One Size Does Not Fit All: Multiple Dimensions of Ability, College Attendance and Wages *

María Prada
University of Maryland

Sergio Urzúa
University of Maryland and NBER

This version: March, 2014

Abstract

This paper studies the role of multiple dimensions of ability on schooling choices and wages. We go beyond the conventional cognitive and non-cognitive taxonomy and show that individuals endowed with high levels of mechanical ability may be less likely to attend college. We estimate a Roy model with a factor structure that deals with the endogeneity of schooling decisions and their consequences on labor market outcomes. Using data from the NLSY79, we find that the probability of attending a four-year college increases by 22.9 and 2.4 percentage points after a one standard deviation increase in cognitive and socio-emotional ability, respectively. But a comparable increase in mechanical ability reduces it by 9.5 percentage points. On the other hand, all three dimensions have positive rewards on the labor market. The economic returns to cognitive and socio-emotional ability are considerably higher: 10.7 and 4.1 percent, respectively compared to 1.4 percent for mechanical ability. However, we find that for individuals with high levels of mechanical but low levels of cognitive and socio-emotional ability, not going to college is associated with higher expected hourly wage.

Keywords: Mechanical ability, Returns to skills, Unobserved heterogeneity.
JEL codes: J24, C38

*María Prada, University of Maryland, 3105 Tydings Hall, Office 3115, College Park, MD; 20852; email, prada@econ.umd.edu. Sergio Urzúa, University of Maryland, 3505 Tyding Hall Office 3115c, College Park, MD; 20852; email, urzua@econ.umd.edu. We have benefited from the discussion with Kasey Buckles, John Ham, Judy Hellerstein, Melissa Kerney, Patrick Kline, Karthik Muralidharan, Nathaniel Baum-Snow and Kenneth Chay. We thank participants at the Seminar in Brown University, ASSA 2014, the Conference on "Skills, Education and Labor Market Outcomes Employment, Productivity and Skills" (LACEA Labor Network); the Workshop for the World of Labor Jobs Knowledge Platform at the World Bank; UMD-WB Conference in Applied Microeconomics; and seminars in University of Notre Dame, Universidad de los Andes (Colombia), Universidad de Chile, and LACEA 2013. This paper was prepared, in part, with support from a Grand Challenges Canada (GCC) Grant 0072-03, though only the authors, and not GCC or their employers, are responsible for the contents of this paper.

1 Introduction

The importance of cognitive and socio-emotional ability in explaining schooling attainment and labor market outcomes has received considerable attention in the literature. Over the last decades, several studies have found that these abilities affect a number of outcomes. In particular, studies have shown that both types of abilities *positively* affect the acquisition of skills and education as well as market productivity as measured by wages. (See Cawley et al., 2001; O'Neill, 1990; Neal and Johnson, 1996; Herrnstein and Murray, 1994; Bowles et al., 2001; Farkas, 2003; Heckman et al., 2006; Urzua, 2008, among others).

But ability is multidimensional in nature and thus, it is reasonable to expect that other dimensions may also affect schooling decisions and labor market outcomes. In fact, economists have recognized that the multidimensionality of ability must be at the "center stage of the theoretical and empirical research on child development, educational attainment and labor market careers" (Altonji, 2010). Also, recent studies in economics, psychology, and other social sciences have been exploring the different components of socio-emotional ability, generally in the form of personality traits (Borghans et al., 2008; Heckman and Kautz, 2013), but less consideration has been given to the exploration of other facets, especially those that might be related to cognition.

This paper investigates a dimension of ability that has been overlooked by economists when analyzing schooling decisions and labor market outcomes. This dimension is related to motor skills, visual motor integration, and potentially to manual dexterity. We label it "mechanical ability".[1]

To analyze the empirical importance of this ability - jointly with the conventional dimensions -, we implement a Roy model of self-selection into college and counter factual adult wages with unobserved heterogeneity. This framework is similar to the setup analyzed in Carneiro et al. (2003) and Heckman et al. (2006), so we follow their identification strategy. In particular, we augment the Roy model with a set of proxy measures containing multiple test scores (measurement system) from which we identify the distribution of a three-dimensional vector of latent abilities: cognitive, socio-emotional and mechanical.

We contribute to the literature by documenting that mechanical ability matters. We show that

[1]Other papers have studied the importance of aspects connected to the idea of "mechanical ability", and their association with labor market outcomes (see for example Hartog and Sluis, 2010; Yamaguchi, 2012; Boehm, 2013, among others). However, this literature does not simultaneously analyze multiple abilities, schooling decisions and labor market outcomes.

it affects schooling decisions and labor market outcomes differently than other measures of ability. In particular, using data from the National Longitudinal Study of Youth of 1979 (NLSY79), we show that, like cognitive and socio-emotional abilities, mechanical ability has a positive economic return, but in contrast to conventional dimensions, it predicts the choice of low levels of schooling. In particular, it reduces the probability of attending four-year college. In this context, this dimension expands the set of abilities explaining differences in human capital and wages in the population.

To identify this ability, we utilize a set of questions from the Armed Services Vocational Aptitude Battery (ASVAB) that has been historically used by the military to determine qualification for enlistment in the United States armed forces. But despite its popularity, only a subset of these questions has been investigated in the literature: the battery of tests used to calculate the Armed Forces Qualification Test (AFQT) score, which is commonly interpreted as a proxy for cognitive ability. This paper highlights the importance of the technical composites of the ASVAB to capture a different dimension of ability.

Our study provides insight into the schooling choices and earnings of individuals conventionally classified as low-ability, but who might be endowed with a high level of mechanical ability. We present evidence that for them, not going to college implies a higher expected hourly wage compared to the expected hourly wage associated with college attendance. This has important implications for public policies promoting general enrollment in four-year colleges.

The paper has six sections. The second section describes mechanical ability and discusses the test used to identify it. The third section describes the data used, explores the relation between of measure of ability and conventional measures, and presents reduced-form estimates of the implied effect of mechanical ability on schooling choices and wages, both unconditional and conditional on conventional observed measures of cognitive and socio-emotional ability. Section four contains the details of our augmented Roy model and the estimation strategy. Section five presents the main results. Section six presents a discussion of the implication of our results. Section six concludes.

2 Beyond Conventional Taxonomy: Mechanical Ability

A large fraction of the literature on the effect of ability on schooling, labor market outcomes, and social behaviors has concentrated on cognitive skills: brain-based skills that are related to the mechanisms behind learning, remembering, problem-solving, and paying attention. In recent years, this literature has successfully incorporated socio-emotional abilities (e.g., persistence, grit, self-control, self-esteem) into the analysis. For example, Heckman et al. (2006) presents strong evidence of the importance of personality traits in explaining economic outcomes and a range of social behaviors. The same traits had already been linked to economic behavior by sociologists and psychologists (see, e.g. Bowles and Gintis, 1976; Edwards, 1976; Jencks, 1979; Wolfe and Johnson, 1995, among many others).

However, there might be other potential dimensions of ability determining, for example, human capital accumulation and labor market productivity. Indeed, common sense suggests that motor, manual dexterity, or even physical abilities may give an advantage to individuals in the labor market, specially if they are employed in certain occupations. We study a dimension of ability related to these aspects and label it mechanical ability. We borrow the name from the set of ability measures (test scores) available in our data, although we recognize that previous work has used a similar terminology.

But beyond its name, defining mechanical ability is a complex task. Cognitive and vocational psychologists as well as neuroscientists have utilized concepts such as mechanical aptitude, mechanical reasoning, and mechanical sense to describe this dimension.[2] Nevertheless, two distinctive components emerge from multiple definitions of mechanical ability. The first component, commonly named mechanical reasoning, is related to the ability to perceive and understand the movement or function of a mechanism either from interacting with it or by observing the mechanism. The second component is related to the ability to describe a mechanism that when, given some specified input, will produce a desired output (Blauvelt, 2006).

On the empirical side of this literature, the rising of the field of industrial psychology has fueled the interest in identifying the underlying traits leading to success in specific careers and occupations.[3] On the other hand, the recent research on cognitive analysis, conducted by cognitive psychologists, has focused on understanding how people reason mechanical devices and concepts. More specifically, this research has provided insights into how the brain acquires, processes, and uses

[2]See Blauvelt (2006) for a detailed literature review.

[3]Studies from vocational psychologists emerged early in the twentieth century Stenquist (1923), Cox (1928), Paterson et al. (1930). In particular, Cox (1928) and Paterson et al. (1930) were interested in finding a special mechanical intelligence which was separate from and complementary to Spearman's general intelligence quotient Spearman (1923).

information about mechanisms and machines.[4] This explains why most of the literature seeking to define mechanical ability focuses on the identification of rules used by the individuals to accomplish these tasks and to account for individual differences in performance.[5] The main abilities identified by these types of studies relate directly to visual-motor integration and the visuospatial reasoning factors of spatial perception and spatial visualization (Hegarty et al., 1988; Carpenter and Just, 1989; Hegarty, 1992).

In economics, the few attempts trying to understand the role of mechanical abilities have examined its predictability power over schooling and labor market outcomes. Willis and Rosen (1979) included mechanical scores and manual dexterity test in their study of the decision of going to college, obtaining that these dimensions reduce the probability of pursuing a college degree. Our results are consistent with this unexplored finding, although they are not fully comparable given the differences in sources of information and empirical approaches between the two papers. Yamaguchi (2012) on the other hand, computes a measure of motor skills in his analysis of occupational choices throughout the life cycle. He finds that motor skills explains a large fraction of the observed wage variance and also a large fraction of wage growth but only for high school dropouts.[6] In addition, Hartog and Sluis (2010), Boehm (2013), and Prada (2014) use a measure of mechanical ability similar to the one analyzed below to study the characteristics of entrepreneurs, the sorting into middle skill occupations affected by polarization, and early occupational choices, respectively.

The line of research started by Autor et al. (2003) has influenced these recent papers. In particular, the literature on task and skill content of jobs has provided a theoretical foundation for the analysis of the heterogeneity of worker's talent and the relationship with the variety of tasks required in the labor market. Mechanical ability can loosely be related with the type of skill needed to perform manual work that is intensively carried out by middle-education occupations (Prada, 2014).

By analyzing the role of mechanical, cognitive and socio-emotional ability in the context of a

[4]Most of the research from cognitive psychologists was produced during the 1980's Hegarty et al. (1988), Hegarty (1992), Carpenter and Just (1989), Heiser and Tversky (2002) to name a few. Studies from neuroscientist concentrate in more specific abilities such as spatial visualization, spatial orientation, visual-motor integration, motor abilities and the like.

[5]And in consequence to investigate the processes that distinguish people who score high or low in psychometric tests of mechanical ability.

[6]It is important to note that the author does not take into account the endogeneity of the schooling decision and thus it is difficult to separate the effect through selection from the productivity effect.

schooling decision model with counter factual adult wages, we continue and extends the previous literature.

ASVAB: Technical Composites

The Armed Services Vocational Aptitude Battery (ASVAB) is a general test measuring knowledge and skills in the following areas: arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, numerical operations, coding speed, general science, auto and shop information, electronics information, and mechanical comprehension.[7]

The literature has extensively analyzed the ASVAB, but typically focusing on the computation of the Armed Forces Qualification Test (AFQT). This test is used by the military services to determine basic qualification for enlistment, and its test score has been widely used as a measure of cognitive skills in economics (see, e.g. Cameron and Heckman, 1998, 2001; Ellwood and Kane, 2000; Heckman, 1995; Neal and Johnson, 1996; Heckman and Kautz, 2013, among many others).

To measure mechanical ability we use the following three sections of the ASVAB, commonly referred as the Technical Composites: the mechanical comprehension, auto and shop information, and electronics information sections. These sections are not used to compute the AFQT; instead, they are designed exclusively to compute the Military Occupational Specialty (MOS) scores.[8]

The questions from the *mechanical comprehension* section measure the ability to solve simple mechanics problems and understand basic mechanical principles, and represent one of the most widely used test measuring mechanical ability. They deal with pictures built around basic machinery such as pulleys, levers, gears, and wedges and ask to visualize how the objects would work together. People who understand mechanical devices can infer the principles of operation of an unfamiliar device from their knowledge of the device's components and their mechanical interactions (Carpenter and Just, 1989).

Moreover, the questions also cover topics such as how to measure the mass of an object, identify simple machines, and define words such as velocity, momentum, acceleration, and force. Some questions ask about the load carried by people or by support structures such as beams or bridges.

[7] The ASVAB is administered by the United States Military Entrance Processing Command and it is used to determine qualification for enlistment in the United States Armed Forces.

[8] The scores on these sections are used by the military to determine aptitude and eligibility for training in specific career fields within the military. Military career areas that require high scores on these three sections of the ASVAB include combat operations, general maintenance, mechanical maintenance, and surveillance and communications.

For example, after showing a diagram with support structures, the question typically asks which one is the strongest or the weakest, or which support in the diagram is bearing the lesser or greater part of the load. Many of the problems require basic mathematical skills such as knowledge on how to divide, work with decimals, and multiply two digit numbers.

The questions from the other two sections are similar to the mechanical section in that they require the ability to understand how objects work, but in the context of automotive and shop practices and electronics.

