

New evidence on how skills influence human capital acquisition and early labour market return to human capital between Canada and the United States

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Abstract

Using the Youth in Transition Survey (YITS-A) we estimate a Roy model with a two dimensional latent factor structure to consider how both cognitive and non-cognitive skills influence endogenous schooling decisions and subsequent labour market outcomes in Canada. Contrasting these estimates with those obtained using US data we observe several similarities including non-cognitive skills playing a similar role in determining income at age 25 as cognitive skills. Further, our findings indicate that it is crucial to account for the dynamics in decision making, since the effect of cognitive skills on adult incomes arises by one increasing the likelihood of obtaining further education in both countries. However there are striking differences when exploring the relationships between genders and across family background. The college graduation rate of Canadian women exceeds that of US women, particularly among those with low cognitive skills. However, the age 25 earnings gradient by either cognitive or non-cognitive skill is much flatter in Canada than the United States. Last, policy simulations indicate a recent emergence of relative inequality in Canada, where high skilled children of less-educated parents now on average earn less at age 25 than children whose cognitive skills are in the bottom decile but have high-educated parents. This evidence appears consistent with both findings on the geographic nature of inequality in the United States and sociological studies which explore whether there is truly equality of opportunity.

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1 Introduction

Commentators in both the popular press and policy circles routinely forecast that economic inequality between skilled and unskilled workers within nations will continue to grow. Skills are now believed to drive economic growth and social progress. Indeed, a mantra among many policy analysts today is that talent is the new driver of global competitiveness and without a sufficient supply of skilled workers that can utilize the latest technologies, a country's economy will fall behind its competitors. After all, globalization and technological progress have already led to massive transformations of many national labor markets over the past three decades and skill shortages and mismatches are now believed to have substantial effects on the productivity of labor. Thus, it is not surprising that educational attainment is no longer sufficient to ensure one's lifetime success and statistics from many developed nations indicate that recent university graduates are facing larger challenges when moving from school to work. Faced with growing anxiety from its citizens in response to many of these claims, governments around the world are continuing to devise policies that aim to either develop, attract or retain high-skilled workers. However, one of the main challenges in devising policies to either improve skill development or the distribution of skills within a nation, is the lack of agreement on what skills and knowledge are required now and in the future.

These disagreements have an evidence base since research has clearly established that ability is not only multidimensional in nature (e.g. see Altonji; 2010, Borghans et al., 2008) but that skills develop in a heterogeneous manner over the lifecycle (e.g. Hansen et al., 2003, Cunha and Heckman, 2008; Ding and Lehrer, 2014). Further, while a substantial body of research (e.g. Cawley et al., 2001; Green and Riddell, 2003; Herrnstein and Murray, 1994; 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.¹

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. Both Canada and the United States have highly educated and skilled work forces, with similar industrial and occupational structures and have witnessed a marked growth in wage inequality over the last two decades. While a voluminous literature has emerged to evaluate alternative explanations for the rise in inequality over the past decades, new research documents a recent reversal in the demand for highly skilled workers (Beaudry et al, 2014, 2016) and growing returns to non-cognitive skills in the US labour force (Deming, 2015). While Beaudry et al (2016) compare occupational employment and wage trends between Canada and the US, to shed light on the relative importance between technology and institutional forces in explaining changes in the returns to skills, we aim to go further and consider how skills jointly influence schooling decisions and early labour market outcomes.

We present the first empirical evidence of the role of different dimensions of skills on these choices using Canadian data and by comparing our results to those obtained with US data we strive to build on the suggestion of Card and Freeman (1993) that "small differences" in policies and institutions have led to differences in economic outcomes. Some of the largest differences between the two countries relate to who each country targets with their immigration policies and the markets for higher education. On the latter, Belley, Frenette and Lochner (2014) estimate a substantially smaller attendance gap by parental income in Canada relative to the US, even after controlling for family background, adolescent cognitive achievement, and local residence fixed effects. This result suggests that the income gradient to higher education is steeper in the United States and we aim to extend this work to determine if this can account for findings that Canada has greater economic mobility than the United States.

¹Beyond labour market outcomes, socio-emotional skills are found to be important determinants of outcomes such as educational attainment, drug use, alcohol use, crime and delinquency (Conard, 2006; Crede and Kuncel, 2008; Duckworth, 2010).

Specifically, to achieve this goal and understand if different roles are being played by non-cognitive traits and cognitive traits in the acquisition of human capital and in the labour market return to human capital between the two countries, we first present new evidence from Canada and then contrast our findings with the existing US literature. That is, we contribute to a growing literature which considers schooling and the labour market jointly along with multiple dimensions of skills using longitudinal data that tracks a cohort of Canadians from late adolescence in grade 10 until they are 25 years of age.² Our empirical analysis, follows earlier research using US data that builds on the economic framework developed in Willis and Rosen (1979) who model self-selection into college and potential earnings within a traditional Roy model.³ Rather than follow Willis and Rosen (1979) who subsequently use proxy variables to account for dimensions of unobserved ability we follow a growing literature that includes Heckman et al. (2006) and Urzua (2008), which treats skills as a vector of low dimensional factors. These papers use linear factor analysis methods to recover latent skills since it offers substantial advantages relative to using proxy variables. For example, we can more accurately capture multiple skill dimensions and also account for potential measurement errors in these latent skills while imposing weaker assumptions on the data.⁴ An additional key feature of our empirical approach is that it incorporates the dynamics in decision making that Altonji et al. (2013) argue is crucial to understand the role of higher education in the economy. After all, individual decisions to invest in higher education reflect in

²To the best of our knowledge, only Foley, Galipoli and Green (2014) have used the combination of factor analysis methods to capture cognitive and non-cognitive skills with the YITS-A data that we employ. Their study solely focuses on a single education outcome: high school drop-out for boys. However, we follow the guidance from their study and carefully account for parenting which was shown to play a large role in drop out decisions.

³In a Roy Model, individuals compare the potential outcomes across each feasible choice such as whether or not to attend university and choose the alternative that yields the highest payoff.

⁴Cunha et al (2010) introduce a nonparametric approach that relaxes the linearity assumptions made in Cunha and Heckman (2008) that is also utilized within this paper. While the computational challenges associated with the former approach are large with a two-dimensional factor structure, we only considered a linear framework since one of our motivations of this study is to compare the results with US evidence that each utilized such an approach.

part skills measured during high school and both skill and educational investments may influence labour market outcomes. By explicitly considering the dynamic pathways, we can separate out how different skills measured at earlier ages are at play for schooling and labour market outcomes. Last, we also contribute to this literature by examining how the estimated relationships differ between the genders and across family background lines.

Our analysis using Canadian data first finds that non-cognitive skills play a role in determining income at age 25 that is on par with that of cognitive skills. Second, we find that accounting for the dynamic in decision making is crucial to understand the channel through which cognitive skills affect adult incomes. The effect of cognitive skills arises by increasing the likelihood of obtaining further education, in this case a university degree. Conditioning on this educational choice, our analysis suggests that cognitive skills are not relevant to yearly earnings at age 25. On the other hand non-cognitive skills, also relevant to later income levels through the channel of educational choice, are rewarded in the labour market at age 25. Third, simulations using the estimated model shows that the cumulative effect of these two channels of influence are at least as great as that of cognitive skills. Simulated growth in social and emotional skills from the lowest to the highest decile results in an increase in tertiary completion by 20 percentage points and an increase in annual income by \$7,900 CAD. This result would suggest equal attention should be given to policies that cultivate different dimensions of non-cognitive skills as those focusing on cognitive

While, the first three findings are consistent with the body of evidence from a number of studies using US data including Heckman et al. (2016), we find very different patterns in the relationship between skills and labour market outcomes by gender and parental background in Canada relative to the US.⁵ Specifically, we observe that the probability of self-reported tertiary education completion at age 25 is

⁵As we discuss in section 5, the majority of work looking at skill development in the US has utilized data from the NLSY79. Given the substantial changes in institutions within the labor market, the well documented rising returns to skills and the claims of specific skill shortages by employers, evidence drawn from this period may better inform policy debates.

above 30% in every cognitive skill decile for girls. In addition, the gradient in college graduation across non-cognitive skill deciles is quite flat for Canadian women. These results contrast sharply with work by Prada and Urzua (2014) that used the NLSY79 and found in the bottom deciles of cognitive skills, college completion rates in the US are below 20%.⁶ A second surprising finding is that we observe that at every skill decile, children of less educated parents 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. Most surprising is that children of less educated parents but with very high skills are found to not earn significantly different amounts than children in the lowest skill decile from high educated parent households.⁷ This analysis suggests that after the 2009 recession, Canadian children whose parents did not study beyond high school will on average earn less than children from other households, irrespective of their skills. Thus, the labour market and career prospects they face differ sharply which may lead to a persistent widening of inequality and convergence of other social and economic trends between the two sides of the 49th parallel.

This paper is structured as follows. Section 2 describes the data we use in this study focusing on the measures that we can use to identify different dimensions of cognitive and non-cognitive skills. We sketch the economic framework that underlies the econometric analysis in section 3. We discuss the conditions needed to identify the structural parameters of the model. Our empirical results using Canadian data are presented and discussed in section 4. We also conduct a number of simulations to more clearly illustrate the role played by the two dimensions of skill on each outcome. In section 5, we summarize evidence from the labour economics that used a similar methodological approach with US data and contrast those results to our findings. Finally, we discuss both future research directions and the policy implications of our main results in the concluding section.

⁶In addition, evidence from US studies generally finds that the gradient in college completion is generally steeper in non-cognitive skills than with cognitive skills.

⁷As we discuss in Section 5, the available US evidence does not uncover these patterns, which may be a result of using data collected in the prior decade.

2 Data

To provide the first piece of Canadian evidence, 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. Each of these students completed the first OECD Performance for International Student Achievement (PISA) reading test as well as being asked to complete a separate YITS survey questionnaire.⁸ In the first cycle, students as well as both their school principal and either a parent or guardian who identified him or herself as "most knowledgeable" about the child completed a survey, provide additional and likely more accurate measures of home and school inputs.⁹ Follow-up surveys were conducted with only the students on a biennial basis until they reached 25 years of age.

An important feature of the YITS-A data is that it 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 the math or science test. In addition there are a battery of questions to measure multiple dimensions of non-cognitive skills. In this draft, 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. Given the data is collected from three sources, a rich set of controls including demographics, parental education and family income are available. In our analyses besides standard conditioning variables, we also use information on the expectation of one's

⁸Of these 29,330 participants completed the survey.

⁹Approximately, 13 percent of the parents did not complete the parental survey which was conducted over the phone.

peers at age 15, family structure, family income and wealth,¹⁰ immigration status, home educational resources and information on parental discipline as additional controls. The definitions of the variables we use in this study are provided in detail in Appendix Table 1.

Throughout our analysis we control for geographic differences since there is substantial regional heterogeneity in both labour 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. Following high schools student can attend a two year Collège d'enseignement général et professionnel or CEGEP as it is commonly known, which further prepares one for a university degree. Those attending university in Quebec normally can complete their studies in three years, compared to four years in the rest of Canada. Last, a number of students interested in a technical program generally attend one for three years at a CEGEP.

