000. *The American Economic Review* 104 (5): 381–386.

Beaudry, Paul, David A. Green, and Ben M. Sand. 2016. The great reversal in the demand for skill and cognitive tasks. *Journal of Labor Economics* 34 (1): 199-247.

Becker, Gary S. 1962. Investment in human capital a theoretical analysis. *Journal of Political Economy* 70 (5): 9-49.

Belley, Philippe, Marc Frenette, and Lance Lochner. 2014. Post-secondary attendance by parental income in the US and Canada: Do financial aid policies explain the differences? *Canadian Journal of Economics* 47 (2): 664-696.

Borghans, Lex, Angela L. Duckworth, James J. Heckman, and Bas ter Weel. 2008. The economics and psychology of personality competencies. *Journal of Human Resources* 43 (4): 972-1059.

Bowles, Samuel, Herbert Gintis, and Melissa Osborne. 2001. The determinants of earnings: A behavioral approach. *Journal of Economic Literature* 39 (4): 1137–1176.

Bowlus, Audra, and Chris Robinson. 2012. Human capital prices, Productivity and growth. *American Economic Review* 102 (7): 3483-3515.

Card, David, and Richard B. Freeman. 1993. Introduction. In *Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States*, ed. D. Card and R. B. Freeman. University of Chicago Press.

Carneiro, Pedro, Karsten Hansen, and James J. Heckman. 2003. Estimating distributions of counterfactuals with an application to the returns to schooling and measurement of the effect of uncertainty on schooling choice. *International Economic Review* 44 (2): 361-422.

Chetty, Raj, and Nathaniel Hendren. 2018. The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *Quarterly Journal of Economics* 133 (3): 1107-1162.

Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2016. The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. *American Economic Review* 106 (4): 855-902.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. Where is the land of Opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics* 129 (4): 1553-1623.

Corak, Miles, Matthew J. Lindquist, and Bhaska Mazumder. 2014. A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States. *Labour Economics* 30 (2): 185-200.

Cornwell, Christopher, David B. Mustard, and Jessica Van Parys. 2013. Non-Cognitive skills and the gender disparities in test scores and teacher assessments: Evidence from primary school. *Journal of Human Resources* 48 (1), 236-264.

Cunha, Flavio, and James J. Heckman. 2008. Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources* 43 (4): 738-782.

Cunha, Flavio, James J. Heckman, and Susanne M. Schennach. 2010. "Estimating the technology of cognitive and noncognitive skill formation," *Econometrica* 78 (3): 883-931.

Ding, Weili, and Steven F. Lehrer. 2007. Do peers affect student achievement in China's secondary schools? *Review of Economics and Statistics,* 89 (2): 300-312.

Ding, Weili, and Steven F. Lehrer. 2014. Understanding the role of time-varying unobserved ability heterogeneity in education production. *Economics of Education Review* 40 (1): 55-75.

Ding, Weili, Yipeng Tang, and Yongmei Hu. 2018. Closing the gender gap in science: New evidence from urban China. *Mimeo.* Kingston, Ontario: Queen's University.

Duckworth, Angela L., Christopher Peterson, Michael D. Matthews, and Dennis R. Kelly. 2007. Grit: Perseverance and passion for long term goals. *Journal of Personality and Social Psychology* 92 (6): 1087-1101.

Dynan, Karen E., Jonathan Skinner, and Stephen P. Zeldes. 2004. Do the rich save more? *Journal of Political Economy* 112 (2): 397-444.

Ferguson, Thomas S. (1983). Bayesian density estimation by mixtures of normal distributions. In *Recent Advances in Statistics: Papers in Honor of Herman Chernoff on his Sixtieth Birthday*, ed. H. Chernoff, M. H. Rizvi, J. S. Rustagi, and D. Siegmund. New York: Academic Press.

Finnie, Ross E., Kaveh. Afshar, Eda Bozkurt, Masashi Miyairi and Dejan Pavlic. 2016. Barista or better? New evidence on the earnings of post-secondary education graduates: A tax linkage approach. *Mimeo.* Ottawa, Ontario: EPRI, University of Ottawa.

Flouri, Eirini, and Denise Hawkes. 2008. Ambitious mothers–successful daughters: mothers' early expectations for children's education and children's earnings and sense of control in adult life. *British Journal of Educational Psychology* 78 (3):411-433.

Foley, Kelly, Giovanni Gallipoli and David A. Green. 2014. Ability, parental valuations of education and the high school drop out decision. *Journal of Human Resources* 49 (4): 906-944.

Foley, Kelly. Forthcoming. The gender gap in university enrollment: Do parents play a role beyond investing in skills? *Canadian Journal of Economics*.

Fortin, Nicole M., Philip Oreopoulos, and Shelley Phipps. 2015. Leaving boys behind: Gender disparities in high academic achievement. *Journal of Human Resources* 50 (3): 549-579.

Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. The homecoming of American college women: The reversal of the college gender gap. *Journal of Economic Perspectives*,20 (4): 133-156.

Green, David A, and W Craig Riddell. 2003. Literacy and earnings: an investigation of the interaction of cognitive and unobserved skills in earnings generation. *Labour Economics* 10 (2): 165-184.

Hansen, Karsten, James J. Heckman, and Kathleen J. Mullen. 2003. The effect of schooling and ability on achievement test scores. *Journal of Econometrics* 121 (1-2): 39-98.

Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann. 2015. Returns to skills around the world: Evidence from PIAAC. *European Economic Review*73 (1): 103-130.

Hartigan, John A., and Alexandra K. Wigdor. 1989. Fairness in employment testing. *Science* 245 (4913): 1-14.

Hartog, Joop, Mirjam Van Praag, and Justin Van Der Sluis. 2010. If you are so smart, why aren't you an entrepreneur? Returns to cognitive and social ability: Entrepreneurs versus employees. *Journal of Economics & Management Strategy* 19 (4): 947-989.

Heckman, James J., and Guilherme Sedlacek. 1985. Heterogeneity, aggregation, and market wage functions: An empirical model of self-selection in the labor market. *Journal of Political Economy* 93 (6): 1077-1125.

Heckman, James J., Jora Stixrud, and Sergio Urzúa. 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics* 24 (3): 411-482.

Heckman, James J., and Stefano Mosso. 2014. The economics of human development and social mobility. *Annual Review of Economics* 6 (1): 689-733.

Heckman, James J., John E. Humphires, and Gregory Veramendi. 2016a. Returns to education: The causal effects of education on earnings, health and smoking. *Journal of Political Economy* 126 (S1): S197-S246.

Heckman, James J., John E. Humphries and Gregory Veramendi. 2016b. Dynamic treatment effects. *Journal of Econometrics* 191 (2): 276-292.

Humphires, John and Fabian Kosse. 2017. On the interpretation of non-cognitive skills – what is being measured and why it matters. *Journal of Economic Behavior & Organization* 136: 174-185.

Jacob, Brian A. and Tamara W. Linkow. 2011. Educational expectations and attainment. In *Whither opportunity: Rising inequality, schools, and children's life chances,* ed G. Duncan and R. J. Murnane. New York: Russell Sage Foundation.

