Confidence and Cognition: Tracking the Effects of Skill Development on Post-Secondary School Choice and Early Labour Market Outcomes

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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. 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 solely on cognitive skills.

Preliminary and Incomplete

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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 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, Heckman and Mullen, 2003, Cunha and Heckman, 2008; Ding and Lehrer, 2014). Further, while a substantial body of research (e.g. Cawley, Heckman, and Vytlacil, 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 individual's 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 or England. Further, the existing evidence base in the economics literature which points to the importance of non-cognitive skills is obtained from studies that focused on i) either schooling or labour market outcomes in isolation, and ii) allowed for only a single domain of non-cognitive skills.[2]

This paper contributes to this growing literature by considering schooling and the labour market jointly along with multiple dimensions of non-cognitive skills using longitudinal data that tracks a cohort of Canadians from late adolescence in grade 10 until they are 25 years of age.[3] To motivate our empirical analysis, we suggest that accounting for different dimensions of non-cognitive skills is likely to be important since different types of skills influence schooling and labour market outcomes.[4] For example, consider motivation and perseverance which

[1]Beyond 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).

[2]That said researchers in the fields of organizational behavior and human resource management report that firms are increasingly making use of non-cognitive assessments to identify ideal candidates for employment. Tests used to assess emotional intelligence are common place and Goelman (2011) presents survey evidence that nearly two thirds of major businesses employ such techniques. There are numerous reports of companies going as far as to profile candidate employee's Facebook and other social media pages. In addition, Dahl (2012) reports that firms are now undertaking training programs that focus on social aspects of the workplace. The presence of informal and formal testing of socio-emotional skills in hiring practices highlights the importance of these abilities in developing and training productive employees.

[3]To 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.

[4]Borghans et al. (2008) argue for classifying these abilities into the Big Five factor scheme favored by some psychologists. The authors provide evidence that conscientiousness has the strongest associations with education outcomes of the five factors. In this paper, we are using confidence somewhat interchangeably with conscientiousness.

can be viewed as two different (but likely correlated) dimensions of non-cognitive skills. We suggest that motivation may play a larger independent role in influencing retention in university, whereas employers may prefer to seek workers that are conscientious rather than simply motivated.

To the best of our knowledge, the only one other paper that considers more than two-dimensional vector of latent factors is Prada and Urzua (2013), but that study focuses on multiple dimensions of cognitive skills alone. Despite this key difference in the heterogeneity of skills being investigated, our study draws a parallel to Prada and Urzua (2013) since we each build on the economic framework developed in Willis and Rosen (1979) who model self-selection into college and potential earnings within a traditional Roy model.[5] Rather than follow Willis and use proxy variables to account for dimensions of unobserved ability, we follow a growing literature including Heckman et al. (2006) and Urzua (2008) that 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.[6] An additional key feature of our empirical approach is that it incorporates the dynamics in decision making that Altonji, Blom and Meghir (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 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

[5]In 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.

[6]Cunha 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. Simply put, the computational challenges associated with the former approach are large with a two-dimensional factor structure and as such to gain timely results we only considered a linear framework given our motivation to this study was investigating additional dimensions of skills.

different skills measured at different ages are at play for schooling and labour market outcomes.

A second contribution of this study is that it provides the first set of evidence using Canadian data that was collected in the last decade. Canada's economy is characterized by substantial geographic heterogeneity and its market for higher education differs sharply from the United States. For example, Belley, Frenette and Lochner (2014) estimate a substantially smaller attendance gaps by parental income in Canada relative to the U.S., even after controlling for family background, adolescent cognitive achievement, and local residence fixed effects. Last, subjects in our data all found work in their 20s during the 21st century. The majority of work looking at skill development 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.

Our analysis at present only focuses on a single dimension of cognitive and non-cognitive skills but has three findings.[7] First, we find 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. This result would suggest equal attention should be given to policies that cultivate different dimensions of non-cognitive skills as those focusing on

[7] We have encountered some computational issues with more than two factors with the YITS data. Since these issues do not occur with simulated data, we believe they will be resolved in time for the next draft.

cognitive skills.

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 analysis in section 3. We carefully discuss the conditions needed to identify the Our empirical results are presented and discussed in section 4. Finally, we discuss the policy implications of our findings for recent debates on wage inequality in the concluding section.

2 Data

We use data from the Youth in Transition Survey (YITS-A) collected by Statistics Canada. This study used a two-stage sampling frame to follow a nationally representative cohort of 15-year olds. In the first stage, 1,187 schools were selected. From these schools, 29,867 students were randomly selected in the second stage. 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

[8] Of these 29,330 participants completed the survey.

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

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 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 i n labour markets and in the education decision. 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

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

those individuals who completed all three PISA tests and have a parental survey along with complete income and education data at age 25. This leads to a substantial loss in the number of observation and we are left with a sample of approximately 1600 individuals. Those kept in the sample represent a group who has both higher cognitive and non-cognitive test scores. The average score is .1 to .4 standard deviations higher than in the full sample. In addition, we dropped subjects that were either home-schooled or attending a school on an Indian reserve at age 15 as well as those that were no longer residing in Canada. Taken together, this analysis is undertaken on a group more skilled than the full population. Given the preliminary nature of this analysis and Statistics Canada's strict regulations on disclosing results we have limited access to display summary statistics at present but they will be available in the next draft.