The *automotive and shop information section* measures technical knowledge, skills, and aptitude for automotive maintenance and repair and for wood and metal shop practices. The test covers the areas commonly included in most high school auto and shop courses, such as automotive components and requires an understanding of how the combination of several components work together to perform a specific function. It also includes questions on types of automotive and shop tools, procedures for troubleshooting and repair, properties of building materials, and building and construction procedures.

The *electronics information section* requires additional knowledge of the principles of electronics and electricity. For example, knowledge of electric current, circuits, how electronic systems works, electrical devices, tools, symbols, and materials is tested. Many of the topics covered in this section are probably covered in high school science classes.[9]

Although the questions answered by the respondents of the NLSY79 are not available, in Figure 1, we present sample questions obtained from the mechanical comprehension section. The two other sections are similar but they include topic specific terms and devices.[10]

The technical composites of the ASVAB have been proven to measure abilities and skills important to predict membership, training success, satisfaction, and job performance in the following career fields within the military: combat operations, general maintenance, mechanical maintenance, and surveillance and communications (Welsh et al., 1990; Wise et al., 1992). Furthermore, according

[9] An obvious concern for our identification strategy is the potential association between the *automotive and shop information* and *electronics information* sections and the material covered in specific classes during high school. This could potentially generate double causality between human capital accumulation and abilities. We follow Hansen et al. (2004) and deal with this potential source of bias by restricting our analysis to the youngest cohort of individuals in the sample as well as by controlling for the highest grade attended by the time of the test. We describe this strategy bellow. In addition, we analyze a small subsample of males for which we have high school transcript information, so we can confirm that they have not taken any elective course related to mechanical skills at the time of the tests. Our results are qualitatively the same.

[10] We present a list of sample questions for the three sections in the appendix.

to Bishop (1988), the universe of skills and knowledge sampled by the mechanical comprehension, auto and shop information, and electronics subtests of the ASVAB roughly corresponds to the vocational fields of technical, trades and industry measured in occupational competency tests. [11] As a consequence, the three subtests of the ASVAB are interpreted as indicators of competence in these areas. All in all, the Technical Composites of the ASVAB should be viewed as measures of knowledge, trainability, and generic competence for a broad family of civilian jobs involving the operation, maintenance, and repair of complicated machinery and other technically oriented jobs (Bishop, 1988).

3 Data and Exploratory Analysis

We now turn to the description of our source of information, a brief discussion of the measure of mechanical ability in comparison with conventional measures of ability, and the reduced-form estimates of the effect of mechanical ability on schooling choices and wages both unconditional and conditional on standard measures of ability. The insights from the descriptive analysis are used in two ways: to document that mechanical ability is correlated with schooling decisions differently than standard measures of ability, and to motivate the use of a model to capture the effect of mechanical ability overcoming the main problems associated with the reduced-form estimates.

3.1 Data

The National Longitudinal Survey of Youth (NLSY79) is a panel data set of 12,686 individuals born between 1957 and 1964.[12] This survey is designed to represent the population of youth aged 14 to 21 as of December 31 of 1978, and residing in the United States on January 1, 1979. It consists of both a nationally representative cross-section sample and a set of supplemental samples designed to oversample civilian blacks, civilian Hispanics, economically disadvantaged Non-Black/ Non-Hispanic youths, and individuals in the military. Data is collected in an annual basis from 1979 to 1994 and biannually until present day.

We use the cross-section sample of white males between the ages of 25 and 30 who were not

[11] Notable examples of occupation specific competency examinations are those developed by the National Occupational Competency Testing Institute and by the states of Ohio and New York to assess the performance of their high school vocational student. See Bishop (1988) for more detail.

[12] 2,439 white males-21 percent of total surveyed individuals and 40 percent of the individuals in the cross-sample.

attending school at the time of the survey and who were, at most, high school graduates at the time of the tests used to measure ability were collected (Survey of 1979 and the summer 1980). We chose to analyze white males in order to have a benchmark to compare our results with previous studies (Heckman et al., 2006; Neal and Johnson, 1996, etc). In addition, we want to abstract from influences that operate differently on various demographic groups. In consequence, our analysis is specific and cannot be generalized to the whole population.

The age selection responds to the interest of analyzing entry level wages abstracting from the cumulative effects of ability on experience and tenure. By the age of 25, more than 97 percent of the sample has reached their maximum level of education. The five-year window is useful to get a smooth average of the first part of the wage profile of the individuals.

From the original sample of 12,686 individuals, 11,406 are civilian, 6,111 belong to the cross-section sample. Nearly 49 percent of that sample are males (2,438 individuals), 1,999 had less than high school complete by the time the ASVAB test was conducted (Summer 1980) , out of them just 1,832 individuals are observed at least once between the ages of 25 and 30 and finally, 1,710 were not attending school by the time the survey was conducted. That sample is further reduced for the analysis according to the variables of interest. We got rid of 244 observations that either are high school dropouts or have no information on schooling. We ended up with a sample of 1,466 individuals. Table 2 presents the description of the variables used.

[Table 2 here]

We analyze one schooling choice, 4 year college attendance. The variables used to determine college attendance are maximum degree attained by the age of 25 and type of college enrolled. The labor market outcome analyzed is the log of the average of the hourly wages reported between 25 and 30 years old.

For the cognitive and mechanical measures we rely on the (ASVAB) that was conducted in the summer and fall of 1980[13]. This questions are used to compute the AFQT that is used by the military services for enlistment screening and job assignment within the military. This test was administrated to over 90 percent of the members of the NLSY panel (individuals were between 15 and 23 years old at the time of the test). The test is composed by a battery of 10 questions

[13]These questions are used to compute the AFQT that is used by the military services for enlistment screening and job assignment within the military.

measuring knowledge and skills in the following areas: arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations, coding speed, mathematics knowledge, general science, auto and shop information, mechanical comprehension, and electronics information. The first 6 are used as measures of cognitive ability while the last 3 are measures of mechanical ability.

For measures of socio-emotional ability we use two tests: the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale. The Rotter Locus of Control Scale measures the degree of control individuals feel they possess over their life[14]. In 1979 the NLSY collected a total of four items selected from the 23-item forced choice questionnaire adapted from the 60-item Rotter Adult I-E scale developed by Rotter (1966). As presented in the NLSY79 documentation: "This scale was designed to measure the extent to which individuals believe they have control over their lives through self-motivation or self-determination (internal control) as opposed to the extent that the environment (that is, chance, fate, luck) controls their lives (external control). The scale is scored in the external direction-the higher the score, the more external the individual".[15]

The Rosenberg Self-Esteem Scale, which is based on 10 questions, measures self-esteem: the degree of approval or disapproval towards oneself (Rosenberg, 1965). The scale is short, widely used, and has accumulated evidence of validity and reliability. It contains 10 statements of self-approval and disapproval with which respondents are asked to strongly agree, agree, disagree, or strongly disagree. The scale has proved highly internally consistent, with reliability coefficients that range from .87 (Menaghan, 1990) to .94 (Strocchia-Rivera, 1988), depending on the nature of the NLSY79 sample selected."[16].

3.2 Measurement of Mechanical Ability in Perspective

In order to establish the relationship between our measure of mechanical ability and standard measures of ability, we show the correlation between the different tests. We also present the results from an Exploratory Factor Analysis that confirms the presence of one factor that is captured by the technical composites, but it is not captured by the other tests.

Table 1 shows the correlation matrix between the three technical composites of the ASVAB (Auto and shop information, mechanical comprehension, and electronics information), six tests used

[14] These measures have been used in the literature as proxies of socio-emotional ability (Heckman et al., 2006)
[15] Extracted from http://www.nlsinfo.org/nlsy79/docs/79html/79text/attitude.htm
[16] Ibid.

to compute AFQT (arithmetic reasoning, word knowledge, paragraph comprehension and math knowledge), the computed AFQT, and a composite measure of socio-emotional ability computed using Rosenberg Self-Esteem Scale and the Rotter Internal Locus of Control Scale. The three technical composites of the ASVAB are highly correlated with the scores in the questions used to compute AFQT, between 0.24 and 0.66, but present a low correlation with a standard measure of socio-emotional ability, between 0.18 and 0.21.

[Table 1 about here]

This is consistent with modern psychological theory which views ability as multidimensional with dimensions that are positively correlated with each other (Dickens, 2008). The positive correlation across abilities could be a manifestation of a general ability, sometimes referred to as the "Spearman g" or g-factor Spearman (1904), or could be the result of overlap in the knowledge required to answer the different tests[17].

Further analysis of the correlation among the variables used to create AFQT and the technical composites highlights the presence of two different components. The results form an Exploratory Factor Analysis (EFA) on the nine subsections of the ASVAB (the three technical composites plus the four set of questions used to create the AFQT) confirm that at least two factors are needed to explain the correlation among the scores in the nine questions.[18]

[Figure 2 about here]

All the loadings corresponding to the first factor are positive and statistically significant, they range between 0.62 and 0.83. In contrast, the loadings for the second factor differ between the questions used to compute the mechanical ability measure and the questions used to compute AFQT. More specifically, for the three tests used to construct the mechanical measure the loadings are high and statistically significant, they range between 0.31 and 0.48 but for the rest of the tests,

[17] More specifically, it could be explained by the fact that all the questions in the three composites of the ASVAB require a certain degree of reading or verbal comprehension or that many of the problems require basic mathematics skills.

[18] In addition, the factor analysis assuming orthogonal factors and allowing for some unique components in the equation keeps the four first factors, because the default criteria is to keep all the factors with positive eigenvalues. The eigenvalue for the first factor is 4.75 and 0.80, 0.22 and 0.17 for the next three factors. The first two factors account for all the shared variance, 85 percent the first and 15 percent the second, so we focus only on them.

the loadings are close to zero.[19]. Panel a) in Figure 2 presents the original estimated loadings.

The results from the EFA suggest a structure where the first factor is important to linearly reconstruct all questions but the second factor is only relevant for the three technical composites of the ASVAB. Figure 2 presents the estimated loadings for each factor, i.e., the estimated coefficients associated with each factor. The suggested structure persists also after several forms of rotation.[20]

In this context, the first factor is capturing all the common information that is expressed by the high positive correlation among the tests and the second factor captures the additional component that makes the three tests used to measure mechanical ability different from the AFQT.

We assume that the first factor, shared by all components of the ASVAB, is measuring cognitive ability. This factor affects the three technical composites of the ASVAB because several questions require a certain degree of reading or verbal comprehension and basic mathematics skills associated with cognitive ability. The second factor, which is only present for the technical composites, may be related to mechanical ability. The part of ability that is related to understanding how things work but it is not captured by the AFQT. We incorporate this ideas in our empirical model. See section 4 for more details.

If we want to describe a trilogy of abilities that are rewarded in the labor market we can say that cognitive abilities capture *conceptual and thinking skills*, while socio-emotional/socio-emotional skills capture human relations skills ,*people skills* and mechanical would be more related to technical skills *how-to-do-it skills*.

3.3 Distributions

The tests are used to create a composite measure for each type of ability. For cognitive ability the measure is constructed using an average of the standardized scores for arithmetic reasoning, mathematical knowledge, paragraph comprehension, word knowledge, numerical operations, and coding speed. For socio-emotional ability the measure is created as the sum of the average of Rotter and Rosenberg scores. Finally, mechanical ability measurement is constructed as the average of

[19]Numerical Operations is an exception because the laoding for the second factor is highly negative (-0.38). The magnitude of the loading is critical because any factor loading with an absolute value of .30 or greater is considered significant (Diekhoff, 1992; Sheskin, 2004, among others)

[20]Rotation is important because of the indeterminacy of the factor solution in the exploratory factor analysis. In panel b) of Figure 2 we present the loadings after a rotation made to maximize the variance of the squared loadings between variables (simplicity within factors).

the standardized scores in mechanical comprehension, electronics information, and auto and shop information.

We are mainly interested in the sorting implied by each measure of ability. Figures 3 and 4 show the cumulative distribution function (cdf) of each measure by schooling choice. For all three measures of ability, the cdf for people with high education stochastically dominates the cdf curve for people with low schooling. As a consequence, people that score higher in these measures of ability tend to sort into high levels of education.

This result is not surprising but in the next section we show that when we control for all three measures, mechanical ability implies a different and interesting behavior, the one that motivates this paper.

[Figure 3 about here] [Figure 4 about here]

3.4 Reduced-form Effect on Schooling Choice

To analyze the effect of the mechanical tests on schooling choices we estimate a probit model for the probability of attending 4-year college. All regressions include a set of family background controls, cohort dummies and dummies for region and urban location.

The unconditional effect of the mechanical test on college attainment is positive as it is the effect of cognitive ability, but the magnitude is smaller. Analyzing the marginal effects evaluated at the mean (MEM) presented in Table 3 (columns 1 and 2) both cognitive and mechanical tests show a similar pattern in terms of the positive impact on schooling attainment but the effect of AFQT more than doubles of the effect of the measure of mechanical ability.

This result is expected given the sorting implied by the distribution of each measure of ability (scores in the tests) as presented in figures 3 and 4.