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 cognitive and non-cognitive skills, we restrict our sample to include those individuals who completed all three PISA tests and have a parental survey along with complete income and education data at age 25. 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 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 approximately 1600 individuals. Those who remain in the sample as a whole represent Canadians who possess both higher cognitive and non-cognitive test scores. Specifically, the average score is .1 to .4 standard deviations higher for this estimation sample relative to the full sample in the YITS-A. In other words, our analysis is undertaken on a group that is more skilled than the general

¹⁰Income 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.

population.

3 Model

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

Briefly, this model involves three steps that are important for the empirical strategy. First, we need to estimate the dimensions of ability when the child reaches age 15. We assume that each child is endowed with a two dimensional ability vector θ at conception. Ability may subsequently develop due to parental investments and other environmental interactions that may interact with the child's invariant genetic characteristics. We will use factor analysis methods to estimate a system of test score equations designed to identify and recover the distribution of latent abilities. With latent abilities we next consider estimating equations that integrate over these distributions to focus on how skills 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. These dynamics in decision making are important since we will assess the importance of latent skills in determining outcomes in early adulthood, while conditioning on university completion. We specifically explore the impact of cognitive and non-cognitive skill levels on employment, income, use of employment insurance in the past 12 months, and voluntary work (once a

month).¹¹ The structural parameters from these estimated equations are then used to simulate outcomes given different levels of the two skills. Our framework is similar to the setup that was used in studies using US data including Carneiro et al. (2003), Heckman et al. (2006) and Prada and Urzua (2014), so to later facilitate comparisons we follow their identification strategy. Below, we expand on elements of the model with a focus on how identification is obtained in each step and then outline the estimation strategy.

3.1 Latent Ability

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 is that many test scores and questionnaires in surveys designed to measure a concept 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 ability are imperfect and based on a noisy signal of an individual’s underlying abilities and thus are subject to error. A growing number of studies by economists have built on insights in Kotlarski (1967) to develop methods to identify the underlying distribution of latent abilities using at least three measures of noisy proxies.¹²

In the first step, we must assume the number of domains of latent ability we wish to identify and which elements of the YITS-A data provide a noisy signal of the skill in question. We consider cognitive skills that will be identified by the latent factor associated with three standardized tests (reading (T_0^c), science (T_2^c), and mathematics (T_1^c)) from the PISA test, as well as non-cognitive ability is governed by the latent factor associated with the scales associated with self-esteem (T_0^{se}), self-efficacy (T_2^{se}), and a

¹¹Results related to income appear in the main text and a discussion of the analyses that consider the other three outcomes is contained in the online appendix.

¹²See Carneiro et al. (2003) for further details but in accuracy to identify f factors we only need $2f + 1$ test scores. In our analysis, we will have one extra test score.

sense of mastery (T_1^{se}).¹³ This factor is loosely interpreted in the remainder of the text as confidence: confidence in oneself or one’s self-image, one’s ability to master material, and one’s ability to influence outcomes.

Equation (1) describes a measurement system which links the relationship between the test measures found in the data, T , the unobserved traits (or factors), θ^s , and the individual context, Q . We use the subscript i to refer to the test of interest and the superscript s to the related skill, c for cognitive and se for socio-emotional or non-cognitive. We are interested in identifying and estimating both the factor loadings and factors’ distributions from the following linear measurement system

$$T_0^c = \pi_0 + \phi_0^c Q^c + \psi_0^c \theta^c + u_0^c \quad (1)$$

$$T_1^c = \pi_1 + \phi_1^c Q^c + \psi_1^c \theta^c + u_1^c \quad (2)$$

$$T_2^c = \pi_2 + \phi_2^c Q^c + \psi_2^c \theta^c + u_2^c \quad (3)$$

$$T_0^{se} = \pi_0 + \phi_0^{se} Q^{se} + \psi_0^{se} \theta^{se} + u_0^{se} \quad (4)$$

$$T_1^{se} = \pi_1 + \phi_1^{se} Q^{se} + \psi_1^{se} \theta^{se} + u_1^{se} \quad (5)$$

$$T_2^{se} = \pi_2 + \phi_2^{se} Q^{se} + \psi_2^{se} \theta^{se} + u_2^{se} \quad (6)$$

where Q^c and Q^{se} include socio-economic status, family composition and background, and parental inputs specific to the skills in question.¹⁴ The key parameters of the equation are given by ϕ_i^s and ψ_i^s . The estimated parameters in vector ϕ_i^s identify the effect of family context, learning environment, and personal characteristics on the given test score. Likewise, the effects of the underlying trait are captured in the parameter ψ_i^s , which is subsequently referred to as the factor loadings. Finally, u_i^s is the vector

¹³Non-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 comparisons with prior U.S. studies that considered only a single non-cognitive domain.

¹⁴To facilitate comparisons with the US literature we follow Heckman et al (2006) and Urzua (2008), among others by assuming that cognitive and non-cognitive factors are independent.

of the error terms that is assumed independent of the observed characteristics, their associated factors as well as being mutually independent with an associated distribution $f_i^s(\cdot)$.¹⁵

In our analysis Q^c and Q^{se} differ only in that former contains home educational resources and the latter also contains parenting measures described in appendix table 1. For identification, we normalize one of the loadings for each factor and set $\psi_2^c = 1$ and $\psi_2^{se} = 1$. By making this normalization and using insights from Kotlarski (1967) we can also identify the distribution of θ for each skill; $F_\theta^c(\cdot)$ and $F_\theta^{se}(\cdot)$.¹⁶ Last, as a robustness exercise in the formulation of equation (1) we considered a variant that allowed the PISA standardized test scores to reflect both cognitive and non-cognitive skills but cognitive skills were excluded in the equations used to measure the scales and there were no major differences in the results but there were computational costs.¹⁷ Doing so also facilitates comparisons to Prada and Urzua (2014) and other studies using U.S. data who also excluded the non-cognitive skill from the equations linking cognitive test scores.

3.2 The Education Decision

We now model the impact of skills on an educational investment decision: whether to complete a university degree or not. This decision is based on expected returns given their levels of latent ability that has been accumulated by age 15 and their potential earnings for each education level. We assume that latent abilities are unobserved by the econometrician but the individual has full information about

¹⁵This independence implies that all the correlation in observed choices and measurements is captured by latent unobserved factors.

¹⁶Kotlarski (1967) shows these distributions are nonparametrically identified and the remaining loadings in equation (1) are interpreted relative to ψ_2^c and ψ_2^{se} . See Carneiro et al. (2003) for further details on identification.

¹⁷There are no natural units for these skills. We follow earlier literature that did not include non-cognitive ability as a determinant of any cognitive test score and vice versa. While these cross-constraints can be relaxed, Urzua (2008) clearly points out that there is a high cost in doing so since it would make the interpretation of the components of the factors to no longer be straightforward.

his/her abilities, as well as knowledge of their returns. We do not consider the exact timing of the decisions and assume that individuals make optimal educational 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 if $D = 1$ if this alternative yields the highest net benefits which is modeled as

$$D = 1[\gamma^D Z + \lambda_c \theta^c + \lambda_{se} \theta^{se} + v > 0] \quad (7)$$

where Z is a vector of personal, family and peer characteristic, θ^c and θ^{se} are the unobserved skills, and v is an idiosyncratic error term with a standard Normal distribution. The estimated parameters, λ_c , λ_{se} 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, one's parents may have emphasized the importance of further education or prepared financially to support a youth's university education. Parental variables that measure attitudes to their child's education may also be correlated with cognitive and non-cognitive skills, and thus to get unbiased estimates of the effects of these skills on educational investment decisions, they must be accounted for.¹⁸ Additionally, the influence of youth peer group is incorporated in the estimating equation via a measure of the youth's perception of the number of her friends that are planning to obtain high education. Since we do not use proxies for the skills in the spirit of Willis and Rosen (1979), we will integrate over the unobservable skill endowments for all the outcomes associated with the model when we conduct estimation as described in the next sub-section.

¹⁸Recall, due to missing data our final sample contains children with higher skills than the general population, reinforcing the need to control for parental variables.

3.3 The Labour Market at Age 25

We separately model a variety of early labour market outcomes. In each case, we consider a pair of outcome equations, each corresponding to a specific education choice. 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

$$Y_1 = \begin{cases} \gamma^{Y_1} X + \lambda_c^{Y_1} \theta^c + \lambda_{se}^{Y_1} \theta^{se} + v_1 & \text{if } D = 1 \\ 0 & \text{if } D = 0 \end{cases} \quad (8)$$

$$Y_0 = \begin{cases} 0 & \text{if } D = 1 \\ \gamma^{Y_0} X + \lambda_c^{Y_0} \theta^c + \lambda_{se}^{Y_0} \theta^{se} + v_0 & \text{if } D = 0 \end{cases} \quad (9)$$

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. While we only discuss the results related to income in this text, in the online appendix we separately consider employment, volunteering and the use of employment insurance at age 25 as outcomes. Note that adding equation (7) to equation (8) is similar to models that underlie a rich literature that explored whether there are sheepskin effects in education in the labour market.

3.4 Estimation

Equation sets (1) and (2) 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 unobserved skills all of the idiosyncratic errors are mutually independent to use maximum likelihood estimation. Since the true underlying distribution for the skills may take many forms, we are flexible and approximate

it using a mixture of normals.¹⁹ Define β to be the vector of all the parameters of the model and $W = \{Q, Z, X\}$. Specifically, the likelihood is

$$L(\beta|W) = \prod_{i=1}^n \iint f(D_i, Y_i, T_i|Q_i, Z_i, X_i, \theta^c \theta^{se}) dF_{\theta^c}^c(\cdot) dF_{\theta^{se}}^{se}(\cdot) \quad (10)$$

where we integrate over the distribution of two factors due to their unobserved nature. In practice, we use Gauss-Hermite quadrature for numerical integration.²⁰ In the next section, we discuss estimates of this model that consider the impact of unobserved abilities on educational choices and income at age 25 as the final outcome.²¹

4 Results

We begin by discussing the parameter estimates, factor loadings and factor distributions obtained from maximizing likelihood estimation of equation (10).²² Table 1 presents estimates of the full factor model

¹⁹To 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.

²⁰We should note that since all of the other labour market outcomes at age 25 that we considered are discrete indicators and as such an individual's contribution to the likelihood function is simply the product of normal CDF evaluations when we condition on the factors.

²¹To facilitate the discussion, we only present the set of results corresponding to this specific labour market outcome. Note, the parameter estimates are extremely similar to those using other outcomes such as volunteering and employment insurance take-up at age 25. Those results and associated discussion are presented in an online appendix and briefly the main findings are that: a) non-cognitive skills alone affect the use of employment insurance (EI); and b) higher cognitive skills are also associated with increased levels of volunteering. Specifically, the simulations demonstrate that for those with a university degree non-cognitive skill are correlated with a decrease in the use of EI while the opposite is true of those without a degree.