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 identifies these factors rather than use 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 will 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). The parameters can then be used to simulate outcomes given different levels of the two skills. 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 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.[11]

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. In this draft, 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 sense of mastery (T_1^{se}).[12] 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. 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. Here, the subscript $_i$ refers to the test of interest and the superscript ^{s} to the related skill, ^{c} for cognitive and ^{se} for socio-emotional or non-cognitive. Finally, u_i^s is the vector 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 $f_i^s(\cdot)$.[13] We are interested in identifying and estimating both the factor loadings and factors' distributions from the following linear

[11] See 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.

[12] Non-cognitive abilities are heterogeneous and difficult to reduce to one factor. In the next draft we will consider additional domains using other data in the YITS-A.

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

measurement system

$$
\begin{aligned}
T_0^c &= \pi_0 + \phi_0^c Q^c + \psi_0^c \theta^c + u_0^c \\
T_1^c &= \pi_1 + \phi_1^c Q^c + \psi_1^c \theta^c + u_1^c \\
T_2^c &= \pi_2 + \phi_2^c Q^c + \psi_2^c \theta^c + u_2^c \\
T_0^{se} &= \pi_0 + \phi_0^{se} Q^{se} + \psi_0^{se} \theta^{se} + u_0^{se} \\
T_1^{se} &= \pi_1 + \phi_1^{se} Q^{se} + \psi_1^{se} \theta^{se} + u_1^{se} \\
T_2^{se} &= \pi_2 + \phi_2^{se} Q^{se} + \psi_2^{se} \theta^{se} + u_2^{se} \qquad (1)
\end{aligned}
$$

where $Q^c$and Q^{se} include socio-economic status, family composition and background, and parental inputs specific to the skills in question. 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 the appendix. In our analysis 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 $F_\theta^{se}(\cdot)$.[14]

3.2 The Education Decision

We now model the impact of skills on an educational investment decision: whether to complete an 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 his/her abilities, as well as knowledge of their returns.

[14]Kotlarski (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.

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

$$D = 1[\gamma^D Z + \lambda_c \theta^c + \lambda_{se} \theta^{se} + \upsilon > 0] \tag{2}$$

where Z is a vector of personal, family and peer characteristic, θ^c and θ^{se} are the unobserved skills, and υ 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, these decisions be largely influenced by parents also. For example, parents may have emphasized the importance of further education or prepare financially to support a youth's university education. These factors may also be correlated with cognitive and non-cognitive skills and are important to incorporate to get unbiased estimates of the effects of these skills on educational investment decisions. Additionally, the influence of youth peer group is incorporate by including the youth's perception of the number of their friends planning to obtain high education. As we outline below, we will not use proxies for and rather in our estimation integrate over the unobservable skill endowments in all the outcomes associated with the model.

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

$$Y_1 = \left\{ \begin{array}{c} \gamma^{Y_1} X + \lambda_c^{Y_1} \theta^c + \lambda_{se}^{Y_1} \theta^{se} + v_1 \; if \; D = 1 \\ 0 \; if \; D = 0 \end{array} \right\} \tag{3}$$

$$Y_0 = \left\{ \begin{array}{c} 0 + \; if \; D = 1 \\ \gamma^{Y0} X + \lambda_c^{Y0} \theta^c + \lambda_{se}^{Y0} \theta^{se} + v_0 \; if \; D = 0 \end{array} \right\} \tag{4}$$

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. In our analysis, we consider four outcomes separately: income, employment, volunteering and the use of employment insurance. Note that adding equation (2) to equations (3) and (4) looks similar to models that underlie a rich literature that explored sheepskin effects 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.[15] Define β to be

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

the vector of all the parameters of the model and $W = \{Q, Z, X\}$. Specifically, the likelihood is

$$L(\beta|W) = \prod_{i=1}^{n} \int f(D_i, Y_i, T_i|Q_i, Z_i, X_i, \theta^c\theta^{se}) dF_\theta^c(\cdot) dF_\theta^{se}(\cdot) \tag{5}$$

where we integrate over the distribution of two factors due to their unobserved nature.In practice, we use Gauss-Hermite quadrature for numerical integration. We should note that since all of the labour market outcomes at age 25 that we consider with the exception of income are discrete indicators, that for those cases an individual's contribution to the likelihood function is simply the product of normal CDF evaluations when we condition on the factors.

4 Results

Maximizing the likelihood function given in equation (5) provides estimates of all parameters in the model including the factor loadings and the factor distributions. In this section we discuss and present the economic implications of these estimates in sequence. We will focus on estimates from the model that consider the impact of unobserved abilities on educational choices and employment as the final outcome. To facilitate the discussion, we only present the set of results corresponding to this specific labour market outcome.[16] Following the discussion of these estimates, we will next present a series of counterfactual policy evaluations that consider the full set of labour market outcomes at age 25 available in our data.[17]

Thus, we begin by presenting results from the full factor model described in Equation 1 in Table 1. These results allow for 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,

on the factor distributions.