But controlling for AFQT, the effect of the mechanical test on educational attainment is reversed. In particular, the marginal effects evaluated at the mean (MEM) presented in column 3 show that once cognitive and socio-emotional scores are taken into account, one standard deviation increase on the mechanical test decreases the probability of attending a 4-year college in 6.23 percentage points. While the same increase on the cognitive test increases college attendance by 20.6 percentage points. This effect is large considering that in the sample the probability of attending college is 29 percent and the predicted probability at the mean of the observed variables is 22.6.

[Table 3 about here]

3.5 Reduced-form Effect on Hourly Wages

Analyzing hourly wages, the return to the score in the mechanical measure is positive and high, even when compared to the return to AFQT In particular, controlling for education, one unit increase in the mechanical test is associated with a 3,58 percent increase in the level of hourly wages. The effect is even bigger than the effect of socio-emotional test scores, although less precise. The effect of the cognitive test on wages is more than twice this value.

[Table 4 here]

So far, the regressions show that mechanical abilities are rewarded by the labor market but imply a different behavior. Those regressions are problematic because 1) schooling choices are endogenous and that must be controlled for if to estimate the returns to unobserved heterogeneity and 2) Test scores are just proxies of abilities and they are influenced by schooling, age and family background variables. The next section presents the model proposed to measure more accurately the effect of mechanical ability.

4 Augmented Roy Model with Factor Structure

The model presented in this section deals with two of the main problems that arise when computing the effect of latent pre-labor market abilities on occupation and wages: the endogeneity of both schooling and occupational choices and the fact that test scores are just proxies for abilities and they are influenced by schooling, age, and family background variables.

The strategy pursued in this paper is based on a model that integrates schooling decisions and wages. The model proposed follows and extends the models presented in Heckman et al. (2006) and Urzua (2008) where a vector of low dimensional factors is used to generate the distribution of potential outcomes. In the spirit of this literature, we model cognitive and socio-emotional abilities, to which we add mechanical. Furthermore, we allow mechanical and cognitive abilities to be correlated. These latent abilities produce measured cognitive, socio-emotional, and mechanical scores and the rest of the outcomes analyzed. Conditioning on observables, these factors account for all of the dependence across choices and outcomes.

The theoretical model is static and does not consider the exact timing of the decisions. As a result, the schooling choice model is evaluated when individual is 25 years old. Agents choose their maximum level of schooling before the age 25 given the information they have at the time. 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 how they affect the potential earnings in each education level. The agent compares the potential outcomes across each feasible choice and chooses the alternative that yields the highest payoff.

Each of the components of the model will be presented in a separate subsection. The model estimated uses one schooling choice (attending a four-year college or not), 3 factors (the three dimensions of ability), 6 cognitive tests, 3 tests on mechanical ability, and 2 tests on socio-emotional abilities.

4.1 Model of Schooling Choice

The latent utility of getting education is given by:

$$D = \mathbf{1}[I_i > 0]$$

$$I_i = X_i\beta + \lambda_D^c\theta_{c,i} + \lambda_D^m\theta_{m,i} + \lambda_D^s\theta_{s,i} + e_i \text{ for } i = 1, ...N$$

$$e_i \sim N(0, 1)$$

where X_i is a matrix of observed variables that affect schooling, β is the vector of coefficients. $\theta = [\theta_{c,i}, \theta_{m,i}, \theta_{s,i}]$ is the vector of latent abilities where subscript c is used to denote the cognitive ability, subscript m denotes mechanical ability and subscript s denotes socio-emotional ability. $\lambda_D^c, \lambda_D^m, \lambda_D^s$, the vectors of returns to these abilities. These coefficients are referred in the literature as the factor loadings. e_i is the error component that is assumed to be independent of X_D, θ and following a standard normal distribution. Then D denotes a binary variable that takes the value of 1 if the individual chooses to attend a 4-year college and 0 otherwise.[21]

[21]Through all the exposition the indicator function will be used, $\mathbf{1}[]$ this function takes a value of one if the condition inside the parentheses is satisfied.

Conditional on X and θ the equations produce a standard discrete choice model with a factor structure. Furthermore, given the set of assumptions exposed, this can be interpreted as the standard probit model.

4.2 Model of Hourly Wages

Analogously, the model of earnings can be expressed as a linear function of $X_{w,i}$ and θ in the following way:

$$\ln w_{D,i} = X_{w,i}\beta_{w,D} + \lambda^{c}_{w,D}\theta_{c,i} + \lambda^{m}_{w,D}\theta_{m,i} + \lambda^{s}_{w,D}\theta_{s,i} + e_{w,D,i}$$

$$e_{w,D,i} \sim N(0,1)$$

for $D = \{0, 1\}$.

4.3 Model of Test Scores: Measurement System

Motivated for the findings of the Exploratory Factor Analysis performed in Section 3 the model of test scores allow each measurement to be a function of the corresponding latent ability. For the mechanical tests we allow them to be a function of both cognitive and mechanical latent factors.

In this context, the model for the cognitive measure C_j is:

$$C_{j,i} = X_{C_j,i}\beta_{C_j} + \lambda^{c}_{C_j}\theta_{c,i} + e_{C_j,i}$$

for $j = \{1, ..., 6\}$.

The model for the mechanical measure M_l is:

$$M_{k,i} = X_{M_k,i}\beta_{M_k} + \lambda^{c}_{M_k}\theta_{c,i} + \lambda^{m}_{M_k}\theta_{m,i} + e_{M_k,i}$$

for $k = \{1, ..., 3\}$.

And the model for the socio-emotional measure S_l is:

$$S_{l,i} = X_{S_l,i}\beta_{S_l} + \lambda^{s}_{S_l}\theta_{s,i} + e_{S_l,i}$$

for $l = \{1, 2\}$.

Finally, all error terms $\{e_i, e_{w,D,i}, e_{C_1,i}, ..., e_{C_6,i}, e_{M_1,i}, ..., e_{M_3,i}, e_{S_1,i}, e_{S_2,i}\}$ for $D = \{0,1\}$, $j = \{1, ..., 6\}$, $k = \{1, ..., 3\}$ are mutually independent, independent of the factors and independent of all observable characteristics. This independence is essential to the model since it implies that all the correlation in observed choices and measurements is captured by latent unobserved factors.

4.4 Latent Factors

The observed level of these latent factors may be the result of some combination of inherited ability, the quality of the family environment in which individuals were raised, cultural differences, etc. These factors are assumed to be fixed by the time the individual is choosing the level of education and thus, by the time the labor and behavioral outcomes considered in this document are determined. In addition, the factors are assumed to be known by the individual but unknown to the researcher. Following standard conventions it is assumed that cognitive and mechanical factors are independent to the Socio-emotional factor while cognitive and mechanical can be correlated.

A mixture of normals is used to model the distribution of the latent abilities. This distribution is selected because as Ferguson (1983) proved, a mixture of normals can approximate any distribution and we want to impose the minimum number of restrictions on the distribution of these unobserved components.

In this case, we use mixtures of two normal distributions (i.e., $K = J = L = 2$) and assume $E[\theta_c] = E[\theta_m] = E[\theta_s] = 0$. Finally, we impose $(\theta_c, \theta_m) \perp \theta_s$. For more details on this and the identification strategy refer to Appendix 2.

4.5 Estimation Strategy

Let $T_i = \{C_{1i}, ..., C_{6,i}, M_{1i}, ..., M_{3,i}, S_{1i}, S_{2,i}\}$ be the vector of test scores for individual i, $X_{T,i} = \{X_{C,i}, X_{M,i}, X_{S,i}\}$ and $\theta = [\theta_c, \theta_m, \theta_s]$ the vector of the latent factors and δ the vector of all the parameters of the model. Thus, our likelihood function is:

$$L(\delta|X) = \prod_{i=1}^{N} f(D_i, \ln w_{D,i}, T_i | X_i, X_{w,i}, X_{T,i})$$

Given that conditional on unobserved endowments all the errors are mutually independent, our likelihood can also be expressed as:

$$L(\delta|X) = \prod_{i=1}^{N} \int_{\Theta} f(D_i, \ln w_{D,i}, T_i | X_i, X_{w,i}, X_{T,i}, \theta) dF(\theta)$$

The model is estimated using MCMC techniques. The use of Bayesian methods in this paper is merely computational to avoid the computation of a high order integral. In consequence, the interest is primarily on the mean of the posterior distribution. Thus, it is viewed from a classical perspective and interpreted as an estimator that has the same asymptotic sampling distribution as the maximum likelihood estimator. See Hansen et al. (2004) and Heckman et al. (2006) for more details.

5 Results

We first compare the distribution of the estimated factors with the observed distribution of the measurements. Then we summarize the main results of the model. Anticipating our main findings, we confirm the results obtained from the reduced-form estimates: Mechanical ability reduces the probability of seeking a professional degree and at the same time, it is positively rewarded in the labor market. We use simulations from our model to explore the implications of being low in the standard types of ability but having high levels of mechanical ability in terms of schooling choices and earnings.

5.1 Observed Test Scores and Estimated Abilities

This paper treats observed cognitive, socio-emotional, and mechanical test scores as the outcomes of a process that has as inputs family background, schooling at the time of the test and unobserved abilities. Here we present the estimated parameters of the distribution of unobserved abilities as well as the fraction of the variance of observed test scores that can be explained with and without the inclusion of unobserved abilities.

Table 5 presents the coefficients on unobserved abilities for each of the tests used. For identification purposes, one loading for each unobserved ability is set to one. The remaining loadings are interpreted in relation to the loading set as the numeraire (for details see Carneiro et al., 2003, and

Appendix 2). The selected numeraires are mathematics knowlegde, mechanical comprehension and the Rosenberg self-esteem scale for cognitive, mechanical and socio-emotional abilities, respectively.

[Table 5 about here]

To analyze the relative importance of each dimension of ability in explaining test scores, Figure 5 presents the variance decomposition of the measurement system. The results show the contribution of observed variables, latent abilities and error terms as determinants of the variance of each test score.

The variance decomposition illustrates the large size of the unexplained component and highlights the consequences of using observed test scores as proxies for unobserved abilities. The contribution of observed variables to the variance of the test scores is never more than 20 percent. After controlling for the latent variables, the error term is still large but we are able to explain a much higher percentage of the total variance, between 34 and 65 percent. The one exception is the Rotter Scale, where we are only able to explain 11 percent of the variance.

We allow both cognitive and mechanical abilities to influence mechanical test scores. While cognitive ability has lower loadings compared to mechanical ability (see Table 5), both abilities are important determinants of the variance in the observed scores[22].

[Figure 5 about here]

Distribution of Abilities

Observed test scores and unobserved abilities are different. In this section we use the estimated parameters for the distribution of each ability to estimate the distribution of cognitive, socio-emotional, and mechanical abilities. We show that the distribution of abilities is very different to the distribution of test scores. For mechanical ability, accounting for this difference is especially important as the implied sorting into schooling is completely different when using observed test scores. The mean and standard deviation of the simulated distribution for each ability are displayed in Table 6.

[22] In a model where mechanical test scores are explained by observed variables and only the cognitive factor, the fraction of the variance explained reduces to a third or two thirds of the fraction that is explained jointly by the two factors.

[Table 6 about here]

Figures 6 and 7 present the marginal cumulative distribution function (cdf) of the estimated factor by schooling for the cognitive and socio-emotional, and mechanical abilities respectively. For cognitive and socio-emotional ability (figure 6) the (cdf) of the ability for people that attended college stochastically dominates the cdf curve for those who did not. Although the distributions are different, the sorting into schooling is similar. In particular, for both observed test scores and unobserved abilities, the cdf for people with high education stochastically dominates the cdf curve for people with low schooling (see figure 3).

However, for mechanical ability the relationship is reversed. The distribution of the estimated factor implies that people with high levels of mechanical ability choose low education. The marginal cummulative distribution function (cdf) of the estimated ability for people that chose to attend four-year college is stochastically dominated by the cdf curve for those that did not attend college (see figure 7). As a consequence, for mechanical ability, the sorting implied by the estimated factor and the observed test scores is completely different in terms of schooling.

The sorting implied by the estimated factor explains why after controlling for the three scores in the reduced-form estimations, the coefficient of the composite mechanical test in the probit of college attendance changed its sign (see section 3).

[Figure 6 about here] [Figure 7 about here]

5.2 Effect of Abilities on Schooling Choice and Hourly Wages

Figures 8 to 13 present the main results of the model in terms of the outcomes of interest: a) the choice of attending a 4-year college and b) log hourly wages. We present two types of figures: joint distributions of the outcome variables by deciles of the factors and marginal effects of each factor on the outcomes of interest integrating out the effect of the other factors.

Figures 8 and 9 present the joint distribution of the probability of attending a 4-year college reported by deciles of cognitive and mechanical and by the deciles of socio-emotional and mechanical, respectively.

In the first case, the opposite effects of the abilities are evident but the positive effect of cognitive is always stronger. As an exercise, we can move along the distributions and compare the effect of increasing one decile on both cognitive and mechanical on the probability of going to college. Given that cognitive has a positive effect and mechanical a negative effect this exercise will show which effect prevails. Starting at the lowest extreme of both distributions (first decile of both cognitive and mechanical) and moving to the next decile of the distributions of both cognitive and mechanical abilities the estimated probability of going to college always increases.