²²In the next subsection, we present a series of counterfactual policy evaluations that consider the full set of labour market outcomes at age 25 available in our data. To a large extent, the primary advantage of using these methods are to conduct these exercises. Wolpin (2013) argues these exercises are indeed one of the main motivations for estimating structural models.

described in equation (1) providing an examination of the importance of the given latent skills, θ^c and θ^{se} alongside other covariates of interest in the six tests measures. To ease interpretation, the scores for each of the tests has been standardized to have a mean of 0 and a standard deviation of 1. The estimates reveal striking regional differences in each cognitive measure. Ontario, the base group, has *ceteris parabus* lower cognitive test scores than in both the western provinces of Canada and Quebec. The Atlantic provinces are only significantly different from Ontario in the math score, which is significantly higher holding all else constant. Since public K-12 education and curriculum decisions are determined by provincial governments in Canada, it is possible that differences in the effectiveness of the school systems are responsible for these regional differences.

The results in table 1 also suggest that holding cognitive skill constant, immigrants only fair worse on the reading test. This is not surprising since language specific tasks should prove difficult for individuals working in a second language but should not necessarily be reflected in other subjects that rely less on language specific abilities. Last, there are interesting gender differences in the test score relationships. Perhaps it is not so surprising to observe girls scoring higher on the PISA reading test, whereas boys score higher in math. While we do not find a significant gender difference in science,²³ there are large gender differences for the non-cognitive scores. For each non-cognitive measure, females perform significantly worse than the males.²⁴

²³Using a novel assessment based on the PISA that was administered in different regions of urban China, Ding et al (2016) demonstrate that gender gaps in scientific performance depend heavily on which domains of scientific intelligence 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.

²⁴We 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 traits such as being a caring or a direct person in adolescence (Borghans et al. 2008b). Individuals partly select occupations that correspond to their orientations. Traits related to grit (persistence and motivation for longterm goals) seems to be essential for success no matter the occupation through their effect on

Our results also suggest that there are important roles played by family contexts and behaviours that enter into test performance. Family income rather than wealth plays a larger role on performance in reading but only a small role on the math test. The channel through which income operates is unclear. While wealth does not significantly influence cognitive test scores, it is found to have a small but significant effect on self-esteem. This may suggest that youth self-worth is tied to their family possessions. Parental education levels are highly correlated to the cognitive test scores measures, even when controlling for the cognitive skill. This suggests that parental education functions as more than a proxy for parental genetics.²⁵ Holding skill constant, youth from non-traditional families perform better on the reading and 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.²⁶ As a whole, these results suggest that the situation at home can be important to determining measures such as grades and thus educational pathways.

Table 2 presents the estimates of λ_v^c , λ_v^{se} and γ from equation (7), providing evidence on the importance of cognitive and non-cognitive skills on the decision to complete university. Notice that both skills enter the decision in a highly significant manner. To provide a more intuitive understanding of the role of each skill we present results from a simple simulation in Figure 3.²⁷ The two panels present the probability of completing a university degree for each decile of the cognitive and non-cognitive skill distribution respectively. Not surprisingly the probability of completing a degree increases dramatically with cognitive ability. The non-cognitive skill also improves the likelihood of university completion.

education achievements (Duckworth et al. 2007).

²⁵Other channels for transmission in student test scores are at play. For example parents with higher education may simply provide additional emphasis on the importance of performance in academics and their children in turn simply put in greater effort.

²⁶Note 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.

²⁷A full description of the simulation procedure appears subsequently in Section 4.1.

While the effects are not as dramatic, levels of non-cognitive skill clearly appear to be important in educational investment decisions. This suggests another dimension through which university education could be encouraged.²⁸

Several other results in table 2 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), family income and wealth are found to not significantly influence the completion of university in Canada. That said, and consistent with our speculative finding on how parental education affects test scores is suggestive of differential parental expectations, we find that a measure of whether parents have put money aside for post-secondary education plays a large role. This on the surface suggests that is more important that there are savings set aside for education than current levels of family income or wealth. These savings reflect a reduction of the opportunity cost of education but may also proxy somewhat for parental expectations of the child's education level. Parental standards and educations levels are also important in influencing the choice to complete university. Similarly, our results also suggests that peers play a significant role in determining educational attainment. Holding skill constant, individuals from the Atlantic provinces are much more likely to go to university. This may reflect the weaker labour market for individuals with less education in these regions.

In Table 3, the parameters λ_0^s , λ_1^s , β_0 , and β_1 from Equation 3 are reported for each of the four conditional labour market outcomes of interest. The headings of D=1 and D=0 refer to those who have completed and not completed a university degree respectively. We begin by discussing the role

²⁸A growing literature examines lack of information as a barrier to college attendance (e.g. Bettinger et al (2013), Hoxby and Turner (2013), among others). While the YITS did not collect data to measure student knowledge of the costs and benefits of higher education and our model does assume perfect information, we simply wish to point out that policies which focus on non-cognitive skill development may boost education decisions and as we will shortly demonstrate in the main text, we present evidence of significant returns in the labour market to these skills among those who choose not to attend.

of the two types of skills on age 25 income and employment status for those who complete university. Notice, cognitive skills do not provide any additional rewards for having a higher income at age 25. Similarly, among those completing university, there is also no effect of the cognitive skills on the rate of employment. These results together suggest that cognitive skill levels of individuals with university degrees are not easily distinguishable by employers and thus not rewarded by age 25.

Whether this result reflects slow employer learning (Lange, 2007) or that education in Canada provides a meaningful signal (Bedard, 2000) remains a topic for further study. After all, it is surprising given that the simulation results in Figure 1c suggest there is high variability in the levels of cognitive skills amongst those with university degrees. In contrast, we observe in Table 3 that cognitive skills do indeed 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 operate mainly through the educational channel. It is likely that employers have a difficult time quickly distinguishing true levels of cognitive skills and are forced to make judgements based on the educational signal provided by the employee.

An alternative interpretation for the limited effect of cognitive skills on early labour market earnings in Canada is that they may also reflect the early age at which these outcomes are examined. It could be the case that at age 25 an employee might be relatively new to firms and have had little opportunity for advancement or adjustment in pay based on their level of cognitive skill; however, the estimates of experience for university graduates is relatively large and significant. This suggests fulfilling the cognitive requirements of a given job may be less important than obtaining workplace skills or firm specific training.

Last we see evidence of our non-cognitive skill being rewarded with higher incomes for university graduates. This is not the case for those without a university degree, though the estimate is of a similar magnitude.²⁹ If the non-cognitive skills, confidence in one's self and one's abilities, manifest

²⁹Interestingly, and as shown in the online appendix, we find that non-cognitive skills do not significantly affect the

themselves in the work place, perhaps as leadership skills or through the ability to have the confidence to be self-directed, we would not be surprised that employers might reward individuals for these skills. These types of skills are unlike cognitive skills in that there is no universal signalling tool such as an educational degree. One might expect these skills to also affect employment opportunities. Notionally, confidence is an important part of a successful interview. Employers, however, might be more keen to employ individuals with particular hard skills or qualifications, such as a university degree, and reward hard to verify non-cognitive skills once discovered in the workplace.

4.1 Simulation: Cumulative Effects of Cognitive and Non-Cognitive Skills

Simulation methods might be the best way to understand the size and significance of the estimated parameters discussed above. To conduct simulations, we first draw random observations from the population and pair them with draws from the two distributions of the latent skills, and the parametrized error terms. The effects of both skills on the outcomes of interest can then be traced across individual contexts and through university completion decisions. The results from these simulations for the decision to complete a university degree is presented in the four panels of Figure 1.

Notice across these panels that conditional on non-cognitive skills, there is a steep gradient for cognitive skills on earnings. In contrast, individuals with either very high cognitive skills or very low cognitive skills face a flat gradient in income for non-cognitive skills. For example, an individual in the top decile of cognitive skills will on average earn \$34,000 if she also has non-cognitive skills in the lowest decile. Her earnings would increase to approximately \$36,000 if she also had non-cognitive skills in the highest decile. In contrast, for an individual in the highest decile of non-cognitive skills would witness their earnings on average increase from approximately \$27,000 to \$36,000 if her cognitive skills moved from the lowest to the highest decile.³⁰

odds that one is employed at age 25.

³⁰We should note that the returns to skills differ across type of work and different reward of set of skills across

The three panels of Figure 2 provide the simulation results corresponding to two income at age 25.³¹ Due to their multidimensional nature, cognitive and non-cognitive skills are rewarded in the labour market according to their combinations (e.g. Carneiro et al. (2007), Prada and Urzúa (2014)). In the first two panels, we present the average simulated outcome and estimated confidence intervals graphed across deciles of both the cognitive skill and non-cognitive skill distributions. The final panel presents a three dimensional graph that explores how the average simulated outcome varies across the two skill distributions when evaluated jointly. This graph provides evidence that the cumulative effect of non-cognitive skills appears to be larger than that of cognitive skills. The average simulated outcome for those in the first decile of the cognitive skill distribution was approximately \$25,000, whereas the tenth decile had a average simulated outcome of \$32,000. In comparison, the simulated incomes across deciles of the non-cognitive skill distribution covered a larger range from \$27,000 to \$34,000. Although, there is overlap in the confidence intervals across deciles, this result is somewhat surprising given that the parameter estimates discussed earlier in isolation would likely lead one to conclude that cognitive skills were much more important than non-cognitive ones in both the decision to invest in education and age 25 annual income conditional on this educational choice. Nonetheless, the panels of Figure 2 highlight the important role of non-cognitive skills in influencing early adult earnings.

The results in Figure 2 additionally suggest that the cumulative effect through education and later demand of these skills is on par with the rewards to cognitive skills. Further individuals with cognitive skills in the higher deciles observe tiny returns to additional non-cognitive skills. The converse pattern 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.

³¹For completeness, we conduct the same analysis corresponding to other outcomes measured age 25. In Appendix Figures 1 and 2 we observe that both being employed and use of employment insurance do not appear to be affected by either skills. In appendix figure 3, 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.

holds as we move across cognitive skill deciles for those with high non-cognitive skills. This suggests that the degree of substitution between skills varies across the distribution, but the labour market returns for those with high cognitive skills does not vary sharply across non-cognitive skills. Looking at figures 1 and 2 in conjunction allow us to conclude that individuals in the top 10% of non-cognitive skills have higher annual income than those in the corresponding decile of cognitive skills. Thus, among those not completing college, non-cognitive skills are indeed associated with higher expected earnings.

4.1.1 Subgroup Analysis

We next elected to explore the heterogeneity of the effects of skills by undertaking the entire analyses on subgroups defined on the basis of gender and parental background. Although evidence with data from the United Kingdom presented in Carneiro et al. (2007) suggests the impact of this measure of non-cognitive skill does not differ in any systematic way across particular subgroups of interest; we motivate this analysis as follows. First, there is little understanding of the economic mechanisms behind the role of skills and since we observe gender sorting by type of occupation, abilities may be rewarded differently in a manner consistent with occupational choices. Second, for policy audiences there is a need to not just determine if there are potential deficits in skills for those who are disadvantaged groups, but to understand what are the potential benefits of any intervention that could foster cognitive or non-cognitive skills.