[16]These parameter estimates are extremely similar to those using other outcomes.

[17]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.

the scores for each of the tests has been standardized to have a mean of 0 and a standard deviation of one. 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 provided by the provincial government it is possible that differences in the effectiveness of the school systems are responsible for these regional differences. 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 scores higher in math. While we do not find a significant gender difference in science, there are large gender differences for the non-cognitive scores. For each non-cognitive measure, females perform significantly worse than the males.

The results in Table 1 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. The channel through which this operates is unclear. Family income plays a small role in the scores for the math test. 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. Other channels for transmission in student test scores are at play. For example parents of higher education may simply provide additional emphasis on the importance of performance in academics and their children in turn simple put in greater effort. Holding skill constant, youth from non-traditional families perform better on the reading and science tests. Not surprisingly those from non-traditional families fair worse on measures of their non-cognitive ability. This is likely related to changes in their self-perception relating to their experiences in transitioning between different family structures. Note that this does not indicate lower levels of non-cognitive skill for those in non-traditional families, though this may be the case, but rather lower scores on the non-cognitive tests given a level of the latent non-cognitive skill. As a whole, these results suggest that situation and setting can be important to determining measures such as grades and thus educational pathways.

4.0.1 Skills and Educational Choice

Table 2 presents the estimates of λ_v^c, λ_v^{se} and γ from Equation 2 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 significantly better understanding of their role we consider a simple simulation in Figure 1.[18] 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. 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.[19]

[18] A full description of the simulation procedure appears in Section 3.1.

[19] There has been numerous studies that have examined information as a limitation to university education. See Bettinger et al (2013), Frenette et al (2013), Hoxby and Turner (2013), among others. While we do not have access to data on student knowledge of the costs and benefits of higher education, we simply wish to point out that policies which focus on non-cognitive skill development may be worthy of consideration to boost education decisions, since they also as we will shortly demonstrate have returns in the labour market for those who choose not to attend.

Several other results in table 2 are consistent with the literature on attending higher education. Females are much more likely than males to complete university, holding other factors constant. Consistent with Belley et al (2013), 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 the parental education effects on test scores reflecting differential parental expectations, we find that a measure of whether parents have put money aside for post-secondary education plays a large role. On the surface this suggest 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 poor labour market for individuals with less education in these regions.

4.0.2 The Effect of Skills Conditional on Education Decisions on Labour Market Outcomes

In Table 3, the parameters λ_0^s, $\lambda_1^s, \beta_0, and\ \beta_1$ from Equation 3 are reported for each of the four outcomes of interest. The headings of D=1 and D=0 refer to those who have completed and not completed a university degree respectively. These equations highlight the importance of the two types of skills following the decision to invest in university education.

We begin by discussing the results for income and employment. Notice that after conditioning on university completion, cognitive skills do not provide any additional rewards for a higher income. Similarly, among those completing university, there is also no effect 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 c suggest there is high variability in the levels of cognitive skills amongst those with university degrees. Cognitive skills do improve employment rates amongst non-university graduates. The benefits, higher income or higher likelihood of having a job, of higher cognitive operate mainly through the educational channel. It is likely that employers have a difficult time 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 this result 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 the defined non-cognitive skill being rewarded with larger incomes for university graduates. This is not the case for those without a university degree, though the estimate is of a similar magnitude. Non-cognitive skills do not significantly effect levels of employment. If the non-cognitive skills, confidence in one's self and one's abilities, manifest themselves in the work place, perhaps as leadership skills or through the ability to have the confidence to be self-directed, we would expect that employers might reward individuals for these skills. These types of skills are unlike cognitive skills in that there is no universal signaling 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 the particular hard skills or qualifications, such as a university degree, and reward hard to verify non-cognitive skills as discovered in work place.

4.0.3 The Effect of Skills Conditional on Education Decisions on Volunteering and Employment Insurance Take-up

Briefly, our results suggest that non-cognitive skills alone affect the use of Employment Insurance. 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. Turning to volunteering, we see that higher cognitive skills are also associated with increased levels of volunteering. Many of the results are quite weak. Note that the model assumes skill at age 25 is the same as age 15. There is no room for the educational choice to affect skill level. This is a strong assumption but one that is necessary to make given the data limitations, which would require additional measures of cognition at the later age. At best, the skill level at age 15 is a proxy for skill at age 25.

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

Simulation might be the best way to understand the size and significance of the parameters estimated in the described set of equations. Simulation is accomplished by drawing random observations from the population and pairing them with draws from the distributions of the latent skills, and the parametrized error terms. The effects of both skills on the outcomes of interest can be traced across individual contexts and through university completion decisions. These simulations are summarized in Figures 1-5. The first of these diagrams examines the decision to complete a university degrees and the other four look at the four outcomes of interest.