A similar exercise on the distributions of socio-emotional and mechanical shows a very flat slope. This is a consequence of the correlation of mechanical and cognitive ability and the opposite effects of mechanical and socio-emotional ability (see Figure 9).

The marginal effect of cognitive ability integrating out the effect of mechanical is presented in panel a of Figure 10 while panel b and c present the analogous for socio-emotional and mechanical ability, respectively.

[Figure 8 about here]

[Figure 9 about here]

[Figure 10 about here]

Table 7 presents the effect on college attendance associated with a one standard deviation increase in each of the factors. According to the estimates, one standard deviation increase in cognitive ability is associated with an increase of 22.9 percentage points in the probability of attending 4-year college, the same increase in socio-emotional ability is associated with a 2.4 increase in the probability while one standard deviation increase in mechanical ability decreases the probability in 9.5 percentage points.

[Table 7 about here]

Figures 11 and 12 present the total effect of ability on log wages, including the direct effect of ability on log wages holding schooling constant, the effect of ability on the decision to attend college and the implied effect of attending or not college on log wages. The effect is positive for all three dimensions of ability.

[Figure 11 here]

[Figure 12 here]

The marginal effect of mechanical ability is considerable small compared with the effect of cognitive and also with the effect of socio-emotional ability (Figure 13). In fact, a one standard deviation increase in cognitive ability is associated with 10.7 percent increase in log hourly wages and 4.1 for socio-emotional ability while the average estimated effect of mechanical is 1.4 percent (see the last row of table 8).

[Figure 13 here]

[Table 8 about here]

The story changes when analyzing the returns to ability by college attendance. In the case of not attending a four-year college the returns to cognitive and mechanical ability are very close, 4.7 and 4.4 precent, respectively. While in the case of attending college the returns to cognitive ability are 10.8 percent compared to the -3.1 percent in the case of mechanical ability. For socio-emotional ability the difference in the returns is smaller although the returns are higher in the scenario of college attendance.

6 Discussion

In this section we analyze the implications of our results in terms of the wage gains asociated with college attendance for individuals with diferent ability profiles. In particular, we are interested in understanding the implications of having low levels of cognitive and socio-emotional ability but high levels of mechanical ability.

Using the estimates from the model we compute the difference between the mean of hourly wages conditional on the schooling choice and the respective counterfactual wage.

$$E[Y_0|D=0] - E[Y_1|D=0] = E[Y_0 - Y_1|D=0]$$

$$E[Y_1|D=1] - E[Y_0|D=1] = E[Y_1 - Y_0|D=1]$$

On average the mean of hourly wages conditional on college attendance is 10 percent higher than the respective counterfactual (i.e., the wage that would have been received if the individual had decided not attending to college). In contrast, conditioning on not attending college the mean of hourly wages is 3.8 percent lower than the mean of the counterfactual. These results would suggest that college is associated with higher wages even for individuals that, given their observable characteristics and latent abilities, decided not attending college.

But this average result does not hold for all individuals, particularly given the special behavior implied by mechanical ability. With this in mind, we investigate the gains of not attending college conditional on the decision of not attending, $E[Y_0 - Y_1|D = 0]$, for different ability profiles.

Table 10 presents the results using the quintiles of the distribution of ability to define specific profiles. The columns correspond to the bottom, middle and top quintiles of mechanical ability and the rows present four extreme ability profiles defined as a combination of different levels of cognitive and socio-emotional ability. The first row corresponds to the standard low ability profile, which means an individual in the lowest quintile of both cognitive and socio-emotional, the second row displays the low cognitive high socio-emotional profile (in the first quintile of the distribution of cognitive ability and 5th quintile of the distribution of socio-emotional ability), the third row presents the opposite case, high cognitive and low socio-emotional, and the fourth row presents the standard high ability type (highest quintile of the distribution of both cognitive and socio-emotional ability).

Given the high return to college education most of the cells in the table are positive. But for individuals in the highest quintile of mechanical ability, the conditional mean of hourly wages is higher than the alternative when the other two abilities are in the bottom of the distribution and also when cognitive is low and socio-emotional is high. This suggests that individuals with very high levels of mechanical ability but low levels of cognitive ability not going to college is associated with the highest expected hourly wage[23].

[Table 10 here]

Finally, we analyze the composition of the population that benefits from not going to college (22 percent of the population). Nearly 65 percent of those who benefit are individuals above the median of the distribution of mechanical ability summing up to 14 percent of the total population (See Figure 14).

[23] According to the estimated distributions of abilities close to 3.5 percent of the population are low cognitive, los socio-emotional and high mechanical ability.

[Figure 14 here]

Although the absolute percentages are useful, it is important to take into account that the amount of population in each specific profile varies. More specifically, the positive correlation between mechanical and cognitive ability would necessarily imply that the amount of population with high levels of both abilities is always higher that the amount of population with low levels of one and high levels of the other. Figure 15 shows that almost 40 percent of the individuals with low cognitive, low socio-emotional and high mechanical ability benefits from not going to college. That percentage decreases pregressively for the low cognitive-high socio-emotional, the high cognitive low socioemotional and the high cognitive and high socioemotional combinations. In consequence, nearly 28 percent of the individuals with high mechanical ability and 15 percent of the individuals with low mechanical ability would obtain a positive difference between the observed hourly wage and the counterfactual wage conditional on the decision of not attending college.

[Figure 15 here]

7 Conclusions

This paper investigates the role of mechanical ability in explaining schooling decisions and labor market outcomes. We show that this dimension of ability is positively rewarded by the labor market, but in contrast to the conventional facets of ability, it predicts the choice of lower levels of education. In particular, controlling for cognitive and socio-emotional aspects, mechanical ability reduces the likelihood of attending a four-year college. As a consequence, mechanical ability comes to enrich the set of factors explaining the observed disparities in schooling decisions and labor market outcomes.

But we do more than simply expand the range of empirically relevant dimensions of abilities. In fact, by including mechanical ability in the analysis we alter the dichotomous paradigm of low and high ability individuals in the context of the previously accepted symmetry of the impact of abilities on schooling decisions and labor market productivity.

Our results suggest a new framework where individuals with low levels of cognitive and socio-emotional ability, may have high mechanical ability and greatly benefit from it. More precisely, we find that despite the high return associated with college attendance, these individuals could expect higher wages by choosing not to attend a four-year college. This conclusion is a direct result of the high returns to mechanical ability in jobs not requiring a four-year college degree which contrast with the negative returns to mechanical ability in jobs requiring it.

The results from our empirical model highlight the importance of moving beyond the "one-size-fits-all" college discourse and explore alternative pathways to successful careers for individuals with a different profile of skills. This message is particularly relevant in a nation where less than half of the students attempting to get a bachelor's degree actually get one and where completion rates are below 20 percent for students who score low in standardized achievement tests during high school[24]. Accepting the multidimensional nature of ability must be accompanied by the implementation of inclusive human capital development strategies with more than one pathway to success.

As a final note, this article leaves some important areas for extensions and future research. First, the analysis of wage growth and the comparison between initial versus late returns to skill. There are many reasons to expect a lower wage gradient for skills in early career spans and the current model does not account for that. Second, it would be useful to incorporate experience and some specific connection between schooling and occupations. Third, it would be interesting to extend the model to analyze gender and race disparities.

[24]NCES (2013) and Rosenbaum et al., 2010.

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8 Tables and Figures

Table 1: Correlation of the Technical Composites of the ASVAB with Tests Used to Create AFQT (cognitive) and a Composite Measure of socio-emotional

	Auto	Mech	Elect	AFQT	Arith	Coding	Math	Word	Parag	Num	SocioE
Auto	1.00										
Mechanical. C	0.68	1.00									
Electronics	0.69	0.70	1.00								
AFQT	0.49	0.64	0.66	1.00							
Arithmetic K.	0.45	0.62	0.59	0.87	1.00						
Coding S.	0.32	0.42	0.40	0.76	0.54	1.00					
Math	0.31	0.53	0.51	0.85	0.78	0.54	1.00				
Word K.	0.56	0.61	0.71	0.83	0.66	0.50	0.62	1.00			
Paragraph C.	0.48	0.58	0.62	0.84	0.67	0.53	0.63	0.77	1.00		
Numerical S.	0.31	0.41	0.42	0.81	0.62	0.67	0.61	0.55	0.57	1.00	
SocioEmot.	0.23	0.25	0.26	0.31	0.26	0.21	0.23	0.33	0.28	0.25	1.00

Note: AFQT is the cognitive measure, it represents the standardized average over the ASVAB score in six of the ten components: math knowledge, arithmetic reasoning, word knowledge, paragraph comprehension, numerical speed and coding speed. Socio-emotional is the standardized average of the scores for the Rotter and Rosenberg tests.

Table 3: Schooling Choice: Probit of College Attendance (MEM*)

	(1)	(2)	(3)
AFQT	0.175***		0.206***
	(0.0154)		(0.0177)
Socio-emotional	0.0161	0.0411***	0.0188
	(0.0133)	(0.0133)	(0.0134)
Mechanical		0.0351**	-0.0623***
		(0.0139)	(0.0163)
Observations	1466	1466	1466
Pseudo R^2	0.261	0.176	0.271

Marginal effects; Standard errors in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sample: males between 25-30 years old,not attending school and up to high school complete by the time of the test. * Marginal effects at the mean. All regressions include family background controls, cohort dummies and geographical controls for region and urban residence at the age of 14

Table 2: Summary statistics

Variable	Mean	(Std. Dev.)	Min.	Max.	N
LogHourly wage 25-30	2.812	(0.41)	0.628	4.053	1385
Attended 4yrcollege by age 25	0.321	(0.467)	0	1	1466
Urban residence at age 25	0.704	(0.457)	0	1	1355
Northeast residence at age 25	0.175	(0.38)	0	1	1466
Northcentral residence at age 25	0.33	(0.47)	0	1	1466
South residence at age 25	0.255	(0.436)	0	1	1466
West residence at age 25	0.158	(0.365)	0	1	1466
Cohort1 (Born 57-58)	0.126	(0.332)	0	1	1466
Cohort2 (Born 59-60)	0.19	(0.392)	0	1	1466
Cohort3 (Born 61-62)	0.334	(0.472)	0	1	1466
Cohort4 (Born 63-64)	0.351	(0.477)	0	1	1466
Family Income in 1979 (thousands)	21.878	(11.849)	0	75.001	1466
Broken home at age 14	0.193	(0.395)	0	1	1463
Number of siblings 1979	2.934	(1.887)	0	13	1466
Mother's highest grade completed	11.442	(3.196)	0	20	1466
Father's highest grade completed	11.535	(3.985)	0	20	1466
Living in urban area at age 14	0.726	(0.446)	0	1	1466
Living in the south at age 14	0.248	(0.432)	0	1	1466
Education at the time of the test	11.22	(1.011)	6	12	1466
AFQT	0	(1)	-3.328	2.007	1466
Mechanical	0	(1)	-3.348	1.985	1466
SocioEmotional	0	(1)	-2.718	2.452	1466

Notes: AFQT is an average of standarized scores for arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, numerical operations and coding speed sections of the ASVAB. socio-emotional is an average of the scores in two tests:Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale. mechanical is an average of standarized scores for auto and shop information, mechanical comprehension and electronics information sections of the ASVAB.

Table 4: Log Hourly Wages: OLS

	(1)	(2)	(3)
College	0.142***	0.214***	0.151***
	(0.0378)	(0.0353)	(0.0380)
AFQT	0.106***		0.0857***
	(0.0167)		(0.0200)
Socio-emotional	0.0359**	0.0433***	0.0338**
	(0.0158)	(0.0158)	(0.0158)
Mechanical		0.0811***	0.0358*
		(0.0161)	(0.0192)
Observations	1355	1355	1355
R^2	0.115	0.104	0.117

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sample: males between 25-30 years old,not attending school and up to high school complete by the time of the test. College is dummy variable for college degree or more. All regressions include cohort dummies as well as geographical controls for region and urban residence at age 25.

Table 5: Loadings on Test Scores

	Cognitive		**Mechanical**		**Socio-emotional**	
Auto	0		1.32	***		
Electronics	0.43	***	0.88	***		
Mech. C	0.38	***	1.00			
Arithmetic K.	1.06	***				
Math	1.00					
Word K.	0.96	***				
Paragraph C.	0.97	***				
Numerical S.	0.79	***				
Coding S.	0.73	***				
Rotter					0.26	***
Rosenberg					1.00	

All regressions include family background controls (mother's and father's education, number of siblings, a dummy for broken family at age 14, family income in 1979), cohort dummies and geographical controls for region and urban residence at the age of 14.

Table 6: Simulated Parameters of the Distribution of Ability

	Mean	SD	Covar(θ^c,θ^i)	Correlation(θ^c, θ^i)
θ^c	-0.001	0.73	0.52	1
θ^m	0.000	0.58	0.22	0.53
θ^s	-0.001	0.89	0	0

Note: Results simulated from the estimates of the model and our NLSY79 sample

Table 7: Estimated Marginal Effects: College Attendance

	Cognitive	**Mechanical**	**Socio-emotional**
College Decision	0.229	-0.095	0.024
	(0.002)***	(0.001) ***	(0.0000) ***

Note: Standard errors in parenthesis. College Decision equation includes family background controls, cohort dummies and geographical controls for region and urban residence at the age of 14. .