We conduct the earlier analyses and for space considerations only report results from the simulation exercises for two selected subgroups – namely boys vs. girls, children from families with low parental education vs. children from families with high parental education. We ensure that within subgroup, the deciles of skills are placed on a comparable scale. Several interesting findings first appear when we explore the results comparing young men to young women in Figures 3 and 4. Notice that the gradient for college completion is much steeper for men than women. College completion rates for men in the top three cognitive skill deciles are above 80%, whereas there is no skill decile for women where the

completion rates exceed 75%. Conversely, in the lowest deciles of the cognitive skill distribution, college completion rates for women always exceed 25%, whereas they are very low for young men with low cognitive skills.³² Further, the gradient of non-cognitive skills on university completion is also much flatter for young women than young men. There is no evidence of there being significant heterogeneity in the completion rates across these non-cognitive skill deciles for women and in each decile, rates of college graduation exceed 50%. In contrast, in the bottom half of the non-cognitive skill distribution for males, college completion rates fall far below and in some deciles at half the rate.

Figures 5 and 6 present a surprising finding that only among men who graduate from university is there a gradient in cognitive skills on age 25 earnings. Young women on average earn similar amounts at each decile of the cognitive skill distribution. However, there exists significant variation in women's earnings across deciles of the non-cognitive skill distribution. Moving from the lowest to the highest decile of non-cognitive skills is associated with an on-average 50% increase in income. In contrast, the gains in earnings for males are much smaller as one moves to higher deciles of the non-cognitive skill distribution.

Dividing the sample along parental education lines present one hopeful and one possibly upsetting findings. Comparing the cognitive skill panels between Figures 7 and 8, we observe similar rates of college completion across these different families. Only among the higher deciles of non-cognitive skills, do we observe a slightly higher rate of college completion for children whose parents are more educated.

Figures 9 and 10 illustrate a disturbing finding that compares children from families who differ by parental education. For children whose parents are less educated, they will earn less at age 25 at every decile of the cognitive skill distribution as compared to a child at any decile from a family whose parents had more education. On non cognitive skills, the graph for children less educated households

³²The opportunity cost in the decision to attend college may also explain the gap in enrollment between women and men. During this period, there was a boom in oil prices leading to local labor demand shocks in Alberta and Saskatchewan that may explain the lower rate by males.

does not always lie below that for children whose parents had higher education at every decile, but the gaps at nearly every decile are of the order of \$10,000. These results demonstrate that among children in the YITS, completing a university degree does not appear to significantly improve their odds of intergenerational mobility. We next discuss how these results contrast with US evidence

5 Does U.S. Evidence Correspond to the Canadian Experience?

Results from empirical studies are not only conditional to their methodology but also of their context. The majority of research using US data that investigates how either or both cognitive skills and dimensions of non-cognitive skills involve using proxy measures. The exceptions which utilize an identical economic framework to that described in Section 2 is Prada and Urzua (2014) and there are variants of this framework were employed in Heckman et al (2006, 2016) and Urzua (2008) who each explore labour market outcomes at the age of 30. Each of these studies use data from the NLSY-79 whose collection permits a longer follow-up, and clearly the context including the time period of data collection and make-up of the population covered by the datasets differs.³³ Most importantly, the metrics used in the factor model to capture the two latent cognitive skills differ.³⁴ Despite these caveats certain commonal-

³³The literature is marked by methodological shortcomings and data limitation. In this regard, transposing the existing evidence to Canada should be taken with caution. The vast majority of evidence comes from the United States and Western Europe, and relate mostly to relatively well educated people at primary age in the 1980s and 1990s. As well, due to the different questions included in the datasets certain control variables such as number of siblings and immigrant status are used in our analysis; whereas measures are to the best of our knowledge not available in the NLSY-79 in which researchers have controlled for disability status and religion.

³⁴For 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.

ities exist in the findings. First, accounting for the dynamics in decision making is important. Second, both types of skills are found to influence education and early labour market outcomes.

Small differences in higher education markets, parental expectations and either the thickness of the labour market or desire to migrate for work may explain differences we observe between our findings and those using US data. In Figure 1, we observed that the probability of self-reported college completion by cognitive skill deciles is steeper in the cognitive domain than the non-cognitive domain. The converse has been reported with data from the United States where non-cognitive skills play a large role particularly at the highest deciles of non-cognitive skills. These differences may reflect the differences in costs and selection mechanisms between the two countries. In the United States, perhaps in response to pressure related to costs, emotional skills may play a particularly important role in allowing them to persist through education.

Finnie et al. (2016) link student level administrative records from 12 Canadian postsecondary institutions information to subsequent income tax data to provide descriptive evidence on graduates' labour market outcomes. Consistent with studies using US data, the patterns of first year earnings levels, subsequent earnings growth, and final earnings levels vary substantially across both college majors and local labour market conditions. However, for all fields the gaps in earnings across institutions are much smaller in Canada than what is reported with data from the United States (see e.g. College Scorecard). In Canada gaps across universities are suggested to correspond to differences in local or sectoral economic conditions. Also similar to the US studies, Finnie et al (2016) show that the wage gap between male and female workers widens each year after graduation but at a larger rate in Canada than the United States.

Our findings of the high university completion rate for women with low cognitive skills may provide an explanation for this widening gap in Canada. This may call into question whether policies that promote high levels of university completion will reduce income inequality observed in recent decades. More research is needed to understand what skills are needed and at which education level could they be

most effectively produced to reduce inequality. In other words, policies that promote degree completion but not skill development may have unintended consequences such as widening the gender wage gap and more attention could focus on developing educational opportunities that promote the development of non-cognitive skills. In simpler terms, pathways to successful careers likely differ based on one's skill set.

Indeed research using US data suggests that the impact of raising student's social and emotional skills is much stronger than that of raising cognitive skills (e.g. Heckman et al. 2006, 2016);³⁵ whereas the Canadian evidence is suggestive of more of an equal role.³⁶ For example, Figure 3 demonstrates that raising one's cognitive skills outweighs raising their non-cognitive skills in Canada. Specifically, a secondary school student who moves from the lowest to the highest cognitive skill decile increases her likelihood of graduating college by 50%, which is double the magnitude if she made an identical shift across deciles of non-cognitive skills.

When comparing patterns across countries, we suggest that the high rates of college completion for those with very low cognitive skills in Canada and low rates for those with very high cognitive skills in the United States are of equal concern. On the latter, this may reflect the poor matches and indeed an emerging literature in behavioral economics is generating new insights as to why many children and their parents do not attend college in the United States.³⁷ The low university completion rates of those with high cognitive skills may explain why the effects of cognitive skills on income and unemployment are so much stronger in the United States than Canada. It is striking that Heckman et al. (2006) find that fewer than half of the Americans in the highest cognitive skill decile complete college. Our results indicate that there are much higher rates of completion of tertiary education at every decile of the

³⁵Prada and Urzua (2014) also find that the wage gains associated with four year college completion has a steeper gradient for non-cognitive than cognitive skills.

³⁶This may reflect the recent reversal in the demand for skills (Beaudry et al, 2014, 2016) since the Canadian analyses was conducted with more recent cohorts.

³⁷See Lavecchia et al. (2016) for a survey of this literature

cognitive skill distribution in Canada relative to the United States.³⁸ This may reflect the differences in the costs of college attendance.³⁹ The quality of colleges and universities in the United States exhibits substantially more variation than Canada. Given the selection mechanisms by elite institutions in which employers make hiring and initial salary decisions based on an individual's academic background, which can be driven by cognitive ability.

Figure 6 of Heckman et al. (2006) provides US evidence of how wages varies across skill deciles by gender. Unlike Canada where there are clear differential returns, the slope of wages appears identical across deciles of cognitive skills and non-cognitive skill for men and women. Similar to our findings, the average wage for males exceed that of females at every decile, but at the top three skill deciles women earn more than men with very low cognitive skills. This may not have been found with Canadian data since complementary work by Morrisette et al. (2015) show that the post-2000 boom in oil prices led to a decline in university enrolment for Canadian men. The wage penalty for dropping out of high school essentially evaporated for young men in the western provinces during the most recent oil boom. To the best of our knowledge, there are no similar industry wide events that can explain major shifts in education and labour market decisions in the US. That said, the YITS-A was collected during a period that Beaudry et al. (2016) suggest there being a reversal in the returns to skills. Unlike natural resource prices, US evidence points to the role of routine-based technological change. Hershbein and Kahn (2016) present compelling evidence using US data that the recent economic downturn led to changes in skill

³⁸It is unlikely that the cohort differences account for these results. Implicitly, in making these comparisons we are suggesting skill deciles are similar between the two countries, an assumption that can not be tested with available data.

³⁹Belley et al. (2014) estimate comparable specifications with Canadian and US data in which they control for observable characteristics such as parental education and cognitive test scores, and find that Canadian children from families with annual income under \$20,000 are about 5 percentage points less likely to attend a four-year university program than children from a family with annual income over \$100,000. Interestingly, this is only about a third of the corresponding difference in the US data. Belley et al. (2014) conclude that credit constraints are not the main driver of family income differentials in university participation in Canada. In reaching this conclusion they also stress that Canada's grant and loan systems are less generous than those in the United States for students from low-income backgrounds.

requirements within occupations and firms, that has persisted now that the economy has rebounded.⁴⁰

The flat returns to cognitive skills on income for female university graduates in Canada is evidence that appears consistent with this educational level simply being a proxy for this dimension of skills. Employers appear to be more quickly able to identify dimensions of non-cognitive skill. We should note that college completion simply being a proxy for skills is a finding reported in with US data.⁴¹ However, our patterns of returns to skills by gender differ from Heckman et al. (2006) who report that i) for males in the 4-year-college market, non-cognitive skills have little marginal value, while cognitive skills have a strong gradient; and ii) for females in the 4-year-college market, both skills command high marginal prices.⁴²

We observe substantial overlap in the distribution of cognitive and non-cognitive skills between genders and across the subsamples by parental education. This degree of overlap differs from Urzua (2008) who finds large differences in the cognitive skill distributions between races in the US;⁴³ although he reports overlap on the distribution of non-cognitive skills between the races. Similar to Urzua (2008) we are able to conclude that gaps in family background are more important than any skill gaps in determining schooling and wage gaps between groups within a nation.⁴⁴

In the labour economics literature, the rising skill premium is considered one of the leading cause

⁴⁰The authors conduct additional analyses that cast doubt that their main findings are driven by a host of cyclical explanations including firms' opportunistically seeking to hire more skilled workers in a slack labour market.

⁴¹See for example the discussion of both Figure 11 of Prada and Urzua (2014) and in Heckman et al (2006).

⁴²A simple explanation for the flat gradient for Canadian women that would be consistent with Bowlus and Robinson (2012) is that since there is a sizable increase in the proportion of the population with a university degree implies that the average ability level of university graduates has also changed over time. As such, these skills may not have the same value to employers.