Jacobs, Janis E., Jacqueline S. Eccles. 1992. The impact of mothers' gender-role stereotypic beliefs on mothers' and children's ability perceptions. *Journal of Personality and Social Psychology*,63 (6): 932-944.

Jacobs, Janis E., Christina S. Chhin, and Martha M. Bleeker. 2006. Enduring links: Parents' expectations and their young adult children's gender-typed occupational choices. *Educational Research and Evaluation* 12 (4): 395-407.

Kotlarski, Ignacy I. 1967. On characterizing the gamma and the normal distribution. *Pacific Journal of Mathematics*,20 (1): 69-76.

Kottelenberg, Michael J., and Steven F. Lehrer. 2018. Does Quebec's subsidized child care policy give boys and girls an equal start? *Canadian Journal of Economics* 51 (2), 627-659.

Leibowitz, Arleen. 1974. Home Investments in Children. *Journal of Political Economy* 82 (2): 111-131.

Levine, Ross and Yona Rubinstein. 2013. Smart and illicit: Who becomes an entrepreneur and does it pay? NBER Working Paper w19726, National Bureau of Economic Research, Cambridge, MA.

Lundberg, Shelly. 2005. Sons, daughters, and parental behavior. *Oxford Review of Economic Policy* 21 (3): 340-356.

Morissette, René, Ping C. W. Chan, and Yuqian Lu. 2015. Wages, youth employment, and school enrollment: Recent evidence from increases in world oil prices. *Journal of Human Resources* 50 (1): 222-253.

Murnane, Richard J., John B. Willett, and John H. Tyler. 2000. Who benefits from obtaining a GED? Evidence from high school and beyond *The Review of Economics and Statistics* 82 (1): 23-37.

Ou, Suh-Ruu, and Arthur J. Reynolds. 2008. Predictors of educational attainment in the Chicago Longitudinal Study. *School Psychology Quarterly* 23 (2): 199-229.

Pintrich, Paul R., and Elisabeth V. De Groot. 1990. Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology* 82 (1): 33-40.

Prada, Marıa F., and Sergio Urzúa. 2017. One size does not fit all: Multiple dimensions of ability, college attendance and wages. *Journal of Labor Economics* 35 (4): 953-991.

Rosenberg, Manny. 1965. *Society and the Adolescent Self-Image*, Princeton: Princeton University Press.

Roy, Andrew D. 1951. Some thoughts on the distribution of earnings. *Oxford Economic Papers* 3 (2): 135-146.

Sacerdote, Bruce. 2011. Peer effects in education: how might they work, how big are they and how much do we know thus far? In *The Handbook of The Economics of Education*, ed. E. A. Hanushek, S. Machin and L. Woessmann. Amsterdam: Elsevier.

Saez, Emmanuel and Gabriel Zucman. 2016. Wealth inequality in the United States since 1913: Evidence from capitalized income tax data. *The Quarterly Journal of Economics* 131 (2): 519-578.

Schneider, Barbara, Venessa Keesler and Larissa Morlock. 2010. The effects of family on children's learning and socialization. In *The nature of learning: Using research to inspire practice*, ed H. Dumont, D. Istance, and F. Benavides. Paris: OECD.

Schneider, Barbara, and David Stevenson. 1999. *The ambitious generation: America's teenagers, motivated but directionless*. New Haven: Yale University Press.

Teachman, Jay D. 1987. Family background, educational resources, and educational attainment. *American Sociological Review* 52 (4): 548–557.

Urzúa, Sergio. 2008. Racial labor market gaps the role of abilities and schooling choices. *Journal of Human Resources* 43 (4): 919-971.

Williams, Benjamin. 2018. Identification of the linear factor model. *Mimeo*. Washington, DC: George Washington University.

Willis, Robert J. and Sherwin Rosen. 1979. Education and self-selection. *Journal of Political Economy* 87 (5): s7-s36.

Wood, Dana, Rachel Kaplan, and Vonnie McLoyd. 2007. Gender differences in the educational expectations of urban, low-income African American youth: The role of parents and the school. *Journal of Youth and Adolescence* 36 (4): 417-427.

Table 1: Mean and Standard Deviation of Key Variables

Variables of Interest	Complete YITS Sample	Two PISA Scores Sample	Imputation Sample	Three PISA Score Full Sample
Factor Test Scores				
PISA Reading Score	0.102	0.330	0.401	0.529
	(0.980)	(0.917)	(0.879)	(1.047)
PISA Math Score	0.079	0.308	0.381	0.331
	(1.004)	(0.936)	(0.899)	(0.876)
PISA Science Score	0.090	0.321	0.388	0.429
	(1.002)	(0.943)	(0.893)	(0.889)
Self-Efficacy	0.002	0.104	0.147	0.159
	(1.000)	(0.973)	(0.960)	(0.962)
Sense of Mastery	0.002	0.090	0.120	0.135
	(1.000)	(0.985)	(0.977)	(0.994)
Self-Esteem	-0.005	0.089	0.125	0.151
	(1.011)	(1.001)	(0.992)	(0.949)
Parent Educational Aspiration for Youth	3.748	3.797	3.831	3.845
	(0.836)	(0.789)	(0.771)	(0.764)
Importance of Post-Secondary Education	3.854	3.854	3.874	3.891
(Parent's Answer)	(0.424)	(0.427)	(0.382)	(0.349)
Importance of Post-Secondary Education	3.717	3.736	3.744	3.749
(Youth's Answer about Parents)	(0.602)	(0.571)	(0.563)	(0.542)
Individual and Family Characteristics, Age 15				
Female	0.501	0.508	0.514	0.496
	(0.500)	(0.500)	(0.500)	(0.500)
Family Income (Thousands)	70.73	73.37	74.48	74.97
	(68.42)	(56.56)	(50.95)	(43.67)
Years of Education Parents (Max)	13.80	14.02	14.17	14.24
	(2.50)	(2.470)	(2.470)	(2.630)
Wealth Index	0.412	0.446	0.489	0.504
	(0.880)	(0.826)	(0.798)	(0.784)
Non-Traditional Family	0.272	0.143	0.115	0.100
	(0.445)	(0.350)	(0.319)	(0.301)
Immigrant	0.131	0.113	0.109	0.118
	(0.337)	(0.317)	(0.311)	(0.323)
Number of Siblings	1.338	1.350	1.350	1.357
	(0.983)	(0.960)	(0.948)	(0.975)
Parental money for	0.652	0.684	0.699	0.693
Post-Secondary Education (Y/N)	(0.476)	(0.465)	(0.459)	(0.461)
Planning for Higher Education	3.251	3.328	3.361	3.391
Among Friends (Scale: 1 to 4)	(0.739)	(0.712)	(0.698)	(0.675)
Individual and Family Characteristics, Age 25				
University Completed	0.519	0.539	0.561	0.577
	(0.500)	(0.499)	(0.496)	(0.494)
Experience (Years)	5.267	4.224	4.144	4.158
	(2.766)	(2.624)	(2.563)	(2.479)
Married	0.174	0.141	0.147	0.148
	(0.379)	(0.348)	(0.354)	(0.355)
Common Law	0.219	0.240	0.231	0.219
	(0.413)	(0.427)	(0.422)	(0.414)
Number of Children	0.041	0.036	0.033	0.024
	(0.223)	(0.206)	(0.194)	(0.168)
Urban Community	0.833	0.824	0.821	0.838
	(0.373)	(0.381)	(0.375)	(0.369)
Observations	29687	9065	6181	1607