Table 8: Estimated Marginal Effects: Log of Hourly Wages

	Cognitive	**Mechanical**	**Socio-emotional**
College=0 (w0)	0.047	0.044	0.033
	(0.002)***	(0.001)***	(0.000)***
College=1 (w1)	0.108	-0.031	0.047
	(0.002)***	(0.001) ***	(0.001) ***
Overall	0.107	0.014	0.041
	(0.000)***	(0.001) ***	(0.001) ***

Note: Standard errors in parenthesis. We control for cohort dummies as well as geographical controls for region and urban residence at age 25. .

Table 9: Comparative Advantage

Formula	**Estimate**
$E[Y_1\|D=1] - E[Y_0\|D=1]$	0.102***
$E[Y_0\|D=0] - E[Y_1\|D=0]$	-0.038***

Table 10: $E[Y_1 - Y_0|D=0]$ by Quintiles of Mechanical Ability and Different Levels of Cognitive and Socio-emotional Abilities

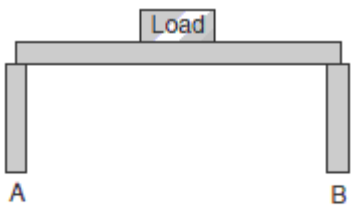
Mechanical	**Quintile 1**		**Quintile 3**		**Quintile 5**	
Low C - Low S	10.4%	***	0.6%		-6.8%	***
Low C - High S	14.5%	***	4.8%	***	-3.9%	**
High C - Low S	24.6%	***	13.1%	***	5.3%	***
High C - High S	25.8%	***	18.0%	***	9.0%	***

Low refers to the first quintile of the distribution of Cognitive (C) or Socio-emotional (S), while High refers to the fifth quintile.

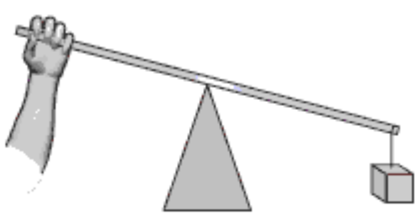
Figure 1: Sample question from the mechanical comprehension section

[a]

1. In the diagram, what can you tell about the load on posts A and B?
   (a) Post B carries more weight.
   (b) Post A carries more weight.
   (c) Post A carries no weight.
   (d) The load is equal on posts A and B.



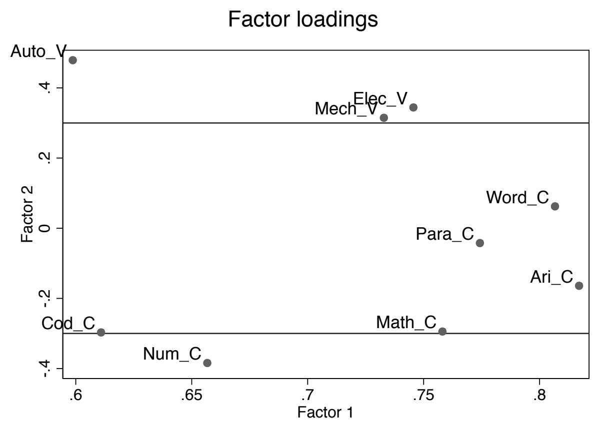
2. The diagram shows a class 1 lever. Which of the following is the same kind of lever?
   (a) A pair of tweezers
   (b) A pair of scissors
   (c) A wheelbarrow
   (d) A pair of tongs



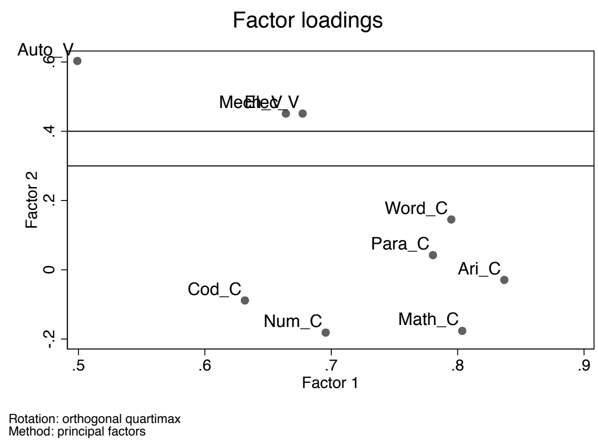
3. Which of the following would feel hottest to the touch if one end were placed in a pot of boiling water?
   (a) A wooden spoon
   (b) A metal fork
   (c) A plastic knife
   (d) A plastic cup

[a] Extracted from http://www.education.com/reference/article/mechanical-comprehension-quiz/

Figure 2: Loadings from Factor Analysis-Orthogonal Factors



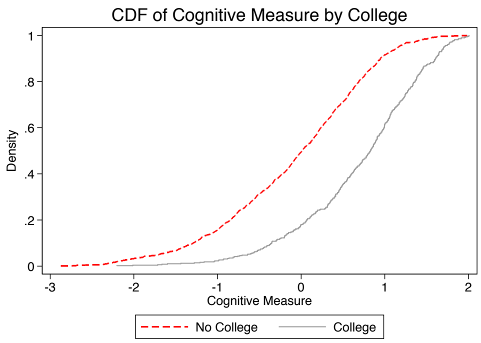
(a) Unrotated



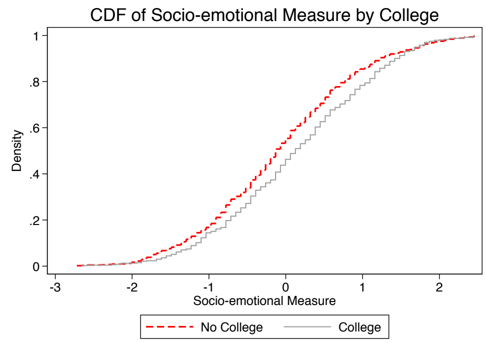
(b) Rotated

"mechanical" is computed by using the three first test that appear in the graph: Auto_V (automotive and shop information), Mech_V (mechanical comprehension) and Elec_V (electronics information). The others are used to measure the cognitive component: Ari_C (arithmetic reasoning), Math_C (mathematics knowledge), Word_C (word knowledge) and Para_C (paragraph comprehension) Num_C (numerical operations) and Cod_C (coding speed). All are used to compute AFQT except from Cod_C. In fact, the calculation of AFQT has changed considerably on time. In 1980 it was computed as the raw sum of arithmetic reasoning, word knowledge, paragraph comprehension and 1/2 numerical operations. After 1989 numerical operations was removed and mathematics knowledge was included.

Figure 3: Measurement of Cognitive and Socio-emotional Ability



(a) Cognitive



(b) Socio-emotional

Figure 4: Measurement of Mechanical Ability

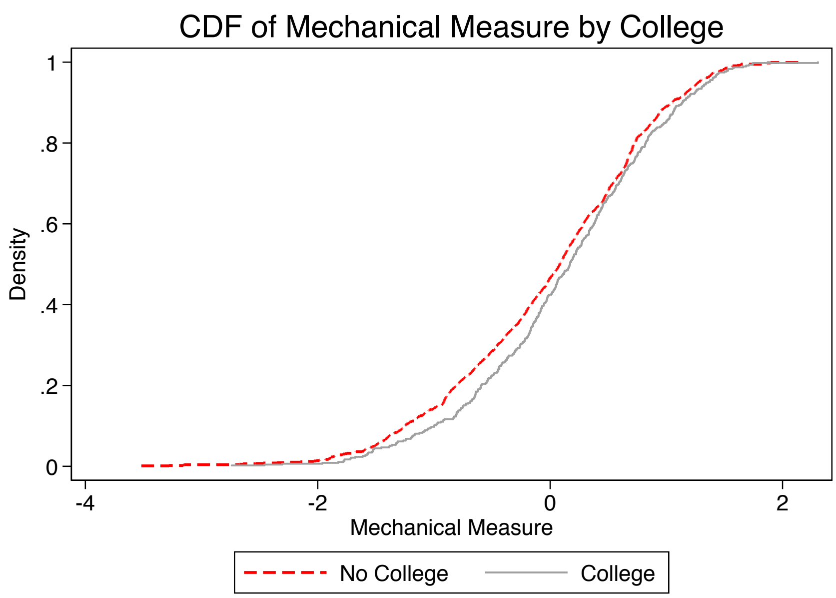


Figure 5: Variance Decomposition

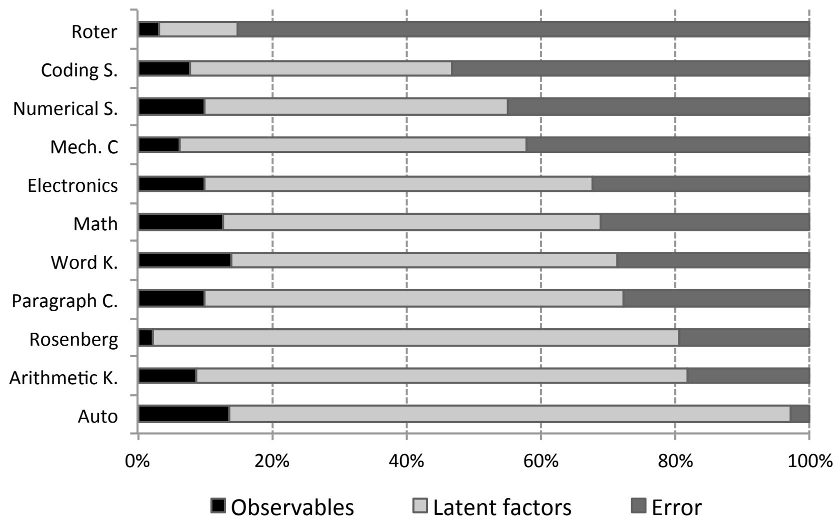
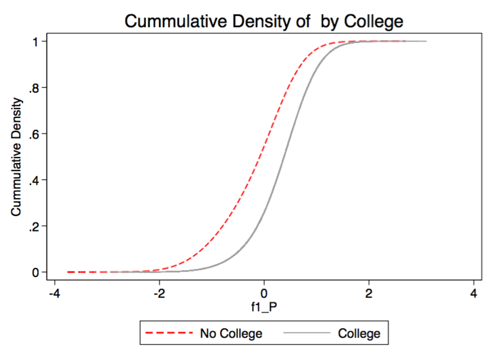
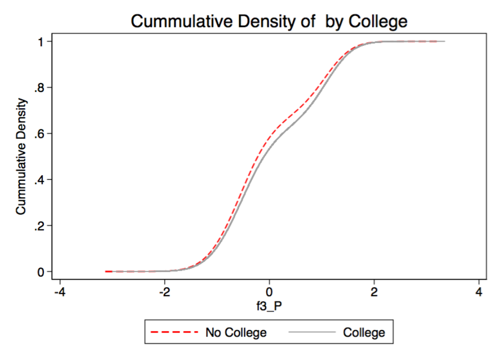