⁴³Urzua (2008) conducts simulations and finds that the racial wage gap would fall by 40% if blacks drew cognitive ability from the distribution for whites.

⁴⁴We should reinforce that we do not see as wide differences in abilities between the groups we examined with Canadian data than studies using US data. This may reflect a sample with complete data or having less variation in school quality at all levels in Canada than the US and having a smaller gradient in access to education in Canada than the US.

of growing inequality in the United States, particularly for males.⁴⁵ However, research documents that the returns to different dimensions of skills are lower in Canada than the United States.⁴⁶ For example, Hanushek et al. (2015) evaluated data from the OECD Programme for the International Assessment of Adult Competencies finding that the returns to a comparable workplace skill is roughly 30% lower on average in Canada than the United States.

Our results in Figure 9 and 10 also question whether commonly stated findings that Canada is much more mobile than the US (i.e. Corak, 2010) will continue to be found in the coming decades. US intergenerational mobility and has been shown in Chetty et al. (2014) to exhibit substantial geographic heterogeneity. Canadian evidence in Murphy and Veall (2015) suggests there is less heterogeneity in Canada. However the patterns identified in Figures 9 and 10 suggest that education may no longer be the pathway to an improved future for young Canadians. We should reinforce that our sample of Canadians has on average, higher levels of both types of skills than the general population so it could potentially be the case that this striking result may not generalize. Further work is needed to understand to what extent are trends in the labour market and the role of family background in Canada on the intergenerational transmission of economic inequality may be converging to the United States.

On a more positive note, another common speculative finding between the countries is that family attitudes toward education influence many educational outcomes. Canadian evidence is provided in Corak et al. (2011), Finnie (2012), Foley et al. (2014), among others; whereas Belley et al. (2014) suggest the link between family income and postsecondary attendance in the United States might be

⁴⁵Firpo et al. (2011) report that the rising returns to education can explain over 95% of the rise of the US male 90/10 earnings ratio between 1984 and 2004.

⁴⁶The lower returns to skills in Canada and less steep gradient for women may also be a response to the increasing number of graduates. The Organization for Economic Co-operation and Development recent “Education at a Glance 2013” report that women in Canada had significantly higher tertiary attainment rates compared to men (56 per cent versus 46 per cent), with a 16 percentage-point gap between the genders among younger adults. The report also notes that Canada has the highest rate of tertiary education completion among all OECD countries.

due to the relationship between family income and parental attitudes to education. Throughout our analysis we did control for these expectations within the household since they significantly influence college-going and college completion. However, there is increasing sociological evidence of inequality in US home environments and the role that this plays in economic inequality. Differences in family attitudes may play large roles in child decisions and also contribute beyond institutional differences in explaining the differences in how skills influence both human capital acquisition and early labour market return to human capital between Canada and the United States. Thus, while small differences in higher education markets are organized across countries may explain why intergenerational mobility was historically higher in Canada,⁴⁷ differences in the operation of labour markets are becoming smaller and many trends related to income inequality in Canada appear to increasingly mirror the U.S. experience.

6 Conclusion

Using the Youth in Transition Survey (YITS-A) we estimate a Roy model with a two dimensional latent factor structure to consider how both cognitive and non-cognitive skills influence endogenous schooling decisions and subsequent labour market outcomes in Canada. Our estimates indicate that non-cognitive skills play a role in determining income at age 25 that is on par with that of cognitive skills. Our analysis demonstrates that it is crucial to account for the dynamics in decision making since this demonstrates that the effect of cognitive skills on adult incomes arises by one increasing the likelihood of obtaining further education. Conditioning on the choice to complete a university degree, cognitive skills are found to play no additional role in determining earnings at age 25. In contrast, non-cognitive skills not only indirectly influence adult income through the channel of educational choice, but they are directly rewarded in the labour market. Last, evidence from policy simulations suggest that equal attention should be given to policies that cultivate different dimensions of non-cognitive skills as those that focus

⁴⁷See Corak et al. (2014) for new evidence and discussion related to intergenerational mobility in Canada and the U. S.

solely on cognitive skills.

The Canadian results mirror other recent findings using US data that economic inequality in labour market outcomes between children of different family backgrounds will continue to grow. The gradient in college completion in Canada among females is much less steep compared to the US, and it is puzzling why the rates of college completion among Americans with the highest skills are low. The structure of the higher education markets likely play a large role in ensuring access but there are likely large gaps in information that persist in both countries among students that could ensure they make improved schooling decisions. With globalization, technological advances and volatile prices for natural resources continuously changing the industry and occupational mixes in the two countries, it is likely that measures of skill malleability would be increasingly rewarded in the two countries. This conjecture is strengthened by recent findings of both growing routine-based technological change in the US labour market and a reversal in the returns to skills in both countries, that taken with our other findings suggest a different angle for education and training policies. Rather than continued focus on policies targeting graduates, gains may be achieved by developing the potential for continuous multidimensional skill development.

Future work using Canadian data can follow Heckman et al. (2016) by considering richer models of individual decision making and potentially examining how the type of higher education people acquire influences career paths. However, the major challenge in both countries relates to data availability and the limited number of longitudinal data collections currently underway for individuals transiting from adolescence to early adolescence at this stage of life is worth stressing. While there are clear benefits to working with rich administrative databases, these sources generally lack measures of different dimensions of skills.

In conclusion, while small differences in higher education markets between Canada and the United States may explain gradients in skills on college completion and small differences in the structure of both the labour markets between the countries can account for the higher labour market returns to skills in the United States; differences in family attitudes towards education also appear to play a role.

Given that the role of family background on life's chance is appearing to converge between the countries, developing policies that are tailored to individual skill sets may hold greater potential than one size fits all education policies to reduce economic inequality in both nations in the future.

References

- [1] Almlund, Mathilde, Angela Lee Duckworth, James J. Heckman, Tim D. Kautz. 2011. “Personality Psychology and Economics.” *NBER Working Paper no. 16822*.
- [2] Altonji, Joseph G. 2010. “Multiple Skills, Multiple Types of Education, and the Labor Market: A Research Agenda.” *note AEA: Ten Years and Beyond: Economists Answer NSF’s Call for Long-Term Research Agendas*.
- [3] Altonji, Joseph G., Erica Blom and Costas Meghir. 2012. “Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers,” *Annual Review of Economics*, 4(1): 185-223.
- [4] 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.
- [5] Beaudry, Paul, Green, David A. and Sand, Ben M. 2014. “The declining fortunes of the young since 2000”, *The American Economic Review*, 104(5): 381–386.
- [6] Bedard, Kelly. 2001. “Human Capital Versus Signaling Models: University Access and High School Drop-outs.” *Journal of Political Economy*, 109(4): 749-775.
- [7] Beaudry, Paul, Green, David A. and Sand, Ben M. 2016. “The great reversal in the demand for skill and cognitive tasks.” *Journal of Labor Economics*, 34(1): 199–247.
- [8] Belley, Philippe, Marc Frenette, and Lance Lochner. 2014. “Post-secondary attendance by parental income in the U.S. and Canada: Do financial aid policies explain the differences?” *Canadian Journal of Economics*, 47(2): 664-696.
- [9] Bettinger, Eric P., Bridget T. Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. “The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment.” *The Quarterly Journal of Economics*, 127(3): 1205-1242.
- [10] Borghans, Lex, Angela Lee Duckworth, James J. Heckman, and Bas ter Weel. 2008. “The Economics and Psychology of Personality Traits.” *Journal of Human Resources*, 43(4): 972–1059.
- [11] Bowles, Samuel, Herbert Gintis, and Melissa Osborne. 2001. “The Determinants of Earnings: A Behavioral Approach.” *Journal of Economic Literature*, 39(4): 1137–1176.
- [12] Bowlus, Audra, and Chris Robinson. 2012. “Human Capital Prices, Productivity and Growth.” *American Economic Review*, 102(7): 3483-3515.

- [13] Card, David, and Richard B. Freeman. 1993. Introduction to "Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States" chapter 1 in *Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States*, David Card and Richard B. Freeman (eds.), University of Chicago Press, 1 – 20.
- [14] Carneiro, Pedro, Claire Crawford and Alissa Goodman. 2007. "The impact of early cognitive and non-cognitive skills on later outcomes." *CEE Discussion Paper 92*.
- [15] 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.
- [16] Cawley, John, James J. Heckman, and Edward Vytlacil. 2001. "Three observations on wages and measured cognitive ability." *Labour Economics*, 8(4): 419-442.
- [17] 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.
- [18] Conard, Maureen A. 2006. "Aptitude is not enough: How personality and behavior predict academic performance." *Journal of Research in Personality*, 40(3): 339-346.
- [19] 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.
- [20] Corak, Miles, Lori Curtis, and Shelley Phipps. 2011. "Economic Mobility, Family Background, and the Well-Being of Children in the United States and Canada." in *Persistence, Privilege and Parenting: The Comparative Study of Intergenerational Mobility*, Tim M. Smeeding, Robert Erikson, and Markus Jantti (eds). New York: Russell Sage Foundation, 2011.
- [21] Corak, Miles (2010). "Chasing the Same Dream, Climbing Different Ladders: Economic Mobility in the United States and Canada." Washington DC: Economic Mobility Project, Pew Charitable Trusts.
- [22] Crede, Marcus, and Nathan R. Kuncel. 2008. "Study Habits, Skills, and Attitudes: The Third Pillar Supporting Collegiate Academic Performance." *Perspectives on Psychological Science*, 3(6): 425-453.
- [23] 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.

- [24] Cunha, Flavio, James J. Heckman and Susanne M. Schennach. 2010. "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, 78(3): 883-931.
- [25] Deming, David J. 2015. "The growing importance of social skills in the labor market." *National Bureau of Economic Research Working Paper 21473*.
- [26] Ding, Weili, Yipeng Tang and Yongmei Hu. 2016. "Closing the Gender Gap in Science: New Evidence from urban China." *mimeo*, Queen's University.
- [27] Ding, Weili, and Steven F. Lehrer. 2014. "Understanding the role of time-varying unobserved ability heterogeneity in education production." *Economics of Education Review*, 40: 55-75.
- [28] 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.
- [29] Duckworth, Angela L. 2011. "The significance of self-control." *Proceedings of the National Academy of Sciences*, 108(7): 2639-2640.
- [30] Ferguson, T. S. (1983). Bayesian density estimation by mixtures of normal distributions. In H. Chernoff, M. Rizvi, J. Rustagi, and D. Siegmund (Eds.), *Recent Advances in Statistics: Papers in Honor of Herman Chernoff on his Sixtieth Birthday*, pp. 287-302. New York: Academic Press.
- [31] Finnie, Ross E., Kaveh. Afshar, Eda Bozkurt, Masashi Miyairi and Dejan Pavlic. 2016. "Barista or Better? New Evidence on the Earnings of PostSecondary Education Graduates: A Tax Linkage Approach." *mimeo*, The Education Policy Research Initiative, University of Ottawa.
- [32] Finnie, Ross E. 2012. "Access to Post-Secondary Education: The Importance of Culture." *EPRI Working Paper 2012-02*. The Education Policy Research Initiative, University of Ottawa.
- [33] Firpo, Sergio, Nicole Fortin, and Thomas Lemieux. 2011. "Decomposition methods in economics." in *Handbook of Labor Economics* volume 4, David Card and Orley Ashenfelter (Eds.), Amsterdam: Elsevier-North Holland, pp. 1-102.
- [34] 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.
- [35] 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.