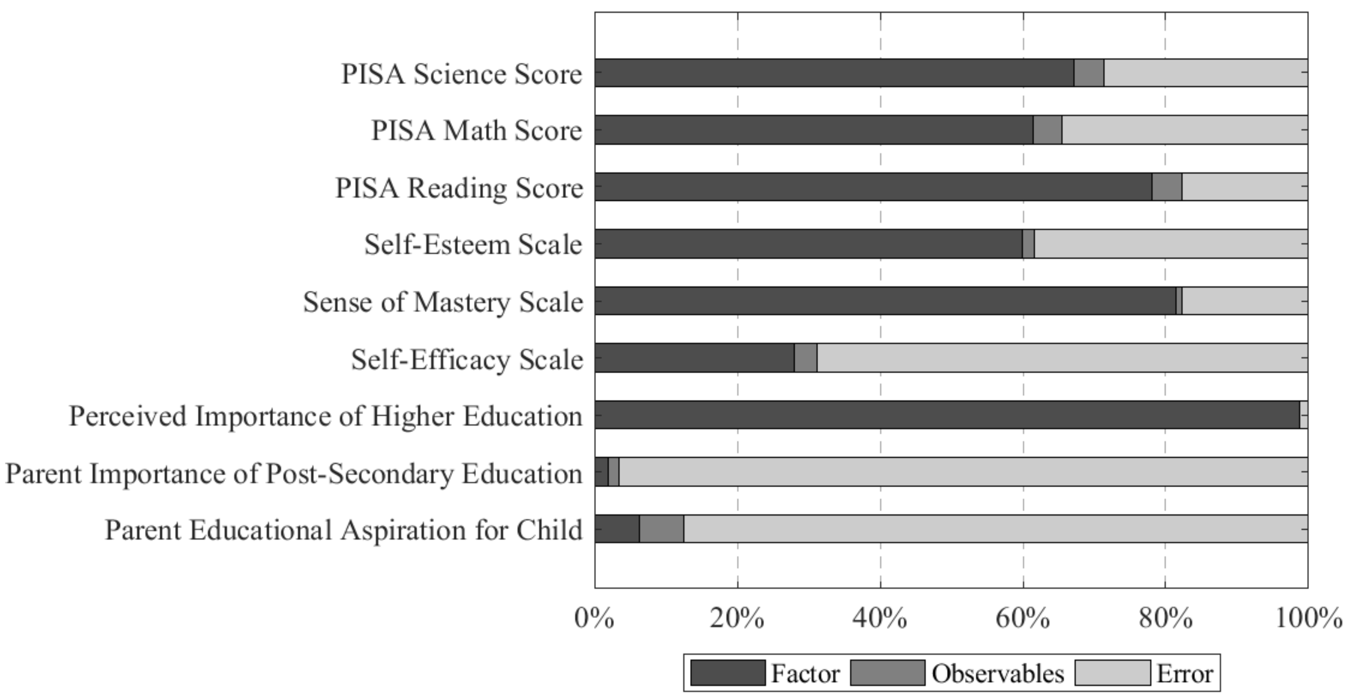
— Note: We present means and standard deviations (in parentheses) for 4 samples of the YITS. The first column uses all data available in the YITS survey. The second includes individuals who have two or more PISA test scores. The third sample restricts that second further by ensuring that all observations are complete cases; and the final sample requires individuals to have all 3 PISA test scores.

Table 2: Test Score Equations

	PISA Reading	PISA Math	PISA Science	Self-Efficacy	Sense of Mastery	Self-Esteem	Parent Educational Aspirations	Importance of PSE (Parents)	Importance of PSE (Youth)
Cognitive Factor	1.331***	0.933***	1	...	...	...	...	...	...
	(0.044)	(0.036)							
Non-Cognitive Factor	...	...	...	0.582***	1.291***	1	...	...	...
				(0.036)	(0.045)				
Parental Factor	...	...	...	...	...	...	0.271***	0.101***	1
							(0.033)	(0.016)	
Female	0.321***	-0.110***	-0.059	-0.240***	-0.053	-0.189***	0.074*	0.013	0.000
	(0.049)	(0.042)	(0.041)	(0.046)	(0.038)	(0.042)	(0.038)	(0.019)	(0.000)
Family Income	0.001	0.000	0.000	0.000	-0.001**	-0.001	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Wealth	0.030	0.052*	0.011	-0.023	0.038	0.044	0.092***	0.034**	0.000
	(0.036)	(0.031)	(0.030)	(0.033)	(0.026)	(0.030)	(0.027)	(0.013)	(0.000)
Years of Education Parents (Max)	0.084***	0.054***	0.074***	0.043***	0.003	0.005	0.057***	0.010**	0.000
	(0.012)	(0.010)	(0.010)	(0.011)	(0.009)	(0.010)	(0.009)	(0.004)	(0.000)
Non-School Activities	0.183***	0.159***	0.147***	0.198***	0.177***	0.183***	-0.052	-0.020	0.000
	(0.056)	(0.048)	(0.047)	(0.053)	(0.042)	(0.048)	(0.043)	(0.022)	(0.001)
Non-Traditional Family	0.126	0.091	0.192***	-0.061	-0.227***	-0.165**	0.105	0.005	-0.001
	(0.087)	(0.076)	(0.074)	(0.083)	(0.067)	(0.076)	(0.068)	(0.034)	(0.001)
Number of Siblings	0.037	0.037	0.037	0.017	-0.002	0.022	0.025	-0.040***	0.000
	(0.027)	(0.023)	(0.023)	(0.025)	(0.020)	(0.023)	(0.020)	(0.010)	(0.000)
Visible Minority	-0.098	-0.116	-0.119	-0.136	-0.168*	-0.027	0.060	-0.024	0.000
	(0.118)	(0.101)	(0.099)	(0.108)	(0.101)	(0.105)	(0.086)	(0.043)	(0.001)
Immigrant	-0.039	0.002	0.092	-0.028	-0.020	-0.039	-0.242***	-0.071**	-0.001
	(0.090)	(0.075)	(0.074)	(0.077)	(0.077)	(0.077)	(0.060)	(0.030)	(0.001)
Region: Atlantic	-0.091	0.108	-0.088	-0.131	-0.132**	-0.140*	0.188***	0.032	0.001
	(0.092)	(0.079)	(0.077)	(0.082)	(0.062)	(0.073)	(0.068)	(0.034)	(0.001)
Region: West	0.248***	0.381***	0.254***	0.003	-0.061	0.019	0.035	-0.026	0.000
	(0.086)	(0.074)	(0.072)	(0.077)	(0.061)	(0.070)	(0.064)	(0.032)	(0.001)
Region: Quebec	0.273***	0.534***	0.227***	-0.022	0.039	-0.003	0.098	-0.095***	0.000
	(0.102)	(0.087)	(0.085)	(0.091)	(0.073)	(0.082)	(0.074)	(0.037)	(0.001)
Constant	-1.278***	-0.907***	-1.064***	-0.406**	0.113	0.071	2.865***	3.812***	3.517***
	(0.197)	(0.168)	(0.165)	(0.179)	(0.163)	(0.171)	(0.149)	(0.073)	(0.146)