Figure 6: Marginal CDF: Cognitive and Socio-emotional Ability



(a) Cognitive



(b) Socio-emotional

Figure 7: Marginal CDF: Mechanical Ability

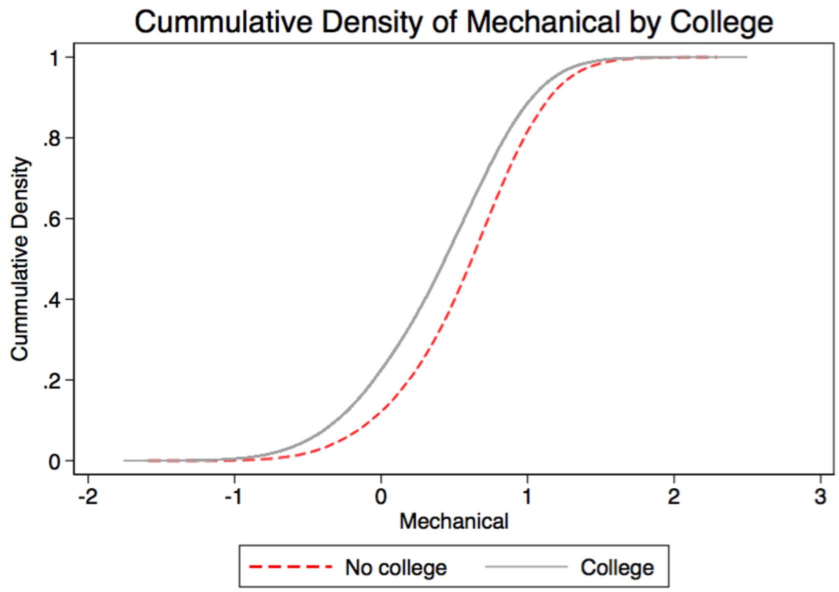
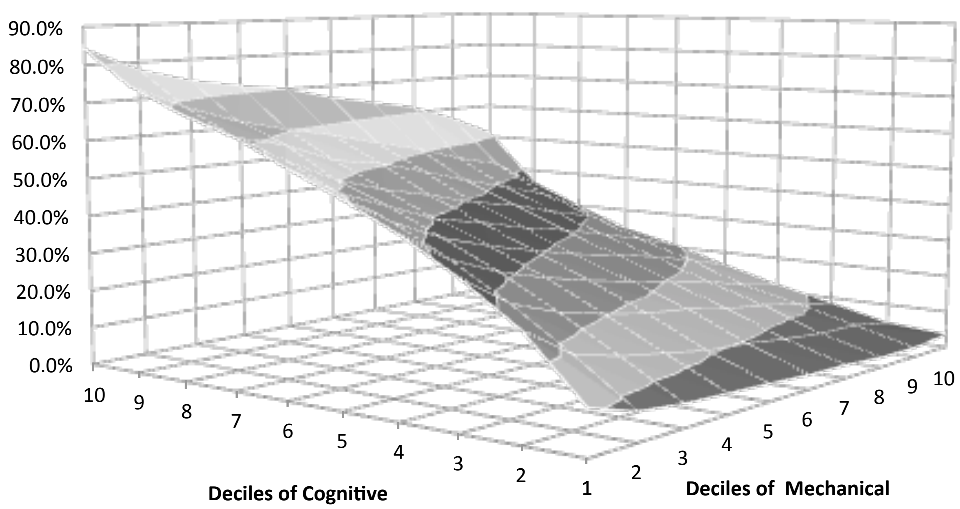
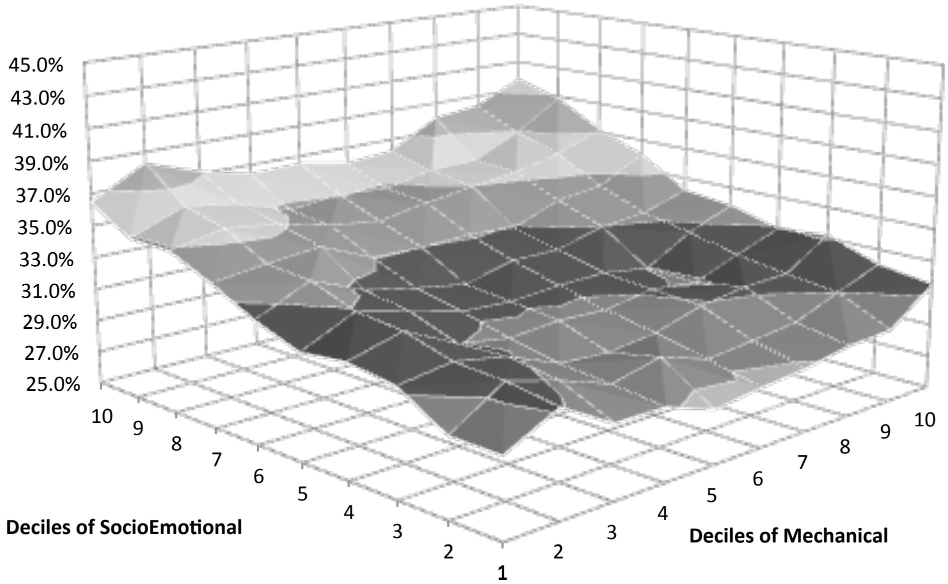


Figure 8: Joint Distribution of College Attendance Decision by Deciles of Cognitive and Mechanical Factors



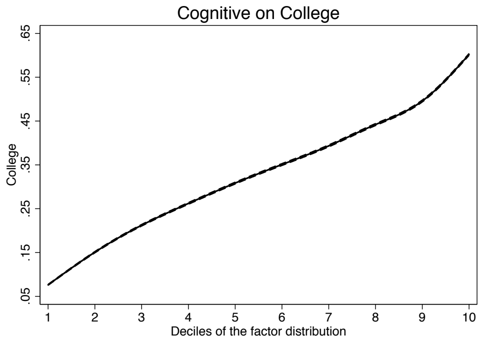
Note: The data are simulated from the estimates of the model and our NLSY79 sample. In the figure we plot $P_{i,j} = \int (Pr(D = 1|\theta_c = d_i, \theta_m = d_j))\, dF\theta_s$ for $d_i = 1, ..10$ and $d_j = 1, ..10$

Figure 9: Joint Distribution of College Attendance Decision by Deciles of Socio-emotional and Mechanical Factors

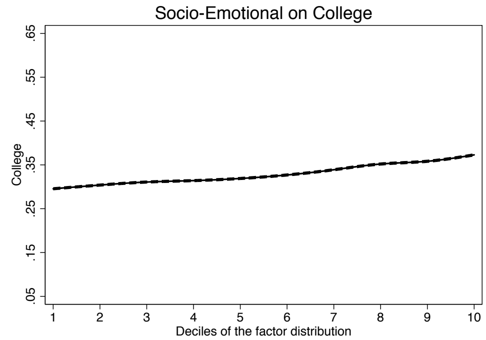


Note: The data are simulated from the estimates of the model and our NLSY79 sample. In the figure we plot $P_{i,j} = \int (Pr(D=1|\theta_m = d_i, \theta_s = d_j))\, dF\theta_c$ for $d_i = 1, ..10$ and $d_j = 1, ..10$

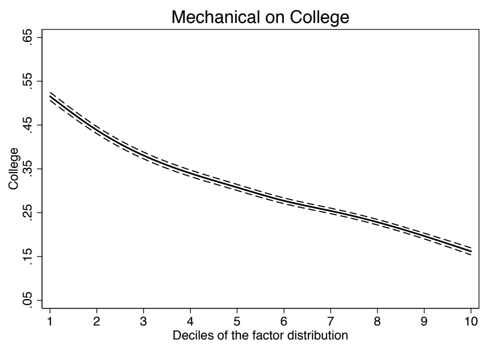
Figure 10: Marginal Effect of Ability on College Attendance



(a) Cognitive



(b) Socio-emotional



(c) Mechanical

Note: The data are simulated from the estimates of the model and our NLSY79 sample.

Figure 11: Average of Log Wage by Deciles of Cognitive and Mechanical Factors

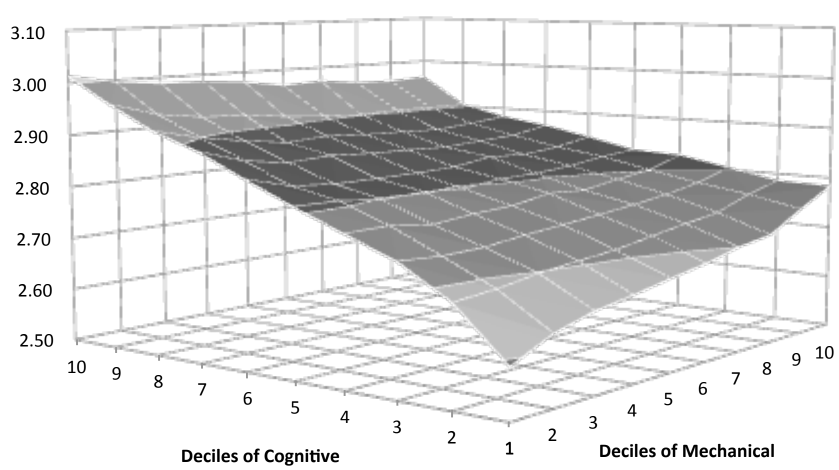


Figure 12: Average of Log Wage by Deciles of Socio-emotional and Mechanical Factors

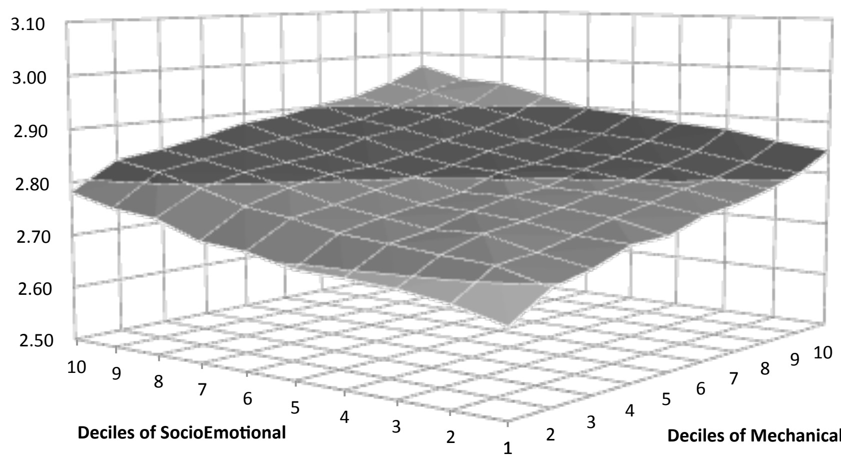
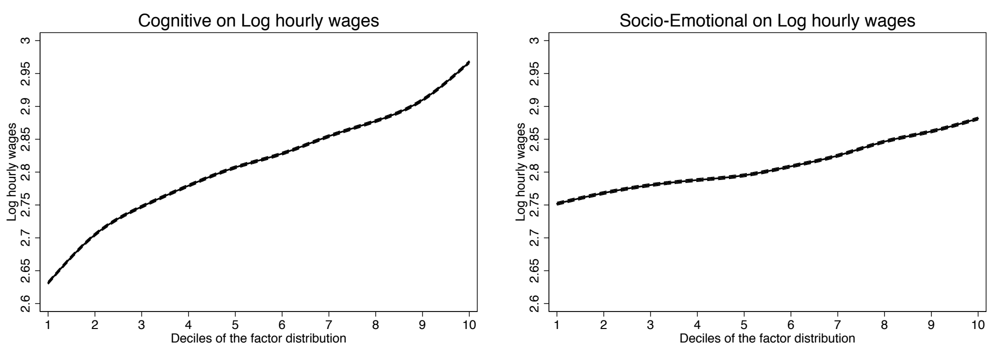
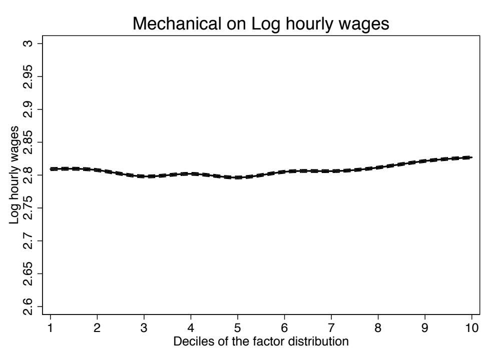


Figure 13: Marginal Effect of Ability on Log Hourly Wages



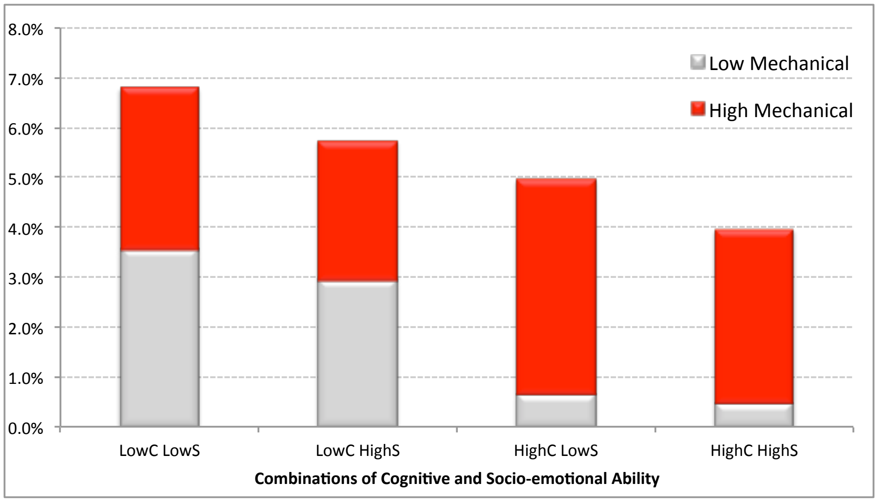
(a) Cognitive

(b) Socio-emotional



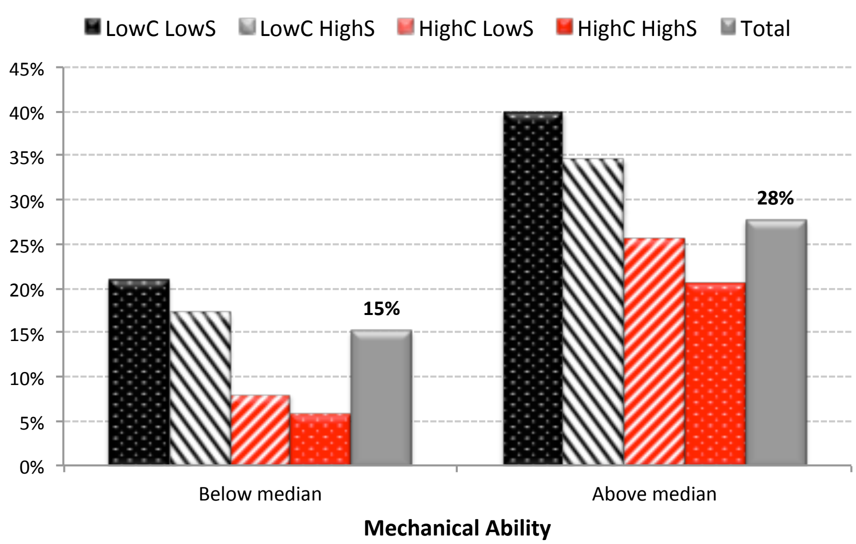
(c) Mechanical

Figure 14: Profile Composition of the Individuals that Benefit from not Attending College



Note: The data are simulated from the estimates of the model and our NLSY79 sample.