- [36] 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.
- [37] Hanushek, E. A., G. Schwerdt, S. Wiederhold and L. Woessmann. 2015. “Returns to Skills around the World: Evidence from PIAAC.” *European Economic Review*, 73(1): 103–130.
- [38] Hartigan, John A., and Alexandra K. Wigdor. 1989. “Fairness in Employment testing.” *Science*, 245(4913): 1-14.
- [39] 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.
- [40] Heckman, James J., John E. Humphries and Gregory Veramendi. 2016. “Returns to Education: The Causal Effects of Education on Earnings, Health and Smoking.” forthcoming in the *Journal of Political Economy*.
- [41] Heckman, James J., Jora Stixrud, Sergio Urzua. 2006. “The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior.” *Journal of Labor Economics*, 24(3): 411-482.
- [42] 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.
- [43] Hershbein, Brad J. and Lisa B. Kahn. 2016. “Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings.” W.E. Upjohn Institute working paper ; 16-254
- [44] Herrnstein, Richard J., and Charles Murray. 1994. “*The Bell Curve Intelligence and Class Structure in American Life*.” New York: Free Press.
- [45] Hoxby, Caroline M., and Sarah Turner. (2013). “Expanding college opportunities for high-achieving, low income students.” *Stanford Institute for Economic Policy Research discussion paper no. 12-014*.
- [46] Kotlarski, Ignacy I. 1967. “On characterizing the gamma and the normal distribution.” *Pacific Journal of Mathematics*, 20(1): 69-76.
- [47] Lange, Fabian. 2007. “The Speed of Employer Learning,” *Journal of Labor Economics*, 25(1): 1-35.
- [48] Lavecchia, Adam M. Heidi Liu and Philip Oreopoulos. 2016. “Behavioral Economics of Education: Progress and Possibilities.” in *Handbook of Labor Economics volume 4*, Eric A. Hanushek, Stephen machin and Ludger Woessman (Eds.), Amsterdam: Elsevier-North Holland, pp. 1–74.

- [49] Levine, Ross and Yona Rubinstein. 2013. “Smart and Illicit: Who Becomes an Entrepreneur and Does it Pay?” *NBER working paper w19726*.
- [50] Morissette, René, Ping Ching Winnie 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.
- [51] 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.
- [52] Murphy, Brian and Michael R. Veall, “A Tale of Two Cities? The Surge of Top Incomes at the City Level in Canada” in Keith G. Banting, Richard Chaykowski and Steven F. Lehrer (eds.), *Thinking Outside the Box: Essays in Honour of Tom Courchene*, McGill-Queen’s University Press.
- [53] Pintrich, Paul R., and Elisabeth V. De Groot. 1990. “Motivational and Self-Regulated Learning Components of Classroom Academic Performance,” *Journal of Educational Psychology*, 1990, 82(1), 33–40.
- [54] Prada, Maria, and Sergio Urzua. 2014. “One Size Does Not Fit All: Multiple Dimensions of Ability, College Attendance and Wages.” *NBER Working Paper No. 20752*.
- [55] Rosenberg, Manny. 1965. *Society and the Adolescent Self-Image*, Princeton, New Jersey: Princeton University Press.
- [56] Roy, A. D. 1951. “Some Thoughts on the Distribution of Earnings.” *Oxford Economic Papers*, 3(2): 135-146.
- [57] Urzua, Sergio. 2008. “Racial Labor Market Gaps the Role of Abilities and Schooling Choices.” *Journal of Human Resources*, 43(4): 919-971.
- [58] Willis, Robert J. and Sherwin Rosen. 1979. “Education and self-selection.” *Journal of Political Economy*, 87(5): s7-s36.
- [59] Wolpin, Kenneth I. (2013). *The Limits of Inference without Theory*. Cambridge, Massachusetts: MIT Press.

Table 1: Test Score Equations

Test Score Equations	T_0^c	T_1^c	T_2^c	T_0^{sc}	T_1^{sc}	T_2^{sc}
	PISA Reading	PISA Math	PISA Science	Self-Efficacy	Sense of Mastery	Self Esteem
Cognitive Factor	1.294 (0.000)***	0.9298443 (0.000)***	1.000			
Non-Cognitive Factor				0.579 (0.000)***	1.199 (0.000)***	1.00
Female	0.341 (0.000)***	-0.0928598 (0.026)**	-0.067 (0.106)	-0.240 (0.000)***	-0.059 (0.165)	-0.173 (0.000)***
Family Income	0.002 (0.000)***	0.0009134 (0.098)*	0.001 (0.109)	0.000 (0.534)	-0.001 (0.17)	-0.001 (0.153)
Wealth	-0.002 (0.96)	0.0269504 (0.366)	-0.028 (0.361)	0.012 (0.722)	0.033 (0.267)	0.057 (0.094)*
Years of Education Parents (Max)	0.104 (0.000)***	0.0721742 (0.000)***	0.084 (0.000)***	0.051 (0.000)***	0.010 (0.317)	0.011 (0.298)
Region: Atlantic	0.009 (0.917)	0.156819 (0.031)**	-0.060 (0.416)	-0.123 (0.133)	-0.094 (0.203)	-0.193 (0.02)**
Region: West	0.319 (0.000)***	0.391705 (0.000)***	0.282 (0.000)***	0.004 (0.957)	-0.031 (0.657)	-0.023 (0.769)
Region: Quebec	0.212 (0.016)**	0.4469722 (0.000)***	0.208 (0.01)**	-0.077 (0.389)	-0.021 (0.793)	-0.051 (0.57)
Non-Traditional Family	0.220 (0.014)**	0.1226519 (0.109)	0.225 (0.003)***	-0.037 (0.657)	-0.185 (0.012)**	-0.179 (0.036)**
Number of Siblings	0.009 (0.728)	0.0133993 (0.548)	0.003 (0.9)	0.016 (0.497)	0.006 (0.778)	0.013 (0.578)
Visible Minority	-0.154 (0.111)	-0.1466683 (0.088)*	-0.216 (0.016)**	-0.119 (0.247)	-0.120 (0.212)	0.026 (0.803)
Immigrant	-0.158 (0.026)**	-0.0614137 (0.33)	0.000 (0.995)	-0.004 (0.964)	0.017 (0.827)	0.001 (0.986)
Parents' Inconsistent Discipline and Rejection-Oriented Behaviour Home Educational Resources	0.088 (0.001)***	0.063 (0.008)***	0.083 (0.000)***	-0.092 (0.000)***	-0.073 (0.001)***	-0.086 (0.001)***
Constant	-1.404 (0.000)***	-1.004 (0.000)***	-0.995 (0.000)***	-0.352 (0.044)**	0.097 (0.568)	0.170 (0.331)

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 2: University Completion (Decision Equation)

University Completion	
Effect of Cognitive Skills on University Decision	0.855 (0.000)***
Effect of Non-Cognitive Skills on University Decision	0.283 (0.000)***
Female	0.537 (0.000)***
Family Income	0.002 (0.133)
Wealth	0.090 (0.12)
Immigrant	-0.357 (0.001)***
Non-Traditional Family	0.294 (0.038)**
Years of Education Parents (Max)	0.172 (0.000)***
Importance of Higher Education for Parents (MAX)	0.310 (0.000)***
Parental money for Post-Secondary Education (Y/N)	0.230 (0.006)***
Planning for Higher Education Among Friends	0.254 (0.000)***
Region: Atlantic	0.375 (0.009)***
Region: West	0.149 (0.264)
Region: Quebec	-0.189 (0.216)
Constant	-4.577 (0.000)***

Results taken from the estimation with employment as an outcome

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Table 3: Outcome Equations

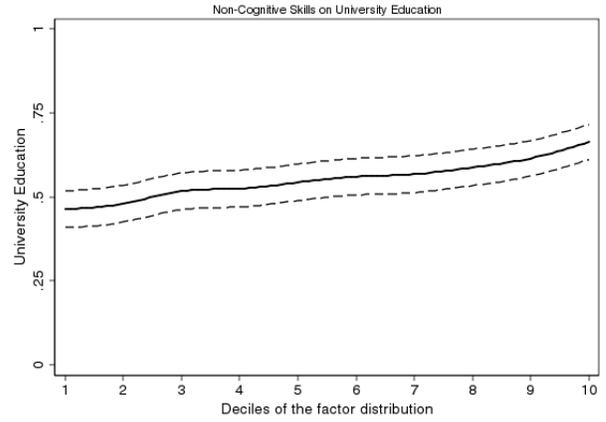
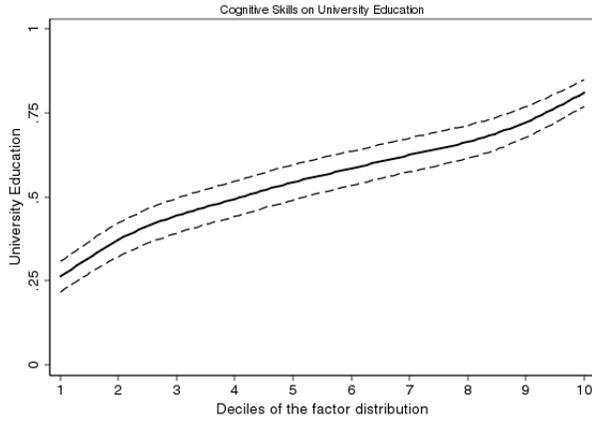
Outcome Equation	Income		Employed	
	D=1	D=0	D=1	D=0
	Cognitive Skills	392.41 (0.826)	-361.20 (0.843)	-0.015 (0.484)
Non-Cognitive Skills	2812.70 (0.055)*	2167.09 (0.273)	-0.021 (0.196)	-0.005 (0.813)
Female	-3660.44 (0.059)*	-9257.04 (0.000)***	0.006 (0.797)	0.034 (0.325)
Experience	2489.43 (0.012)**	-244.67 (0.831)		
Experience Squared	-373.60 (0.000)***	64.67 (0.509)		
Region: Atlantic	-3303.49 (0.165)	-7513.96 (0.011)**	0.014 (0.649)	-0.070 (0.104)
Region: Quebec	-1852.92 (0.505)	-7984.22 (0.008)***	0.000 (0.993)	-0.084 (0.051)*
Region: West	913.65 (0.68)	1329.59 (0.625)	-0.043 (0.123)	-0.080 (0.041)**
Married	18436.22 (0.000)***	9980.68 (0.003)***	0.069 (0.127)	0.014 (0.773)
Married * Female	-19645.98 (0.000)***	-13219.38 (0.004)***	-0.156 (0.005)***	-0.183 (0.005)***
Common Law	8418.59 (0.01)***	12738.34 (0.000)***	-0.048 (0.258)	0.080 (0.05)**
Common Law * Female	5.78 (0.999)	-12023.84 (0.004)***	0.103 (0.047)**	-0.113 (0.063)*
Immigrant	158.81 (0.944)	-1341.15 (0.649)	-0.019 (0.519)	-0.043 (0.321)
Visible Minority	-4655.09 (0.133)	-5839.47 (0.193)	-0.094 (0.015)**	-0.026 (0.688)
Number of Children	-14956.81 (0.493)	-5233.30 (0.258)	0.083 (0.779)	-0.091 (0.173)
Number of Children * Female	9659.93 (0.683)	-6975.28 (0.244)	-0.356 (0.265)	-0.218 (0.011)**
Urban Community	4386.57 (0.028)**	1147.93 (0.537)	0.016 (0.527)	0.006 (0.823)
Constant	29126.84 (0.000)***	36210.19 (0.000)***	0.940 (0.000)***	1.017 (0.000)***