—Note: We present the estimates for the measurement system linking the latent factors and the test measures from the full sample. Standard errors are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Figure 1: Variance Decomposition of Test Scores



—Note: We present the variance-decomposition of the test score. Factors are simulated using the estimates of from the full sample. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

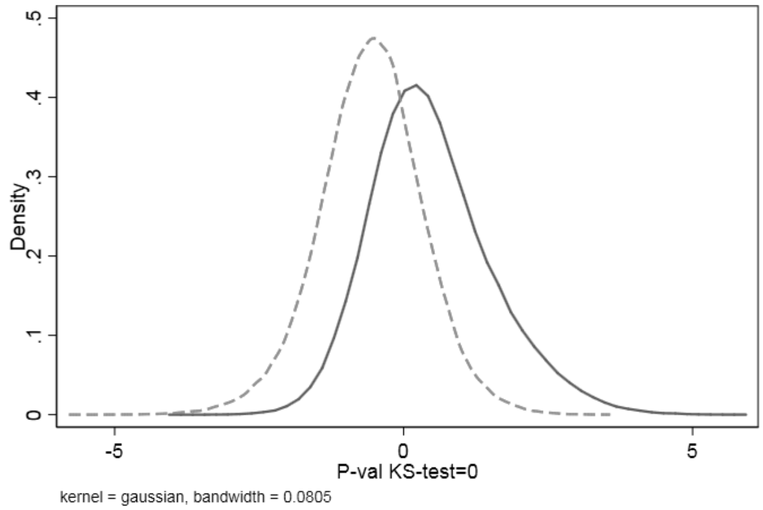
Table 3: Decision Equation: University Completion

	Full	Imputation	Male	Female
Cognitive Factor	0.882***	0.765***	0.893***	0.908***
	(0.100)	(0.183)	(0.140)	(0.143)
Non-Cognitive Factor	0.267***	0.242***	0.524***	0.200**
	(0.088)	(0.058)	(0.137)	(0.102)
Parental Factor	0.398***	0.247***	0.276**	0.408***
	(0.067)	(0.077)	(0.111)	(0.104)
Parental Money for Post-Secondary Education	0.229***	0.238***	0.308**	0.199*
	(0.084)	(0.061)	(0.127)	(0.121)
Female	0.556***	0.47***	...	...
	(0.077)	(0.099)		
Family Income	0.001	0.002***	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Family Wealth	0.062	0.084***	0.050	0.129
	(0.054)	(0.031)	(0.079)	(0.084)
Parental Education (Max)	0.170***	0.175***	0.147***	0.182***
	(0.019)	(0.035)	(0.028)	(0.028)
Planning for Higher Education (Among Friends)	0.251***	0.263***	0.370***	0.142*
	(0.055)	(0.057)	(0.084)	(0.081)
Immigrant Status	-0.322***	-0.343***	-0.626***	0.063
	(0.107)	(0.084)	(0.163)	(0.156)
Non-Traditional Family	0.157	0.047	0.113	0.410*
	(0.133)	(0.061)	(0.194)	(0.210)
Region: Atlantic	0.367***	0.438***	0.282	0.463**
	(0.138)	(0.105)	(0.210)	(0.198)
Region: West	0.219*	0.231***	0.321	0.032
	(0.129)	(0.074)	(0.200)	(0.181)
Region: Quebec	-0.169	-0.034	-0.253	-0.079
	(0.149)	(0.068)	(0.224)	(0.217)
Constant	-3.440***	-3.56***	-3.236***	-3.132***
	(0.352)	(0.707)	(0.516)	(0.511)

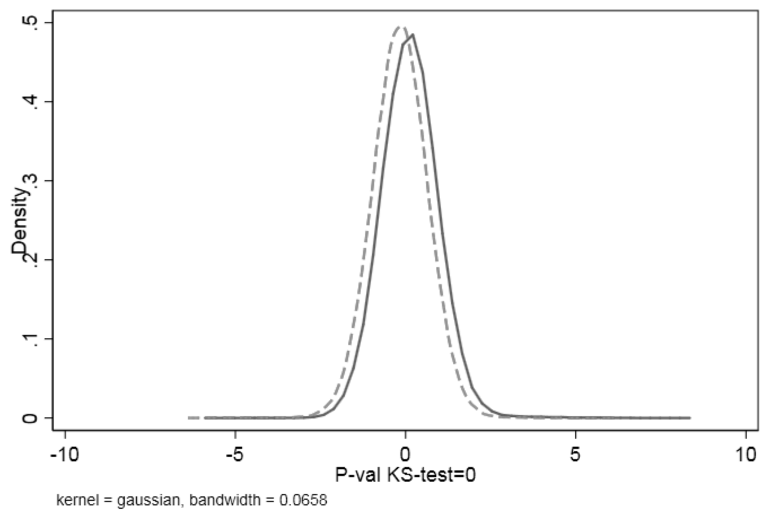
—Note: We present the estimates and standard errors in parentheses of decision equation for four samples. For the imputation sample, we present the average estimate across the imputations iterations, β^I. The standard error in the imputation model, s_{β^I} is given by $\sqrt{w + (1 + \frac{1}{m})B}$ where m is the number of imputations, $w = \frac{1}{m}\sum_{i=1}^{m} s_\beta^i$ and $B = \frac{1}{m-1}\sum_{i=1}^{m}(\beta_m^i - \beta^I)^2$. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Figure 2: **Distribution of Latent Factors by Education**

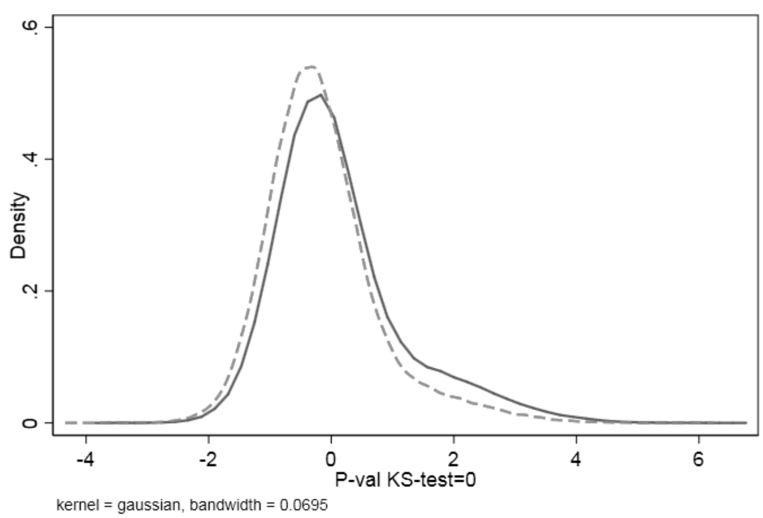
(a) Cognitive Factor



(b) Non-Cognitive Factor



(c) Parental Factor



—Note: Using the full sample we present the simulated distributions of the factor scores by the education decision, where university completion, D=1, is the solid line. P-values from the Kolmogorov–Smirnov test comparing the two distributions are presented below each figure.