Figure 2-5 provide the simulation results of the outcome of interest across the distribution of the skills. Each figure has three parts: (a) the deciles of the cognitive skill distribution graphed against the average simulated outcome, (b) the deciles of the non-cognitive skill distribution graphed against the average simulated outcome, and (c) a three dimensional graph looking at the distributions of the two skills simultaneously in conjunction with average simulated outcome. Confidence bounds are provided in figures (a) and (b).

Figure 2, looking at income, is the most interesting. From the models estimated parameters make evident that non-cognitive skill are important to the decision to invest in education and also to yearly income accounting for this educational choice. These parameters also suggested that cognitive skills were much more important than non-cognitive ones. Somewhat surprisingly, the cumulative effect of non-cognitive skills appears to be larger than that of cognitive skills. The average simulated outcome in the first decile of the cognitive skill distribution was approximately \$25000 and whereas the tenth decile had a average simulated outcome of \$32000. In comparison the simulated incomes for the non-cognitive skill at first and tenth deciles is \$27000 and \$34000, a larger range. Admittedly, there is overlap in the confidence intervals. Nonetheless, this highlights the important role of non-cognitive skills in influencing adult earnings. These results suggest that the cumulative effect through education and later demand of these skills is on par with the rewards to cognitive.

Figures 3-5 show less interesting results. Employment and use of employment insurance do not appear to be affected by either skills. Volunteering is increasing in both skill but more prominently affected by cognitive skills. The effects are small and difficult to distinguish from a non-effect.

5 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 solely on cognitive skills.

Our next draft will consider additional domains of non-cognitive skills.

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Table 1: Test Score Equations

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

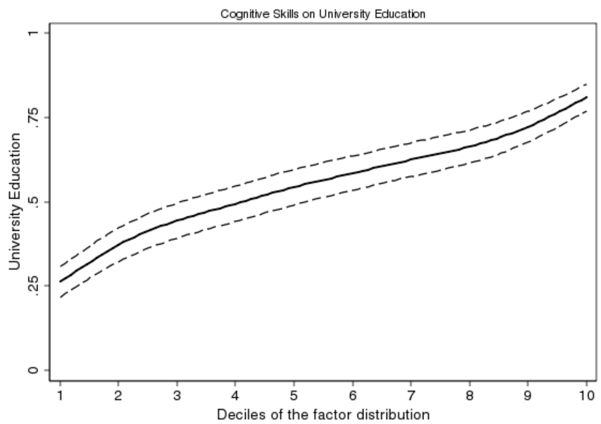
Outcome Equation	Income		Employed		Volunteer (Once a Month)		Employment Insurance	
	D=1	D=0	D=1	D=0	D=1	D=0	D=1	D=0
Cognitive Skills	392.41	-361.20	-0.015	0.043	0.067	-0.001	-0.033	0.020
	(0.826)	(0.843)	(0.484)	(0.097)*	(0.073)*	(0.973)	(0.195)	(0.584)
Non-Cognitive Skills	2812.70	2167.09	-0.021	-0.005	0.031	0.010	-0.044	0.073
	(0.055)*	(0.273)	(0.196)	(0.813)	(0.298)	(0.754)	(0.023)**	(0.049)**
Female	-3660.44	-9257.04	0.006	0.034	0.062	0.075	0.005	-0.065
	(0.059)*	(0.000)***	(0.797)	(0.325)	(0.121)	(0.077)*	(0.841)	(0.176)
Experience	2489.43	-244.67						
	(0.012)**	(0.831)						
Experience Squared	-373.60	64.67						
	(0.000)***	(0.509)						
Region: Atlantic	-3303.49	-7513.96	0.014	-0.070	0.041	0.074	0.053	0.166
	(0.165)	(0.011)**	(0.649)	(0.104)	(0.408)	(0.157)	(0.116)	(0.005)***
Region: Quebec	-1852.92	-7984.22	0.000	-0.084	-0.082	0.006	0.012	0.104
	(0.505)	(0.008)***	(0.993)	(0.051)*	(0.148)	(0.906)	(0.752)	(0.08)*
Region: West	913.65	1329.59	-0.043	-0.080	-0.002	0.104	-0.009	0.058
	(0.68)	(0.625)	(0.123)	(0.041)**	(0.96)	(0.028)**	(0.765)	(0.284)
Married	18436.22	9980.68	0.069	0.014	0.034	0.064	0.003	-0.050
	(0.000)***	(0.003)***	(0.127)	(0.773)	(0.649)	(0.272)	(0.96)	(0.444)
Married * Female	-19645.98	-13219.38	-0.156	-0.183	-0.055	-0.067	0.110	0.165
	(0.000)***	(0.004)***	(0.005)***	(0.005)***	(0.544)	(0.399)	(0.077)*	(0.066)*
Common Law	8418.59	12738.34	-0.048	0.080	-0.058	-0.026	-0.020	-0.040
	(0.01)***	(0.000)***	(0.258)	(0.05)**	(0.4)	(0.593)	(0.666)	(0.483)
Common Law * Female	5.78	-12023.84	0.103	-0.113	-0.022	-0.048	0.048	0.129
	(0.999)	(0.004)***	(0.047)**	(0.063)*	(0.795)	(0.518)	(0.408)	(0.124)
Immigrant	158.81	-1341.15	-0.019	-0.043	0.003	-0.030	0.032	-0.047
	(0.944)	(0.649)	(0.519)	(0.321)	(0.947)	(0.56)	(0.312)	(0.425)
Visible Minority	-4655.09	-5839.47	-0.094	-0.026	-0.054	0.095	-0.046	-0.057
	(0.133)	(0.193)	(0.015)**	(0.688)	(0.4)	(0.222)	(0.284)	(0.519)
Number of Children	-14956.81	-5233.30	0.083	-0.091	0.629	-0.088	-0.095	-0.133
	(0.493)	(0.258)	(0.779)	(0.173)	(0.193)	(0.281)	(0.771)	(0.15)
Number of Children * Female	9659.93	-6975.28	-0.356	-0.218	-1.093	0.037	-0.075	0.128
	(0.683)	(0.244)	(0.265)	(0.011)**	(0.037)**	(0.722)	(0.831)	(0.283)
Urban Community	4386.57	1147.93	0.016	0.006	0.061	0.074	0.075	0.130
	(0.028)**	(0.537)	(0.527)	(0.823)	(0.143)	(0.023)**	(0.008)***	(0.000)***
Constant	29126.84	36210.19	0.940	1.017	0.348	0.089	0.073	0.191
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.175)	(0.066)*	(0.011)**