Figure 15: Who Benefits from not Attending College?



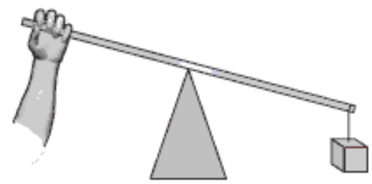
Note: The data are simulated from the estimates of the model and our NLSY79 sample. Figure presents the percentage of people that benefits from not attending college in each category.

9 Appendix

9.1 Appendix 1: Sample Questions

The set of questions was extracted from: http://www.education.com/reference/article/mechanical-comprehension-quiz/

9.1.1 Mechanical Comprehension Section

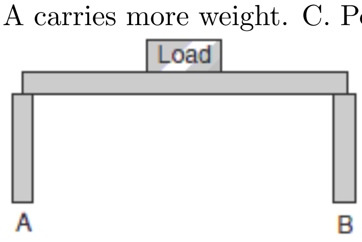
1. The diagram shows a class 1 lever. Which of the following is the same kind of lever? A. A pair of tweezers B. A pair of scissors C. A wheelbarrow D. A pair of tongs 

2. The diagram shows a class 2 lever. Which of the following is the same kind of lever? A. A seesaw B. A pair of scissors C. The human forearm D. A wheelbarrow

3. When a mass of air expands, which of the following is most likely to happen? A. The air warms up. B. The air cools down. C. The air stays at the same temperature. D. The air contracts.

4. The diagram shows a class 3 lever. Which of the following is the same kind of lever? A. A pair of tweezers B. A wheelbarrow C. A seesaw D. A wedge

5. Which of the following would feel hottest to the touch if one end were placed in a pot of boiling water? A. A wooden spoon B. A metal fork C. A plastic knife D. A plastic cup

6. In the diagram, what can you tell about the load on posts A and B? A. Post B carries more weight. B. Post A carries more weight. C. Post A carries no weight. D. The load is equal on posts A and B. 

7. Water is flowing through this pipe. Which statement is true? A. Water is moving faster at point A than at point B. Water pressure is equal at points A and B. C. Water pressure is

greater at point A than at point B. D. Water pressure is greater at point B than at point A.

8. What is the advantage of using triangle shapes in constructing a bridge? A. Triangles are sturdier than other shapes. B. Triangles are very flexible. C. Triangles are inexpensive to manufacture. D. Triangles are attractive to look at.

9. Shifting to a smaller gear on a mountain bike will have an effect on the speed of travel. The smaller sized gear will make pedaling easier but it will also a. increase the speed of travel. b. decrease the speed of travel. c. have no effect on the speed of travel. d. make the bicyclist work harder.

10. Which of the following examples does not make use of a wedge? a. Choosing a sand wedge to hit your golf ball b. Splitting firewood with a chisel and sledge hammer c. Chopping wood with an axe d. Using a lever to lift a load

11. A block and tackle refers to a device which is used to a. put under the wheel of a vehicle to prevent it from rolling backward. b. prevent fish from escaping the hook. c. leverage a stationary object. d. hoist an object into the air by means of rope and pulleys.

12. Downshifting an auto or a truck causes a. a decrease in speed and an increase in torque. b. an increase in speed and a decrease in torque. c. no change in speed and no change in torque. d. None of the above

13. Shifting to a higher gear in a car or truck causes a. a decrease in torque and an increase in speed. b. an increase in torque and a decrease in speed. c. an increase in both speed and torque. d. None of the above.

9.1.2 Automotive and Shop Information

1. A car uses too much oil when which of the following parts are worn? A. pistons B. piston rings C. main bearings D. connecting rods

2. What system of an automobile or truck determines the vehicle's cornering ability and ride stiffness? a. Steering system b. Braking system c. Electrical system d. Suspension system

3. The purpose of a transfer case is to a. make a vehicle ride more smoothly. b. make the steering more responsive to driver input. c. distribute power to front and rear wheels in a 4 x 4 vehicle. d. shorten the braking distance.

4. The reason a particular quarter inch nut may not fit a particular quarter inch bolt is because a. they may be of different thread classifications. b. a quarter inch bolt is incompatible with a quarter inch nut of the same size. c. the metal alloys from which the nut and bolt are made may cause the nut to seize.d. quarter-inch bolts require a nut of a slightly larger size to fit.

5. The kerf is a. a type of wood file. b. the angle of the blade on a circular saw. c. a slot or cut made by the blade of a saw as it cuts into the wood. d. a term of measurement used in vehicle wheel alignment.

6. It would be better to use thick viscosity motor oil in a. cold climates (makes vehicle startups easier). b. tropical climates (engine heat build-up). c. Eastern United States. d. four-wheel drive vehicles.

7. The part of the motor vehicle electric system which distributes the spark to the various combustion cylinders is the a. battery. b. rotor and distributor assembly. c. injection system. d. ignition coil.

8. A punch is used for a. hammering knots from wooden objects. b. marking metal or wooden objects to prepare for drilling or other activities and for driving small headed nails. c. filing the sharp edges of metal or wooden objects. d. drilling holes.

9. For a better grip on a stubborn fastener nut, it is better to use a. an adjustable wrench. b. an open-end wrench. c. a box-end wrench. d. a pipe wrench.

9.1.3 Electronics Information

1. Ohm's Law states that a. $E = I \times R$. b. $R = E \times I$. c. voltage is equal to the current multiplied by the resistance. d. Both a and c

2. The electrons revolve around the nucleus in a cumulative series of orbits which are called a. neutrons. b. subatomic particles. c. shells. d. circulating cores.

3. The part of the atom's shell that determines electrical properties is the ______ shell. a. insulator b. nucleic c. valence d. electronic

4. A semi-conductor is an element or substance which a. conducts electricity better than a conductor. b. is useful for certain conductive requirements necessary to some electrical technologies. c. completely inhibits the flow of electrons around the outer shell. d. insulates electrical current from contact with other materials.

5. When applied to electrical conductivity of household current, 60 hertz means that a. current flows in only one direction. b. current flows in two directions. c. current flows first in one direction and then another. d. 60 voltage cycles take place in one second.

6. The three necessary components of an electrical circuit are a. an electrical load, conductors, and a circuit for the electricity flow to follow. b. a switch, a resistor, and a path to follow. c. a 60 hertz receptacle, a switch, and a power source. d. a closed circuit, a battery, and radio waves.

7. Doping is a term used in the semiconductor process when a. impurities are added into the crystal structure of silicon. b. hydrogen atoms are added to the crystal structure of silicon. c. impurities are removed from the crystal structure of silicon. d. semiconductors are used for medical purposes.

8. The property of electricity that pushes and moves it along a circuit is called a. alternating current. b. amperage. c. resistance. d. voltage.

9.2 Appendix 2: Identification of the Model

This section presents the identification of the empirical model. We follow Carneiro et al. (2003). For notational simplicity, we keep the conditioning on X implicit and focus on the factors (latent abilities).

Let C_j denote the cognitive test scores

$$C_j = \lambda^c_{C_j}\theta_c + e_{C_j}$$

for $j = 1, ..., 6$

where θ_c is the cognitive factor, $\lambda^c_{C_j}$ is the loading of the cognitive factor in test j and e_{C_j} is the error term (uniquenesses).

We can compute

$$
\begin{aligned}
COV(C_1, C_2) &= \lambda^c_{C_1}\lambda^c_{C_2}\sigma^2_{\theta_c} \\
COV(C_1, C_3) &= \lambda^c_{C_1}\lambda^c_{C_3}\sigma^2_{\theta_c} \\
COV(C_2, C_3) &= \lambda^c_{C_2}\lambda^c_{C_3}\sigma^2_{\theta_c}
\end{aligned}
$$

Since we observe the left hand side, we can form

$$
\begin{aligned}
\frac{COV(C_1, C_2)}{COV(C_2, C_3)} &= \frac{\lambda^c_{C_1}}{\lambda^c_{C_3}} \\
\frac{COV(C_1, C_2)}{COV(C_1, C_3)} &= \frac{\lambda^c_{C_2}}{\lambda^c_{C_3}}
\end{aligned}
$$

By normalizing $\lambda^c_{C_3} = 1$, we get $\lambda^c_{C_1}$ and $\lambda^c_{C_2}$. With this we can also get $\sigma^2_{\theta_c}$ and apply the same procedure for the rest of the tests C_4, C_5, C_6.

Finally, we can rewrite the system as:

$$
\frac{C_j}{\lambda^c_{C_j}} = \theta_c + \frac{\varepsilon_{C_j}}{\lambda_{C_j}} = \theta_c + \varepsilon'_{C_j}
$$

and we can apply Kotlarski's Theorem (Kotlarski, 1967) to identify

$$
f_{\theta_c}(\cdot), f_{\varepsilon_{C_j}}(\cdot)
$$

for $j = 1, ..., 6$

To implement the model we need to assume $\lambda_{C_j} = 1$ for some j. This assumption sets the scale of θ_c. In this case we set the scale of unobserved cognitive ability by normalizing to one the coefficient associated with θ_c in the equation for mathematics knowledge.

For the identification of the distribution of socio-emotional ability we use a similar argument. In particular, consider the two noncognitive test scores and the latent variable associated with the schooling model.

$$S_1 = \lambda^s_{S_1}\theta_s + e_{S_1}$$

$$S_2 = \lambda^s_{S_2}\theta_s + e_{S_2}$$

$$I = \lambda^c_D\theta_c + \lambda^m_D\theta_m + \lambda^s_D\theta_s + e$$

Given that $\theta_c \perp \theta_s$ and $\theta_m \perp \theta_s$, we can compute

$$\begin{aligned} COV(S_1, I) &= \lambda^s_{S_1}\lambda^s_D\sigma^2_{\theta_s} \\ COV(S_2, I) &= \lambda^c_{S_2}\lambda^s_D\sigma^2_{\theta_c} \end{aligned}$$

and

$$\frac{COV(S_1, I)}{COV(S_2, I)} = \frac{\lambda^s_{S_1}}{\lambda^s_{S_2}}$$

so the normalization $\lambda^s_{S_1} = 1$ ensures the identification of the loading $\lambda^s_{S_2}$. With $\lambda^s_{S_2}$ in hand, we secure the identification of the distribution of θ_s using Kotlarski's theorem. In this case we normalize the coefficient associated with θ_s in the equation for the Rosenberg Self-Esteem Scale.

Finally, for the mechanical measure M_k we have to consider that both θ_c and θ_m are present in the equations and they are not independent. In order to use the same chain logic applied to the identification of the other to factors we rewrite the system in terms of two independent factors. For this purpose we assume that

$$\theta_m = \alpha_1\theta_c + \alpha_2\theta_2$$

where

$$\theta_c \perp \theta_2$$

and both θ_c and θ_2 are distributed as a mixture of normals as follows:

$$\theta_{c,i} \sim \sum_{k=1}^{K} p_k N\left(\mu_c^k, \left(\sigma_c^k\right)^2\right)$$

$$\theta_{2,i} \sim \sum_{j=1}^{J} p_j N\left(\mu_2^j, \left(\sigma_2^j\right)^2\right)$$

and the distribution of θ_m is the convolution of the densities of θ_c and θ_2

$$f_{\theta_m}(\theta_m) = \int_{-\infty}^{+\infty} \int_{-\infty}^{\theta_m - \theta_1} f(\theta_1, \theta_2) d\theta_2 d\theta_1$$

Without loss of generality we assume $\alpha_2 = 1$ so we normalize the contribution of θ_c to θ_m. So the original model for the mechanical measure can be rewritten in terms of θ_c and θ_2 as follows:

$$\begin{aligned}
M_k &= \lambda_{M_k}^c \theta_c + \lambda_{M_k}^m \theta_m + e_{M_k} \\
&= \lambda_{M_k}^c \theta_c + \lambda_{M_k}^m (\alpha_1 \theta_c + \theta_2) + e_{M_k} \\
&= a_k \theta_c + \lambda_{M_k}^m \theta_2 + e_{M_k}
\end{aligned}$$

for $k = 1, ..., 3$

we can compute

$$\begin{aligned}
COV(C_1, M_1) &= \lambda_{C_1}^c a_1 \sigma_{\theta_c}^2 \\
COV(C_1, M_2) &= \lambda_{C_1}^c a_2 \sigma_{\theta_c}^2 \\
COV(C_1, M_3) &= \lambda_{C_1}^c a_3 \sigma_{\theta_c}^2
\end{aligned}$$

to recover a_1, a_2 and a_3.