Table 4: Outcome Equation: Income

	Full		Imputation		Male		Female	
	D=0	D=1	D=0	D=1	D=0	D=1	D=0	D=1
Cognitive Factor	-789	839	785	262	-1148	2832	336	-1542
	(1962)	(2032)	(1499)	(1587)	(2779)	(2832)	(2301)	(2285)
Non-Cognitive Factor	385	2131	581	456	-999	1688	2436	1830
	(2205)	(1600)	(800.9)	(648.7)	(3687)	(2848)	(1812)	(1518)
Parental Factor	564	3380**	955	1806**	449	-1438	1054	5232***
	(1193)	(1688)	(619.7)	(893.4)	(1646)	(3181)	(1544)	(1985)
Female	-8538***	-3129*	-9396***	-2930***	...	...	...	...
	(2382)	(1860)	(2192)	(1088)				
Experience	-362	2359**	-549	838*	59	1197	-192	4070***
	(1135)	(962)	(494.4)	(452.7)	(1658)	(1650)	(1320)	(1255)
Experience Squared	64	-368***	34	-175***	77	-223	10	-571***
	(97)	(103)	(37.63)	(53.62)	(140)	(161)	(115)	(148)
Married	9324***	19652***	8558***	12923***	9430***	17977***	-1916	-781
	(3100)	(3358)	(2333)	(3077)	(3657)	(3917)	(2369)	(2290)
Married * Female	-12842***	-20796***	-11851***	-10653***	...	...	...	...
	(4368)	(4136)	(3230)	(3003)				
Common Law	13319***	8105**	8346***	7990***	13052***	7517**	-305	9113***
	(2749)	(3175)	(2145)	(2256)	(3172)	(3655)	(2378)	(2184)
Common Law * Female	-13734***	-248	-6306***	-1604	...	...	...	...
	(4107)	(3906)	(2402)	(2067)				
Immigrant	-1826	266	1272	1531	1158	6823*	-3417	-5576**
	(2862)	(2150)	(1526)	(1166)	(4557)	(3628)	(3141)	(2767)
Visible Minority	-5947	-5442*	-6161**	-1261	-649	-6612	-11384**	-5326
	(4421)	(3022)	(2727)	(1605)	(6662)	(4904)	(5174)	(3971)
Number of Children	-4989	-14704	-4897*	15499*	-5653	-14178	-11105***	-3532
	(4611)	(21614)	(2791)	(8399)	(5268)	(24147)	(2681)	(8105)
Number of Children * Female	-5601	9536	-3716	-25674***	...	...	...	...
	(5745)	(23381)	(3224)	(9903)				
Urban Community	1169	4354**	1197	678	4604	6497*	-3045	3696*
	(1812)	(1931)	(974.7)	(986.5)	(2818)	(3891)	(2010)	(2170)
Region: Atlantic	-6829**	-3008	-6328***	-2275*	-8363*	-2741	-6686**	-3808
	(2883)	(2309)	(1895)	(1258)	(4400)	(4333)	(3262)	(2669)
Region: Quebec	-7450**	-1548	-4382**	-1830	-7493*	1111	-6049*	-3012
	(2951)	(2714)	(1716)	(1393)	(4420)	(4903)	(3461)	(3236)
Region: West	1173	1861	3603**	4873***	4810	3647	-3042	434
	(2663)	(2159)	(1525)	(1437)	(4078)	(3853)	(3013)	(2592)
Constant	36378***	27436***	35249***	29159***	28770***	23895***	33455***	27143***
	(4776)	(3198)	(7156)	(5831)	(7317)	(5404)	(5186)	(3771)

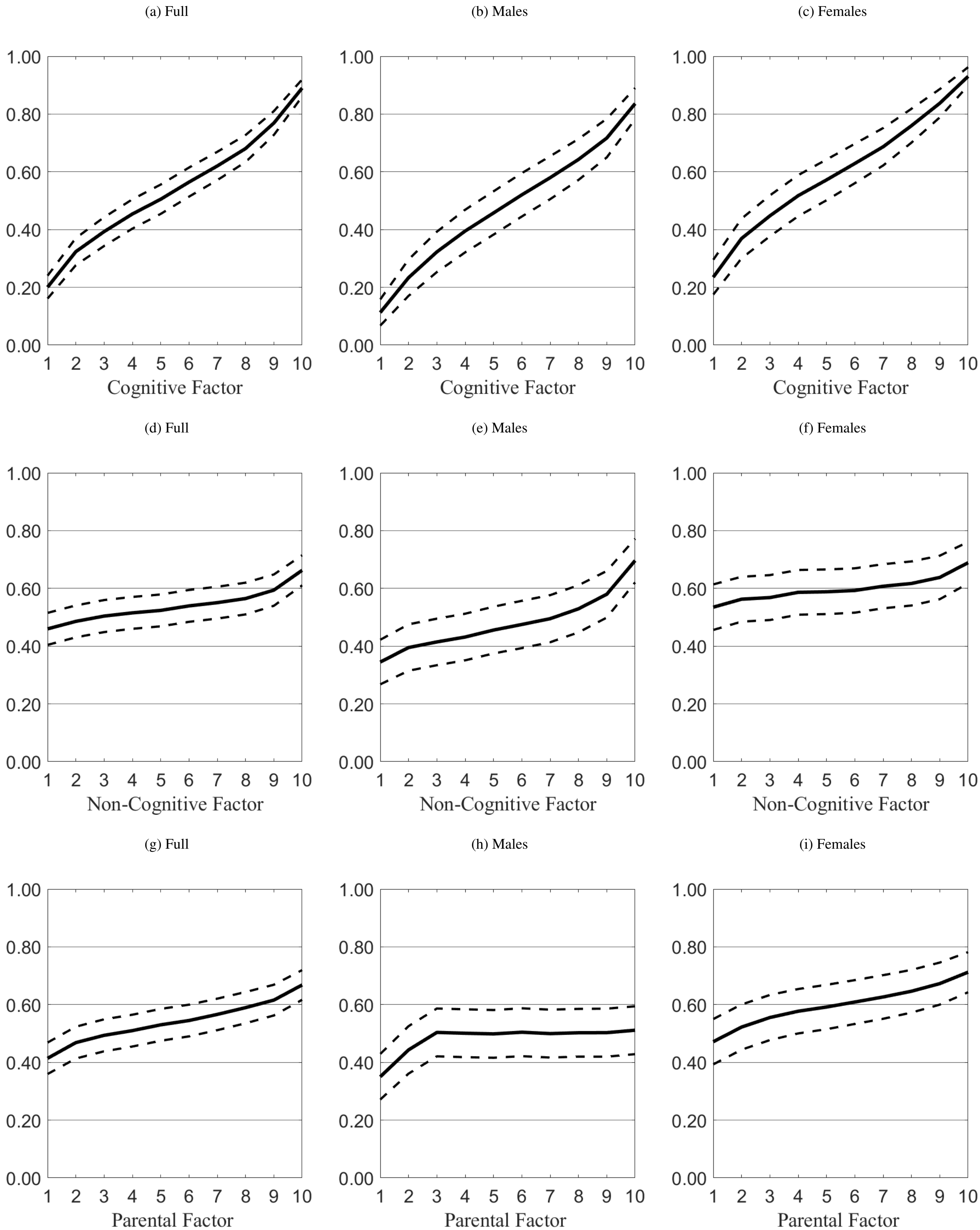
—Note: We present the estimates and standard errors in parentheses for outcome equations examining income. For the imputation sample, we present the average estimate across the imputations iterations, β^I. The standard error in the imputation model, s_{β^I} is given by $\sqrt{w + (1 + \frac{1}{m})B}$ where m is the number of imputations, $w = \frac{1}{m}\sum_{i=1}^{m} s_{\beta}^{i}$ and $B = \frac{1}{m-1}\sum_{i=1}^{m}(\beta_m^i - \beta^I)^2$. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 5: Outcome Equation: Employment