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

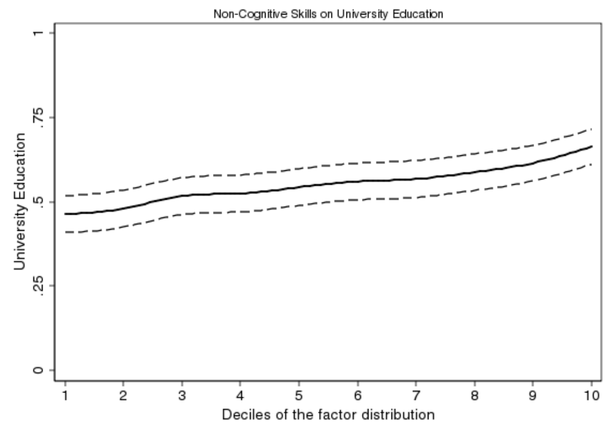
Simulation Results

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

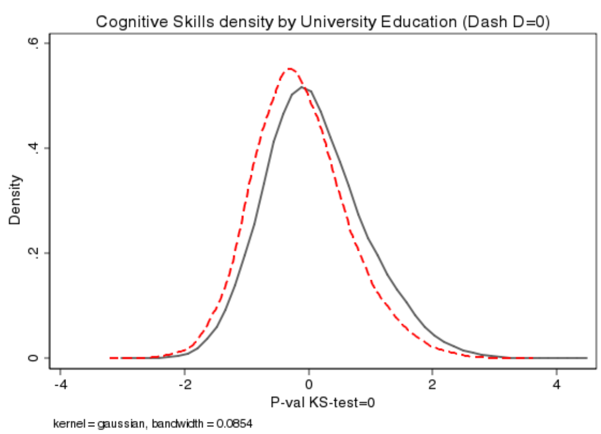
(a) Effect of Cognitve Skills on University Completion



(b) Effect of Non-Cognitve Skills on University Completion



(c) Cognitve Skills Distribution by Education



(d) Non-Cognitve Skills Distribution by Education

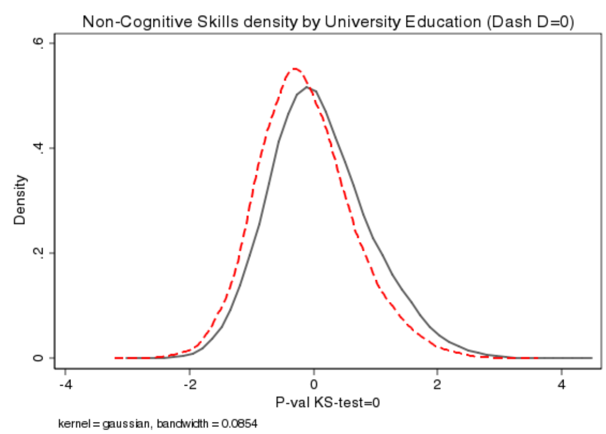
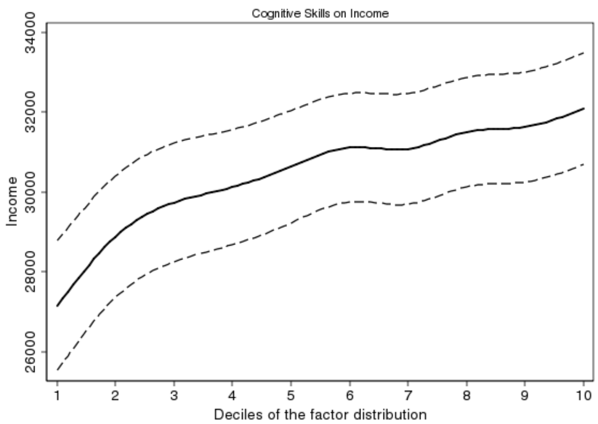
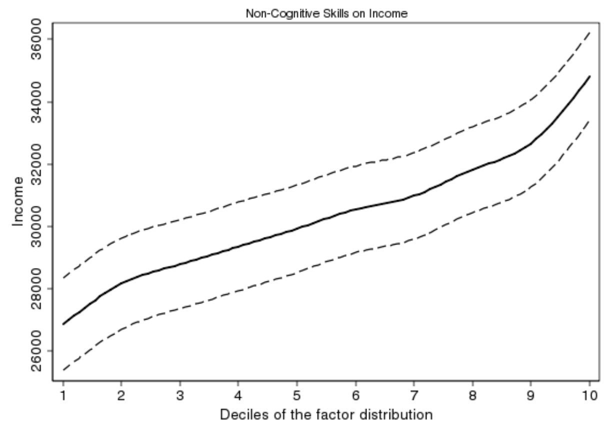