***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Simulation Results

Figure 1: **Effect of Cognitive and Non-Cognitive Skills on University Completion**

(a) Effect of Cognitive Skills on University Completion (b) Effect of Non-Cognitive Skills on University Completion



(c) Cognitive Skills Distribution by Education

(d) Non-Cognitive Skills Distribution by Education

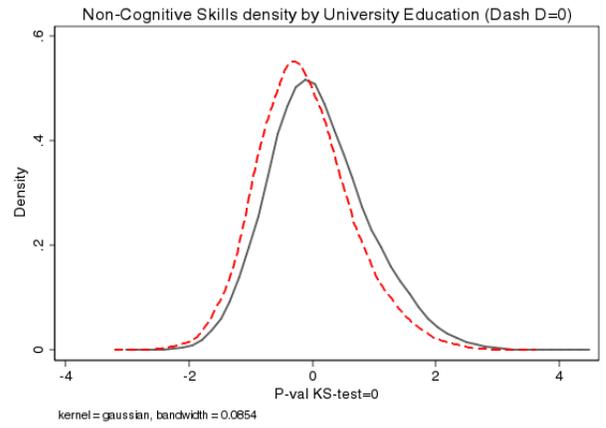
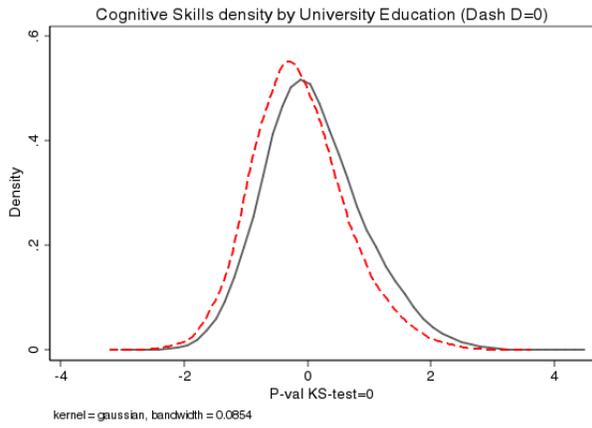
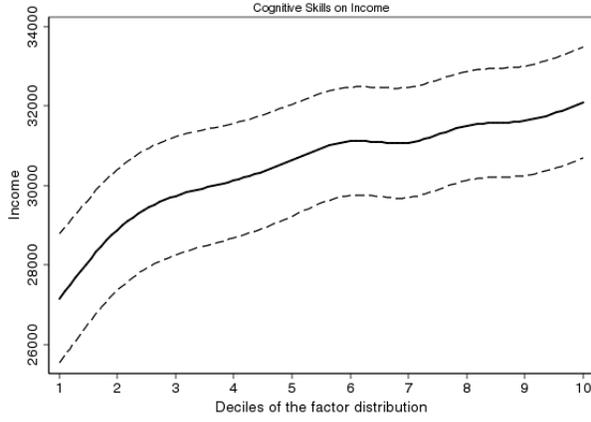
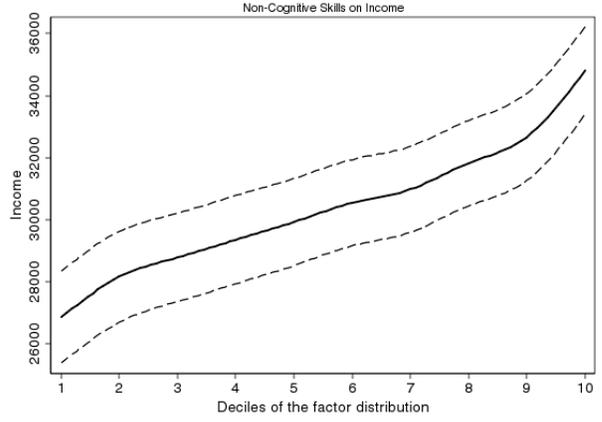


Figure 2: Overall Effects of Skills on Income

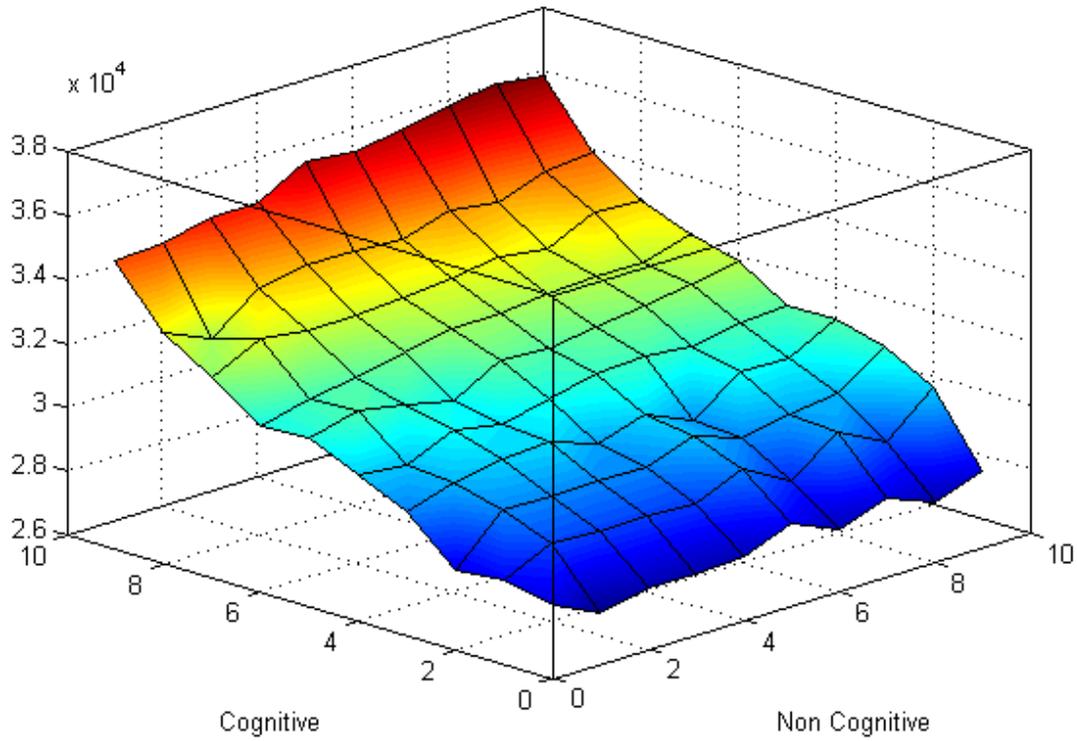
(a) Cognitive Skills



(b) Non-Cognitive Skills



(c) Income by Deciles of Cognitive Skills and Non-Cognitive Skills



Overall Effects of Skills on University Decision

Figure 3: Females

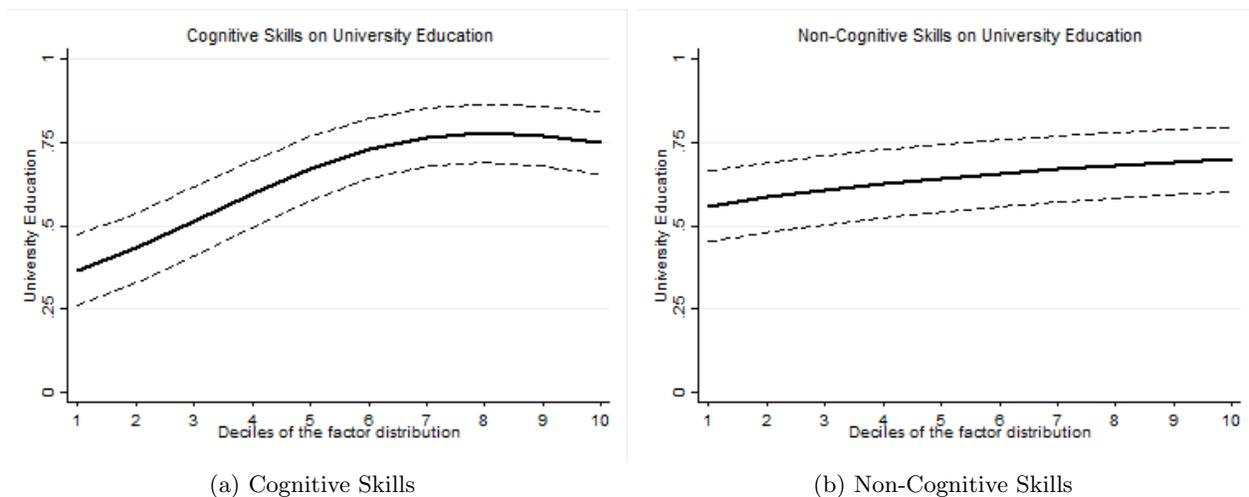
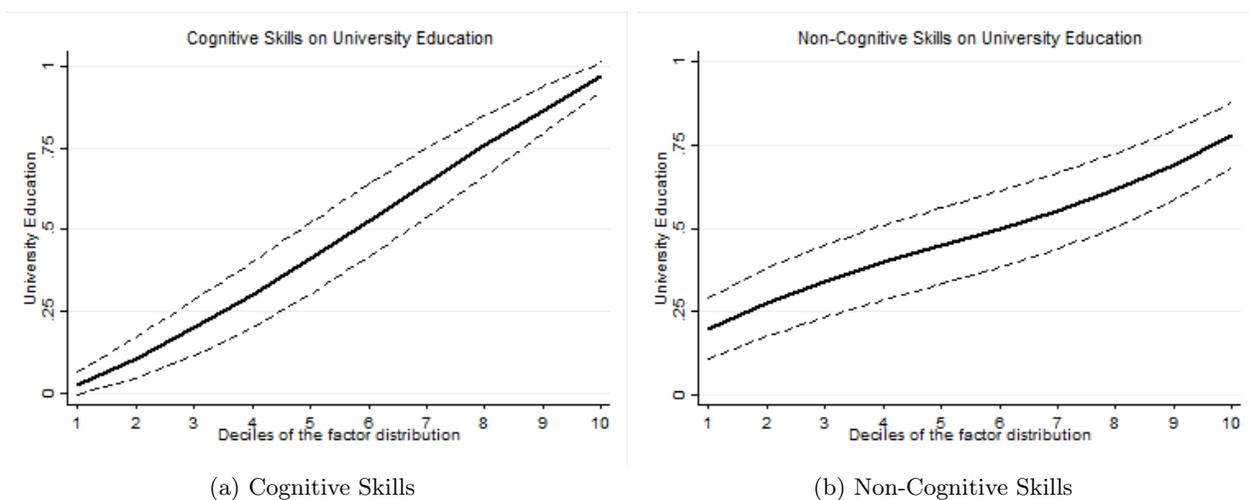