	Full		Imputation		Male		Female	
	D=0	D=1	D=0	D=1	D=0	D=1	D=0	D=1
Cognitive Skills	0.060**	-0.013	0.024	-0.009	0.055*	-0.029	0.062	0.009
	(0.030)	(0.023)	(0.023)	(0.018)	(0.032)	(0.034)	(0.059)	(0.034)
Non-Cognitive Skills	-0.028	-0.017	-0.016	0.005	0.054	0.019	-0.005	-0.033*
	(0.027)	(0.017)	(0.012)	(0.007)	(0.048)	(0.034)	(0.034)	(0.019)
Education Expectations Factor	-0.022	0.070***	-0.002	0.025**	0.001	0.017	-0.024	0.104***
	(0.018)	(0.023)	(0.01)	(0.011)	(0.020)	(0.039)	(0.034)	(0.028)
Female	0.038	0.006	0.007	0.019*	...	...	...	...
	(0.050)	(0.024)	(0.018)	(0.011)				
Married	0.023	0.079*	0.013	0.026	0.016	0.069	-0.164***	-0.091***
	(0.051)	(0.045)	(0.024)	(0.022)	(0.042)	(0.047)	(0.052)	(0.032)
Married * Female	-0.196***	-0.162***	-0.131***	-0.074***	...	...	...	...
	(0.074)	(0.055)	(0.033)	(0.027)				
Common Law	0.089	-0.051	0.024	0.022	0.087**	0.063	-0.045	0.053*
	(0.080)	(0.041)	(0.021)	(0.02)	(0.036)	(0.043)	(0.052)	(0.030)
Common Law * Female	-0.121	0.106**	-0.042	-0.005	...	...	...	...
	(0.102)	(0.051)	(0.03)	(0.025)				
Immigrant	-0.042	-0.018	0.023	0.011	0.012	0.041	-0.064	-0.059
	(0.042)	(0.028)	(0.022)	(0.013)	(0.052)	(0.044)	(0.071)	(0.037)
Visible Minority	-0.026	-0.106***	0.012	-0.026	0.022	-0.045	-0.068	-0.155***
	(0.063)	(0.039)	(0.035)	(0.019)	(0.075)	(0.057)	(0.111)	(0.053)
Number of Children	-0.096	0.072	-0.022	0.079	0.103*	0.074	-0.282***	-0.277**
	(0.067)	(0.293)	(0.038)	(0.1)	(0.060)	(0.303)	(0.060)	(0.116)
Number of Children * Female	-0.193**	-0.346	-0.078*	-0.218**	...	...	...	...
	(0.085)	(0.317)	(0.046)	(0.106)				
Urban Community	0.009	0.018	-0.024*	0.012	0.028	0.020	-0.016	0.040
	(0.027)	(0.025)	(0.014)	(0.012)	(0.032)	(0.046)	(0.045)	(0.030)
Region: Atlantic	-0.072*	0.017	-0.027	0.016	0.043	0.023	-0.102	0.013
	(0.042)	(0.030)	(0.021)	(0.014)	(0.050)	(0.052)	(0.074)	(0.036)
Region: Quebec	-0.090**	0.000	-0.018	-0.022	0.073	0.044	-0.096	-0.022
	(0.043)	(0.034)	(0.022)	(0.016)	(0.051)	(0.056)	(0.077)	(0.042)
Region: West	-0.077**	-0.037	-0.038*	0.009	0.027	0.038	-0.136**	-0.027
	(0.039)	(0.028)	(0.02)	(0.013)	(0.046)	(0.045)	(0.068)	(0.035)
Constant	1.019***	0.925***	0.911***	0.888***	0.946***	0.880***	1.123***	0.938***
	(0.056)	(0.035)	(0.027)	(0.017)	(0.067)	(0.054)	(0.088)	(0.044)