Figure 2: Overall Effects of Skills on Income

(a) Cognitve Skills



(b) Non-Cognitve Skills



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

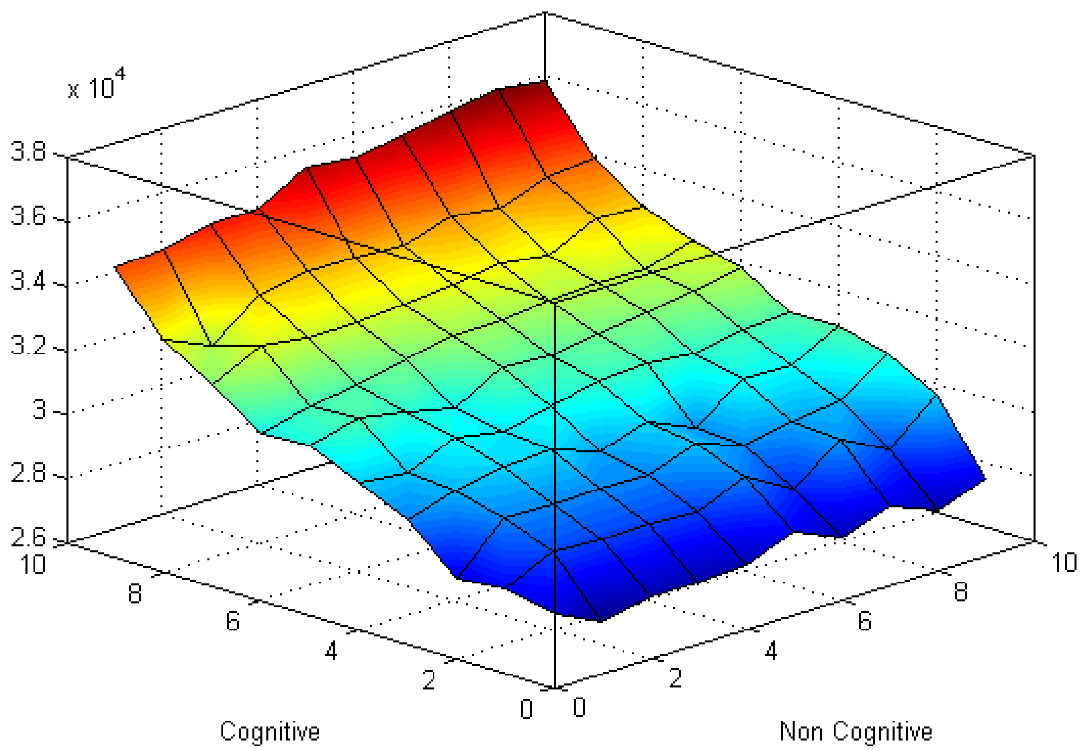
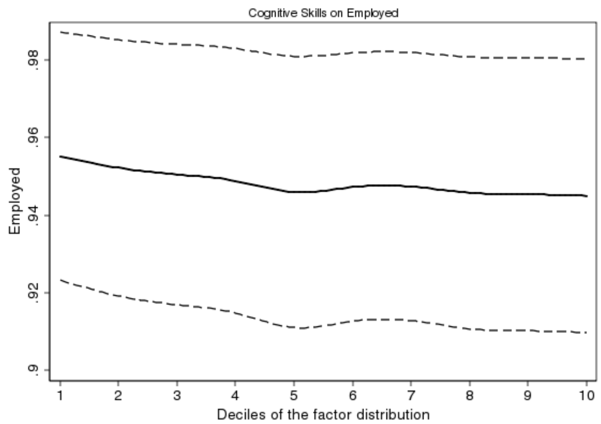
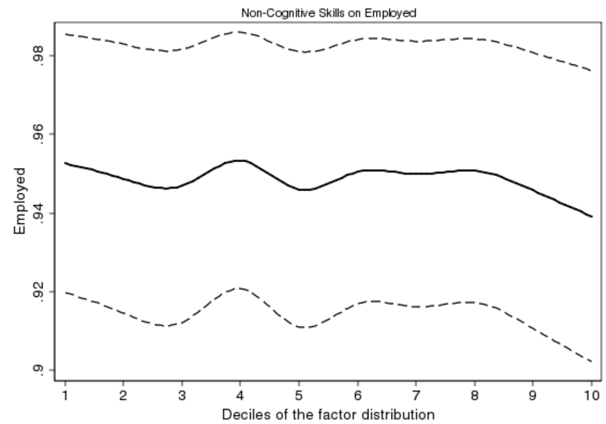