Figure 4: Males



Overall Effects of Skills on Income

Figure 5: Females

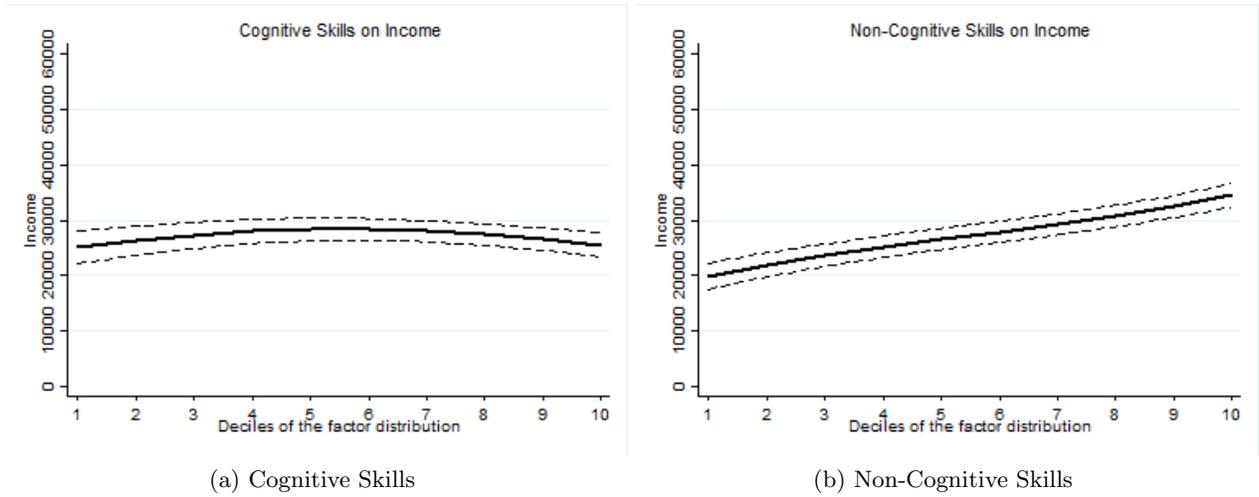
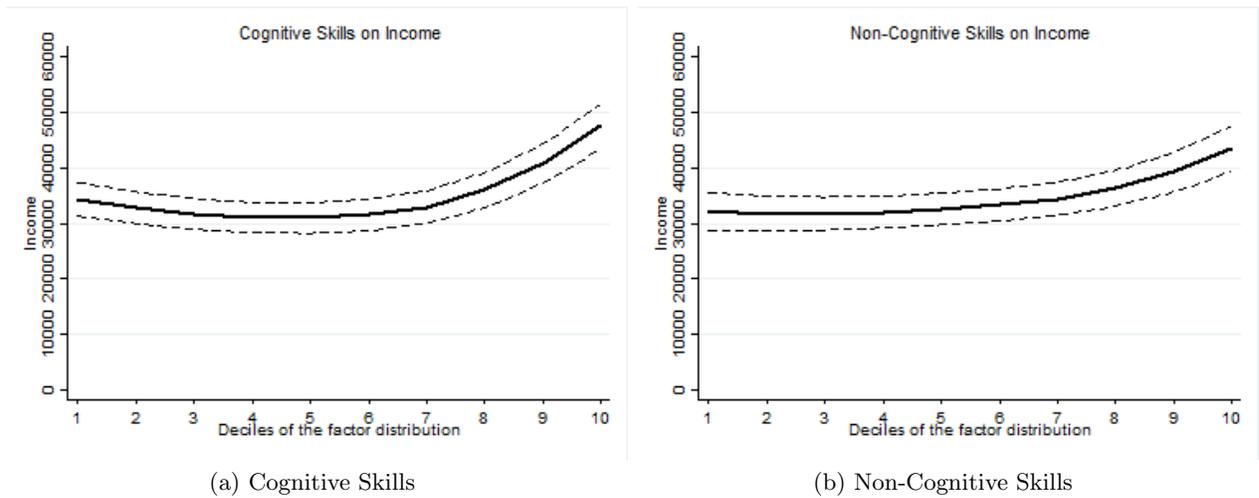


Figure 6: Males



Overall Effects of Skills on University Decision

Figure 7: Parent's with Low Education

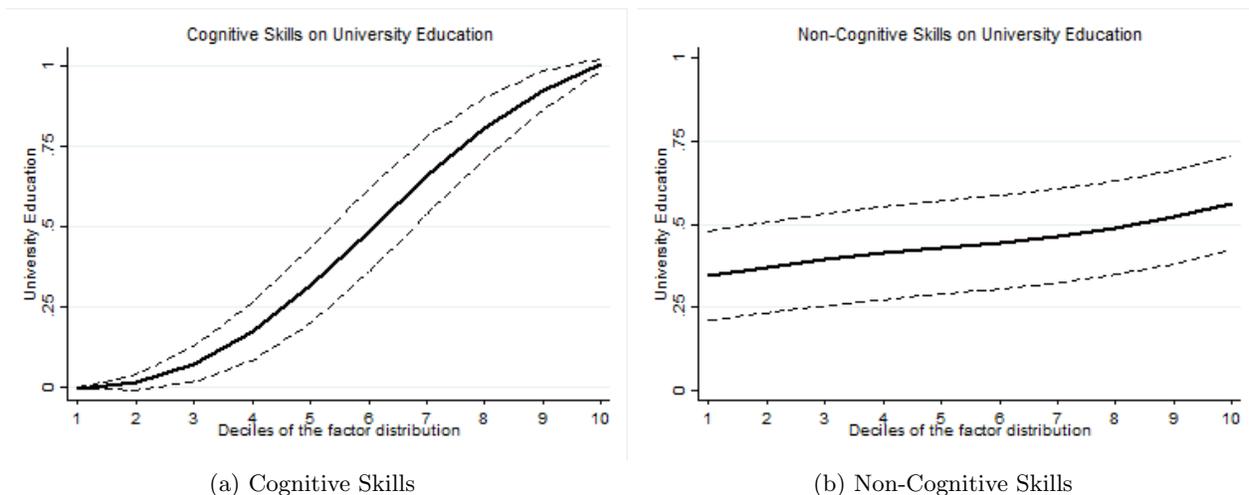
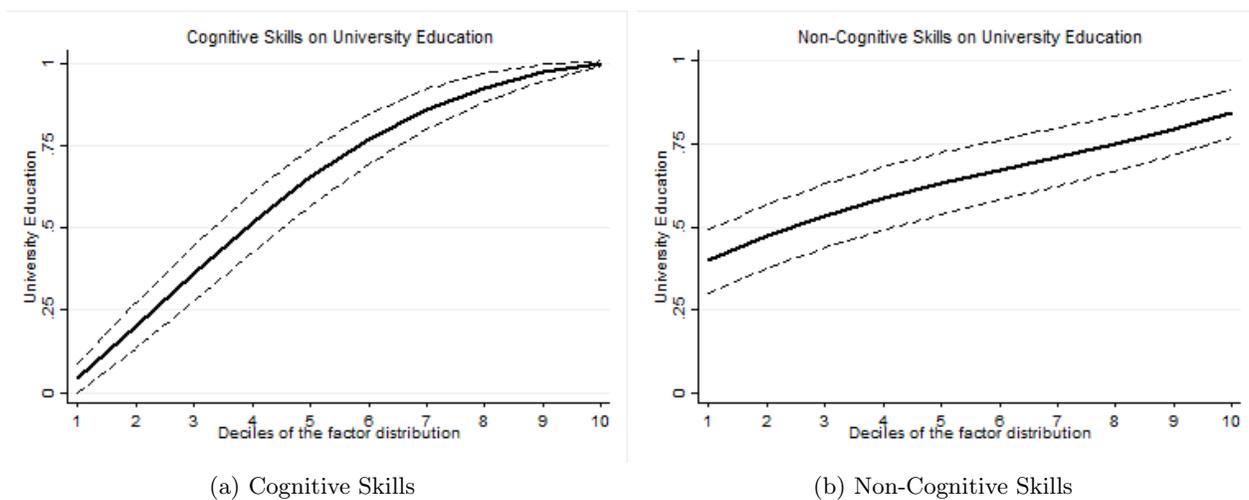


Figure 8: Parent's with High Education



Overall Effects of Skills on Income

Figure 9: Parent's with Low Education

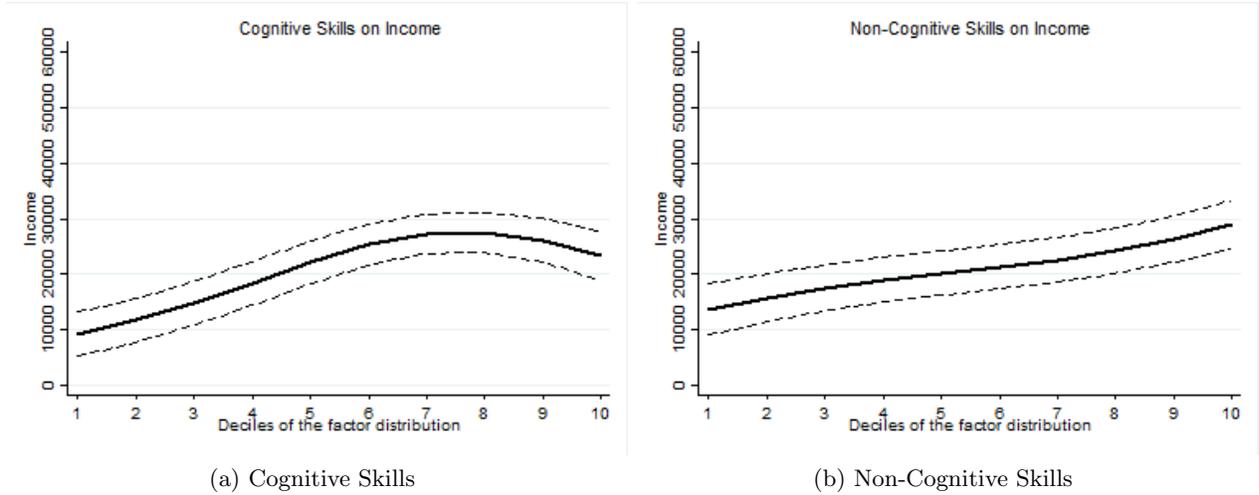


Figure 10: Parent's with High Education