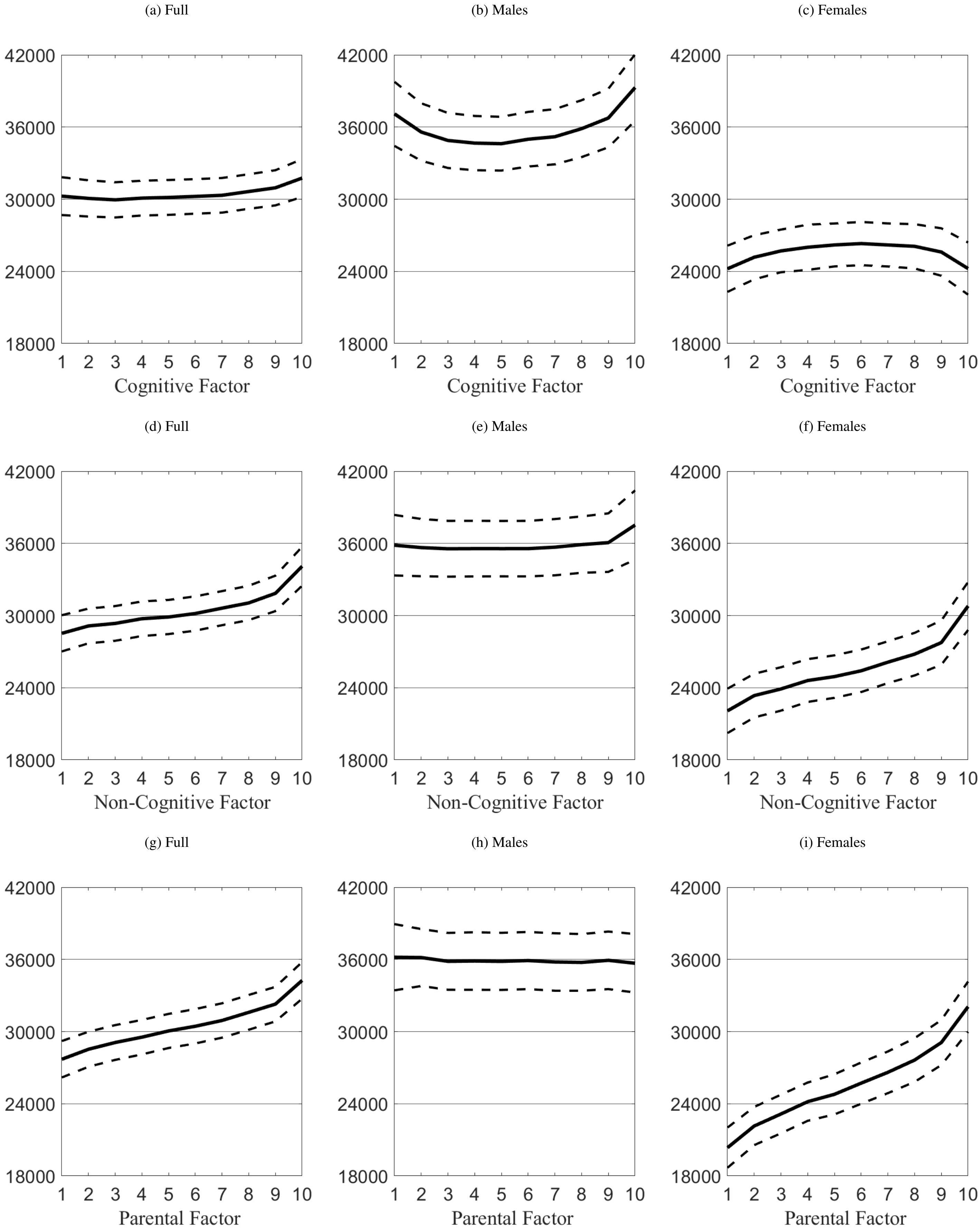
—Note: We present the estimates and standard errors in parentheses for outcome equations examining employment. For the imputation sample, we present the average estimate across the imputations iterations, β^I. The standard error in the imputation model, s_{β^I} is given by $\sqrt{w + (1 + \frac{1}{m})B}$ where m is the number of imputations, $w = \frac{1}{m}\sum_{i=1}^{m} s_{\beta}^{i}$ and $B = \frac{1}{m-1}\sum_{i=1}^{m}(\beta_m^i - \beta^I)^2$. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Figure 3: Simulation of University Completion by Deciles of the Factor Distribution



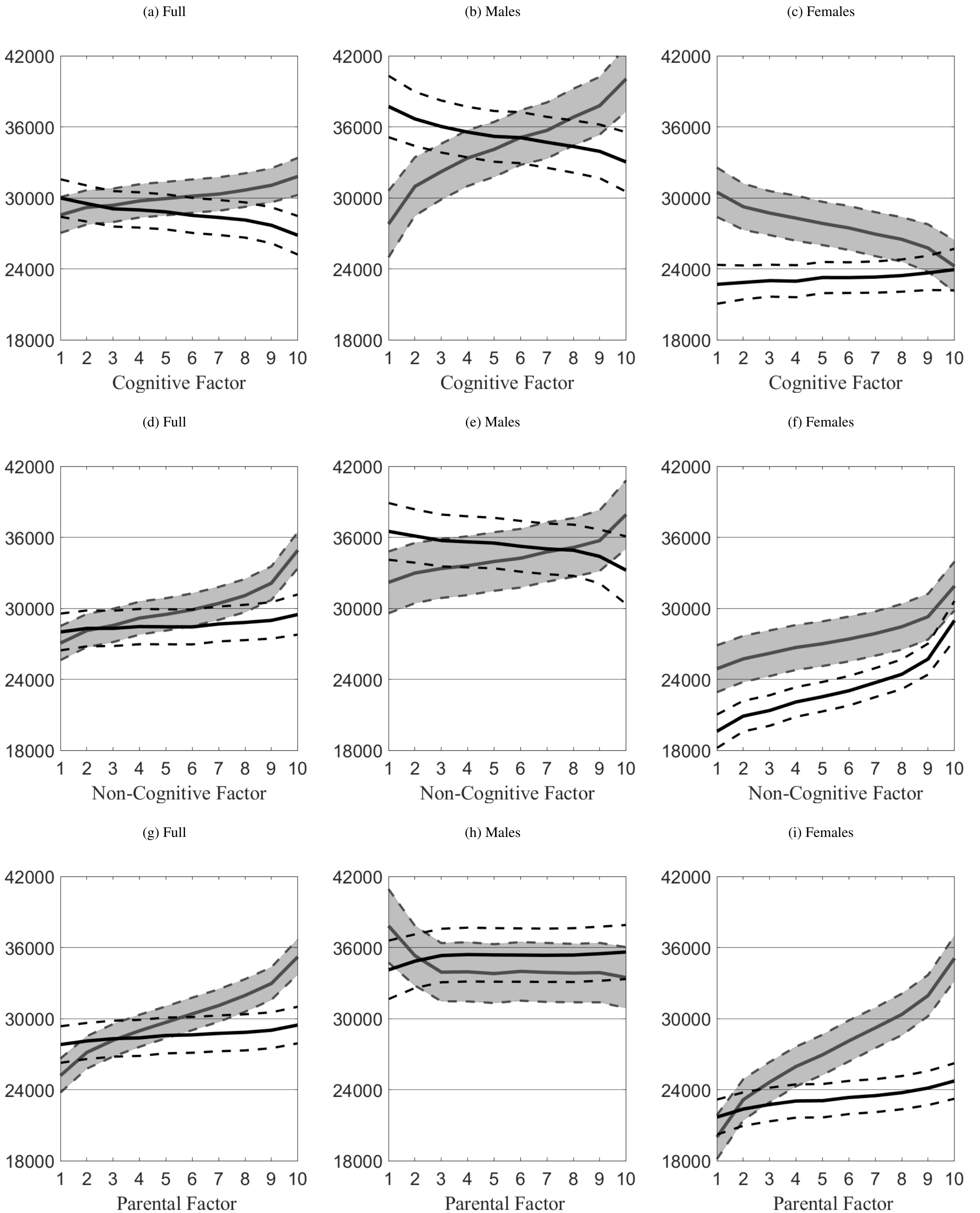
—Note: The solid line represents average university decision within each decile of the factor distribution calculated using simulations of the model based on the estimated parameters for the given sample. The dashed line are the 95% confidence intervals for these estimates.