Figure 3: Overall Effects of Skills on Employment

(a) Cognitve Skills



(b) Non-Cognitve Skills



(c) Employment by Deciles of Cognitve Skills and Non-Cognitve Skills

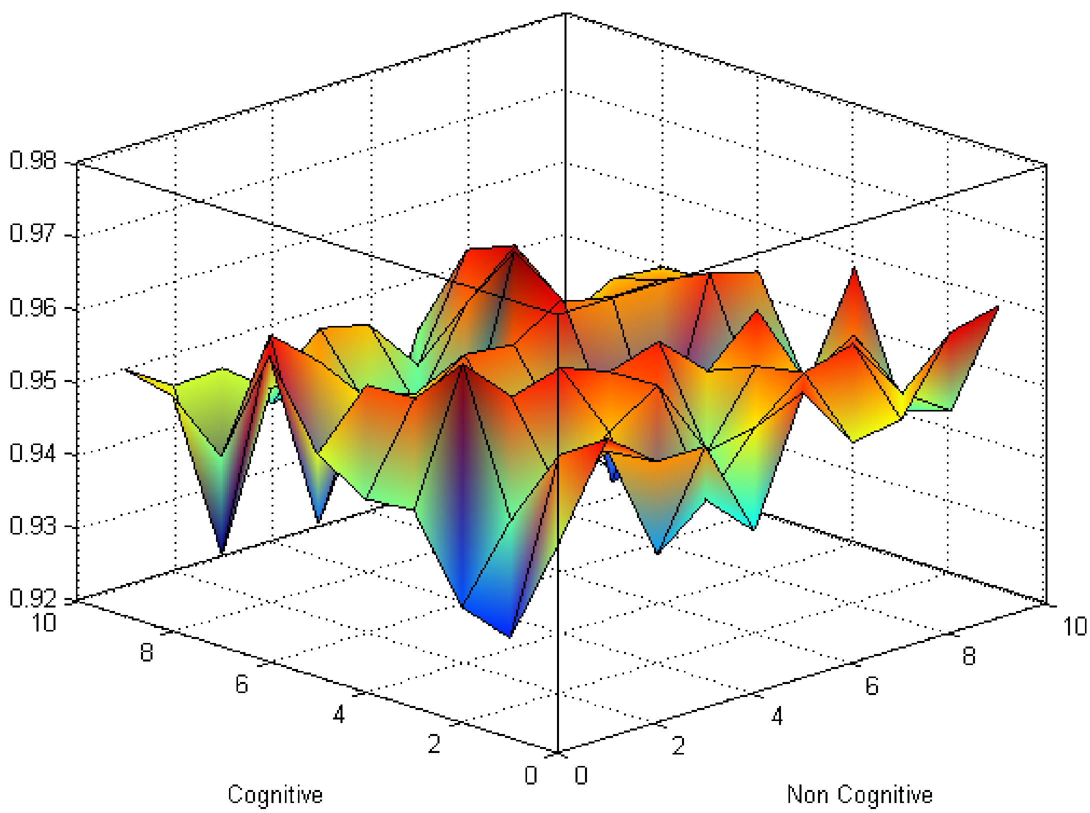
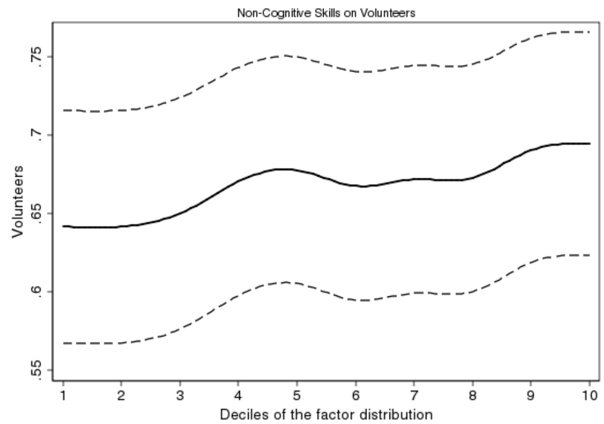