Figure 4: Simulation of Income by Deciles of the Factor Distribution



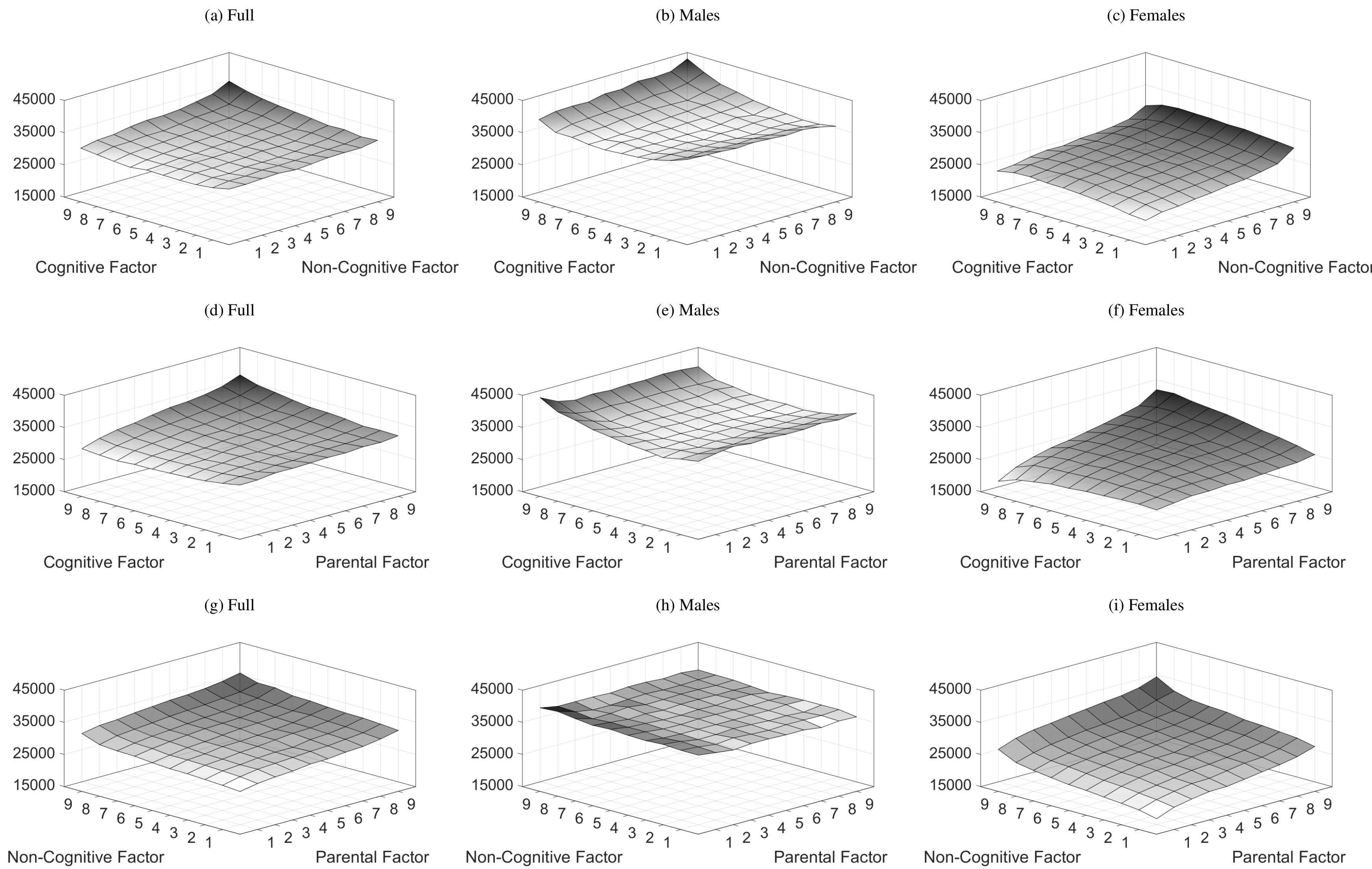
—Note: The solid line represents average income within each decile of the factor distribution calculated using simulations of the model based on the estimated parameters for the given sample. The dashed line are the 95% confidence intervals for these estimates.

Figure 5: Simulation of Income by University Completion Status by Deciles of the Factor Distribution



—Note: In this figure we present the average income within each decile of the factor by educational decision. The presented data are based on the estimated parameters for the given sample. The estimates and 95% confidence intervals for those that completed university in the simulations are given by grey lines and shaded area. Similarity, the black lines give the same data for those who did not complete university.

Figure 6: Simulation of Income By Deciles of the Factor Distributions



—Note: In this figure we present the average income (z-axis) within pairs of deciles from the two factors labeling the x-axis and y-axis. Each row of figures pairs a different combination of the factors. The presented data are based on the estimated parameters for the given sample.

Table 6: Simulated Marginal Effects

	Full	Male	Female
Effect on university completion of a standard deviation change in the:			
Cognitive Factor	0.268***	0.265***	0.276***
	(0.011)	(0.016)	(0.016)
Non-Cognitive Factor	0.08***	0.132***	0.061***
	(0.007)	(0.012)	(0.009)
Parental Factor	0.098***	0.069***	0.096***
	(0.008)	(0.009)	(0.011)
Effect on income of a standard deviation change in the:			
Cognitive Factor	775***	1830***	63
	(120.4)	(197.4)	(166.7)
Non-Cognitive Factor	1516***	506***	2529***
	(69.01)	(136.1)	(78.99)
Parental Factor	2017***	-665***	3352***
	(78.73)	(100.6)	(123.4)
Indirect effect on income through education of a standard deviation change in the:			
Cognitive Factor	278**	-488***	1334***
	(118.2)	(187)	(168.6)
Non-Cognitive Factor	105	-169	272***
	(64.52)	(130.2)	(79.42)
Parental Factor	128*	-69	437***
	(71.8)	(94.62)	(99.44)
Direct effect on income of a standard deviation change in the:			
Cognitive Factor	497***	2317***	-1270***
	(19.57)	(73.69)	(32.61)
Non-Cognitive Factor	1410***	675***	2257***
	(22.28)	(44.52)	(11.58)
Parental Factor	1889***	-596***	2915***
	(29.72)	(31.93)	(61.09)
Effect on employment of a standard deviation change in the:			
Cognitive Factor	0.001	-0.005	0.007
	(0.004)	(0.006)	(0.007)
Non-Cognitive Factor	-0.005*	-0.007	-0.004
	(0.003)	(0.005)	(0.004)
Parental Factor	0.006*	0	0.007
	(0.003)	(0.004)	(0.005)
Indirect effect on employment through education of a standard deviation change in the:			
Cognitive Factor	-0.003	0.000	-0.009
	(0.01)	(0.014)	(0.015)
Non-Cognitive Factor	-0.002	-0.003	-0.002
	(0.006)	(0.01)	(0.006)
Parental Factor	-0.002	-0.003	-0.003
	(0.005)	(0.009)	(0.008)
Direct effect on employment of a standard deviation change in the:			
Cognitive Factor	0.003	-0.005	0.016
	(0.009)	(0.013)	(0.013)
Non-Cognitive Factor	-0.003	-0.005	-0.002
	(0.005)	(0.009)	(0.006)
Parental Factor	0.007	0.003	0.01
	(0.005)	(0.008)	(0.008)
Effect of completing university			
Average Treatment Effect	1501***	-824**	4290***
	(228.4)	(380.6)	(288.9)

—Note: Using simulations based on the estimated parameters of the model we calculate the given effects for each sample. Standard errors are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.