Figure 4: Overall Effects of Skills on Volunteering

(a) Cognitve Skills

(b) Non-Cognitve Skills



(c) Volunteering by Deciles of Cognitve Skills and Non-Cognitve Skills

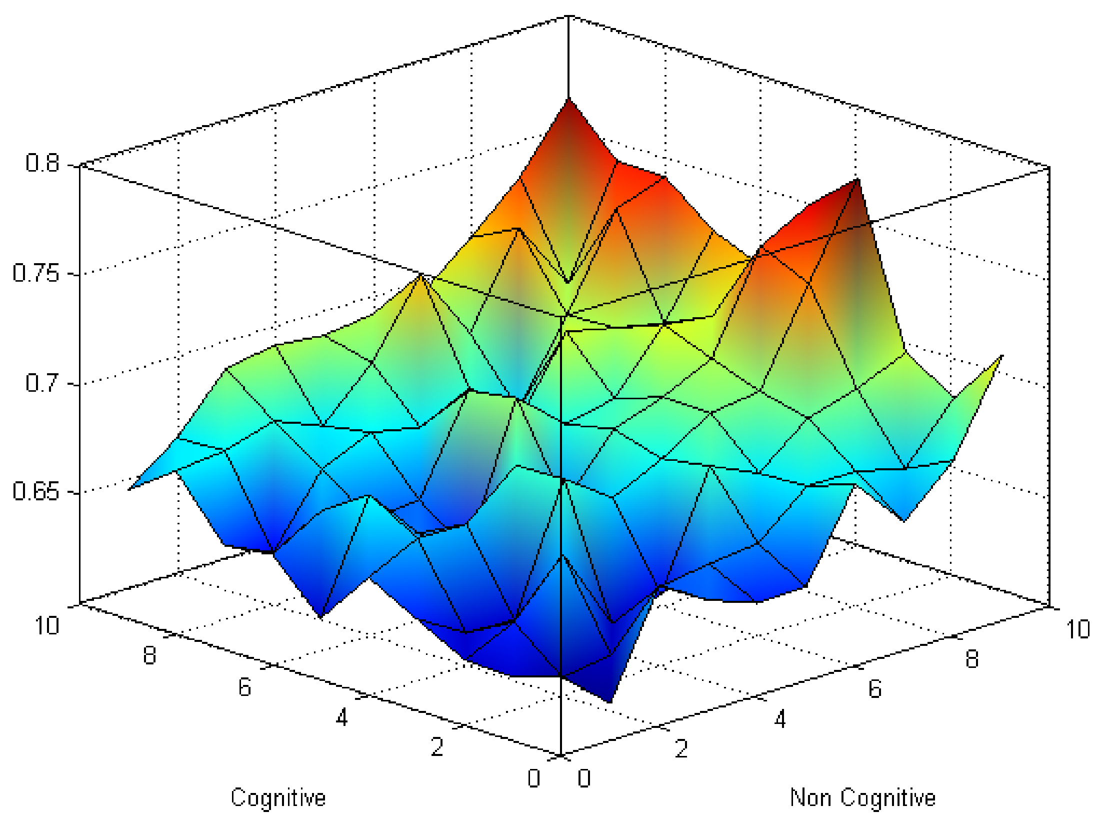
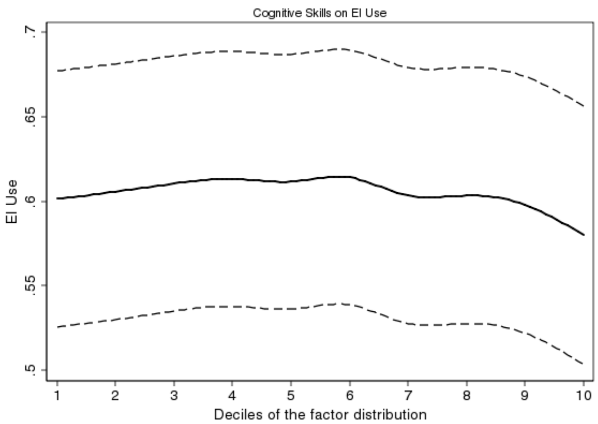
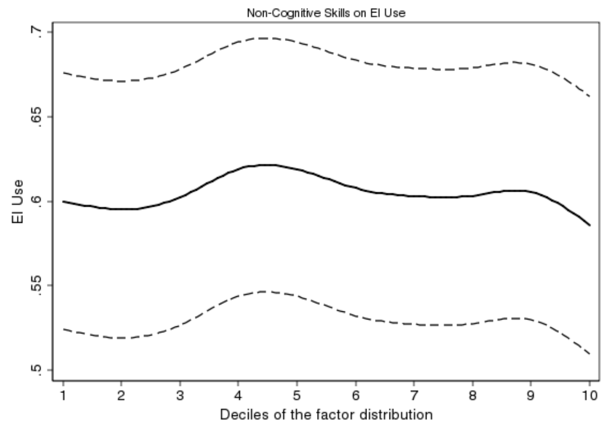


Figure 5: Overall Effects of Skills on Use of EI

(a) Cognitve Skills



(b) Non-Cognitve Skills



(c) Use of EI by Deciles of Cognitve Skills and Non-Cognitve Skills