As for the other test scores, we normalize $\lambda_{M_3}^m = 1$. To apply Klotarski's Theorem we rewrite the system as:

$$
\begin{aligned}
\frac{M_1 - a_1\theta_c}{\lambda^m_{M_1}} &= \theta_2 + e^{'}_{M_1} \\
\frac{M_2 - a_2\theta_c}{\lambda^m_{M_2}} &= \theta_2 + e^{'}_{M_2} \\
M_3 - a_3\theta_c &= \theta_2 + e^{'}_{M_3}
\end{aligned}
$$

and we identify the the distribution of $f_{\theta_2}(\cdot)$, $f_{e_{M_k}}(\cdot)$ for $k = 1, 2, 3$

Finally, to recover all the parameters associated with θ_m we need to get α_1 so one extra assumption is needed since we have three equations and four unknowns in the following system:

$$
a_1 = \lambda^c_{M_1} + \lambda^m_{M_1}\alpha_1
$$

$$
a_2 = \lambda^c_{M_2} + \lambda^m_{M_2}\alpha_1
$$

$$
a_3 = \lambda^c_{M_3} + \alpha_1
$$

we assume that $\lambda^c_{M_1} = 0$, the implication of the assumption is that the cognitive factor θ_c affects the score only through its effect on the mechanical factor θ_m[25]

In the implementation of the model we normalize to one the coefficient associated with θ_m in the equation for mechanical comprehension.

9.3 Appendix 3: Standard Errors of the Estimates

In order to justify the computation of standard errors presented in this paper it is necessary to introduce some Bayesian concepts and the corresponding notation.

Let θ be the parameter of interest in our case $\theta = (\alpha, \beta, \lambda)$, $f(\theta)$ the density of θ, called the prior distribution. $Y = \{y_{1,..,}y_N\}$ is the sample of N independent observations, where $f(y_n|\theta)$ is the probability of outcome y_n, and $f(Y)$ the marginal distribution of the data (marginal over θ). The posterior distribution is denoted by $f(\theta|Y)$ and the probability of observing the sample outcomes

[25] In the implementation of the model M_1 is the score associated with the automotive and shop information section. We selected this test because it has the lowest loading on the cognitive factor in the premilinary factor analysis (see 2) Our current results do not depend on this assumptions, results are qualitatively similar if we select any section on the technical composites of the ASVAB (mechanical comprehension or electronics information). Results are available upon request.

Y is the likelihood function of the observed choices $L(Y|\theta) = \prod_{i=1}^{N} f(y_n|\theta)$.

In this context $f(Y) = \int L(Y|\theta)f(\theta)d\theta$ and using the Bayes' rule the following equality is true and serves to compute the desired posterior distribution of θ.

$$f(\theta|Y)f(Y) = L(Y|\theta)f(\theta)$$

$$f(\theta|Y) = \frac{L(Y|\theta)f(\theta)}{f(Y)}$$

$$f(\theta|Y) \propto L(Y|\theta)f(\theta)$$

Finally, the mean of the posterior distribution is

$$\bar{\theta} = \int \theta f(\theta|Y)d\theta \tag{1}$$

The use of Bayesian methods in this paper is merely computational; in consequence, the interest is primarily on the mean of the posterior distribution $\bar{\theta}$ which is viewed from a classical perspective, i.e., as an estimator that has the same asymptotic sampling distribution as the maximum likelihood estimator.[26] In this sense, the interest is to find the sampling distribution of the statistic$\bar{\theta}$in order to make inference about it.

The Bernstein-von Mises theorem, described by Train (2003) in three related statements establishes the properties of the sampling distribution of $\bar{\theta}$:

1. $\sqrt{N}(\theta - \bar{\theta}) \rightarrow^d N(0, (-H)^{-1})$[27]

2.$\sqrt{N}(\bar{\theta} - \theta^{MLE}) \rightarrow^p 0$

3.$\sqrt{N}(\bar{\theta} - \theta^{*}) \rightarrow^d N(0, (-H)^{-1})$

In this context, the variance of the posterior is the asymptotic variance of the estimates. From 1 we have that the asymptotic variance of the posterior distribution is $(-H)^{-1}/N$ which by 3 is the asymptotic sampling variance of the estimator $\bar{\theta}$. So, estimation can be performed by using

[26] From a bayesian perspective, the mean of the posterior distribution is the value that minimizes the posterior loss in the quadratic loss case. As stated in Train (2003) is the value that minimizes the expected cost of the researcher being wrong about the parameter, if the cost is quadratic in the size of the error.

[27] With $-H$ being the information matrix (the negative)

the moments of the posterior, as in this paper, where the mean of the posterior provides a point estimate and the standard deviation of the posterior provides the standard errors.

In the paper, we use MCMC as a method to obtain draws from the posterior distribution. Starting with a vector of initial parameters drawn from the transition kernel, we use Gibbs Sampling as the algorithm to create a Markov Chain such that, as size of the sequence increases ($n \to \infty$), the limiting distribution is the posterior. After convergence is achieved and a burning period of 60,000, we make 1,000 draws from the posterior distribution of the parameters to compute the mean (the simulated approximation of the mean $\bar{\theta}$ that we call $\breve{\theta}$) and standard errors (provided by the sd of the posterior which is simulated by taking the the standard deviation of the R draws) reported in the text.

$$\breve{\theta} = \frac{\sum_{r=1}^{R} \theta^r}{R}$$

$$SE_{\breve{\theta}} = \sqrt{\frac{\sum_{r=1}^{R} (\theta^r - \bar{\theta})^2}{R}}$$

According to Gelman and Shirley (2011) when simulation-based inference is for functions of the parameters $g(\theta)$. "Such inference will typically be constructed using a collection of 1000 (say) simulations of the parameter vector, perhaps summarized by a mean and standard deviation, or maybe a 95% interval using the empirical distribution of the simulations that have been saved. Even if these summaries could be computed analytically, we would in general still want simulations because these allow us directly to obtain inferences for any posterior or predictive summary".

Table 11: Estimates of the Model: Measurement Equations

	cons	Sibl	Med	Fed	FamY	urban	south	coh1	coh2	coh3	hgtest	c	m	s
Auto	-2.64	-0.02	0.01	0.01	0.00	-0.16	-0.19	0.53	0.34	0.07	0.23	0	1.32	
SE	0.39	0.01	0.01	0.01	0.00	0.05	0.06	0.10	0.09	0.08	0.04	0.00	0.08	
Elec	-2.93	-0.05	0.01	0.02	0.00	-0.07	-0.17	0.20	0.04	-0.09	0.25	0.43	0.88	
SE	0.39	0.01	0.01	0.01	0.00	0.05	0.06	0.10	0.09	0.08	0.04	0.04	0.05	
Mech	-2.94	-0.01	0.02	0.01	0.00	-0.15	-0.15	-0.06	-0.17	-0.18	0.25	0.38	1.00	
SE	0.40	0.01	0.01	0.01	0.00	0.05	0.06	0.10	0.09	0.08	0.04	0.04	0.00	
Ari.	-3.40	0.00	0.03	0.02	0.00	-0.02	-0.19	-0.30	-0.44	-0.34	0.27	1.06		
SE	0.39	0.01	0.01	0.01	0.00	0.05	0.05	0.09	0.09	0.08	0.04	0.03		
Math	-2.83	-0.02	0.02	0.04	0.01	-0.01	-0.19	-0.60	-0.62	-0.25	0.21	1.00		
SE	0.37	0.01	0.01	0.01	0.00	0.05	0.06	0.09	0.09	0.08	0.04	0.00		
Word	-3.80	-0.05	0.03	0.03	0.00	-0.04	-0.13	-0.10	-0.30	-0.34	0.30	0.96		
SE	0.38	0.01	0.01	0.01	0.00	0.05	0.06	0.09	0.09	0.08	0.04	0.03		
Para	-3.51	-0.02	0.02	0.04	0.00	-0.05	-0.06	-0.31	-0.39	-0.29	0.28	0.97		
SE	0.38	0.01	0.01	0.01	0.00	0.05	0.06	0.10	0.09	0.08	0.04	0.04		
Num	-3.49	-0.02	0.02	0.02	0.01	-0.01	-0.14	-0.24	-0.41	-0.24	0.27	0.79		
SE	0.37	0.01	0.01	0.01	0.00	0.06	0.06	0.10	0.09	0.08	0.04	0.03		
Cod	-2.98	-0.01	0.01	0.02	0.01	0.01	-0.18	-0.14	-0.13	-0.19	0.23	0.73		
SE	0.38	0.01	0.01	0.01	0.00	0.05	0.06	0.10	0.10	0.08	0.04	0.04		
Rotter	-1.93	0.00	0.00	0.01	0.00	0.00	-0.02	0.08	-0.04	-0.08	0.15			0.26
SE	0.40	0.01	0.01	0.01	0.00	0.06	0.06	0.11	0.10	0.08	0.04			0.03
Rosen.	-0.82	-0.02	0.01	0.01	0.00	0.00	0.00	0.18	0.18	0.16	0.05			1.00
SE	0.38	0.01	0.01	0.01	0.00	0.05	0.05	0.10	0.09	0.08	0.04			0.00

Note: This table presents estimates of the model. Using data from the NLSY79, white males between 25-30 years old. Since the model is estimated using Bayesian methods, they represent the mean estimates over 1,000 iterations after discarting the first 30,000. The computation of standard errors is explained in appendix 3. cons is the constant, Sib is the number of siblings in 1979, Med is the mother's highest grade completed at age 17, Fed is the father's highest grade completed at age 17, FamY is the family income in 1979 in thousands, urban is a dummy variable for living in an urban area at age 14, south is a dummy variable for living in the south at age 14, Coh1 refers to the first cohort (born 57-58), Coh2 refers to the second (born 59-60), Coh3 refers to the last cohort of individuals, those that were born between 61-62, hgtest is the highest grade attended by the time the test was presented and c, m, s refers to the cognitive, mechanical and sociemotional factors respectively. The first three rows refer to the scores in the technical composites of the ASVAB, the next six scores are the tests used to capture cognitive ability and the last two rows are the socio-emotional test scores.

Table 12: Estimates of the Model: College Decision Model

Pr(Attending college)	**Coefficient**	**SE**
Constant	-2.02	0.25
Number of siblings	-0.06	0.03
Mother's highest grade completed	0.05	0.02
Father's highest grade completed	0.09	0.01
Family Income 1979 (thousands)	0.01	0.00
Living in urban area at age 14	0.12	0.11
Living in the south at age 14	0.05	0.11
Cohort1 (Born 57-58)	-1.42	0.19
Cohort2 (Born 59-60)	-1.11	0.14
Cohort3 (Born 61-62)	-0.36	0.11
Cognitive	1.22	0.09
Mechanical	-0.74	0.12
Socio-emotional	0.11	0.05

Note: This table presents estimates of the model. Using data from the NLSY79, white males between 25-30 years old. Since the model is estimated using Bayesian methods, they represent the mean estimates over 1,000 iterations after discarting the first 30,000. The computation of standard errors is explained in appendix 3.

Table 13: Estimates of the Model: Log of Hourly Wage

	No college	SE	College	SE
Constant	2.83	0.05	2.91	0.06
Northeast residence	0.02	0.04	0.22	0.06
Northcentral residence	-0.11	0.04	0.01	0.06
South residence	-0.13	0.04	0.03	0.06
Cohort2 (Born 59-60)	0.01	0.03	-0.02	0.07
Cohort3 (Born 61-62)	-0.03	0.03	-0.02	0.04
Local Unemployment rate	0.08	0.46	-1.50	0.65
Cognitive	0.06	0.02	0.15	0.04
Mechanical	0.08	0.03	-0.05	0.05
Socio-emotional	0.04	0.02	0.05	0.02

Note: This table presents estimates of the model. Using data from the NLSY79, white males between 25-30 years old. Since the model is estimated using Bayesian methods, they represent the mean estimates over 1,000 iterations after discarting the first 30,000. The computation of standard errors is explained in appendix 3.

Table 14: Parameters of the Distribution of Unobserved Abilities

	Cognitive		Mechanical Aux		Socio-emotional	
	Estimate	SE	Estimate	SE	Estimate	SE
μ_1	-0.57	0.29	-0.39	0.12	1.05	0.11
μ_2	0.39	0.11	0.37	0.05	-0.53	0.07
$1/\sigma_1^2$	2.42	0.75	4.33	0.92	6.39	1.92
$1/\sigma_2^2$	4.26	1.14	12.54	2.77	4.15	1.26
p	0.44	0.19	0.50	0.10	0.34	0.05
1-p	0.56	0.19	0.50	0.10	0.66	0.05

Note: This table presents estimates from the Model. Since the model is estimated using Bayesian methods, they represent the mean estimates over 1,000 iterations after discarting the first 30,000.The computation of standard errors is explained in appendix 3. Mechanical Aux. presents the results from the auxiliar component of the factor, θ_2, that is independent from cognitive ability. Where $\theta_m = \alpha_1\theta_c + \theta_2$ with $\alpha_1 = 0.42$

Table 15: Goodness of Fit: Wage Distribution (Ho:Model=Data)

	3 factors	2 factors
χ^2	46.61	272.46
p-value	0.19	0.00
Critical at 90%	50.66	50.66
Critical at 95%	54.57	54.57

Note: The table presents a Chi-squared test computed using equiprobable bins.

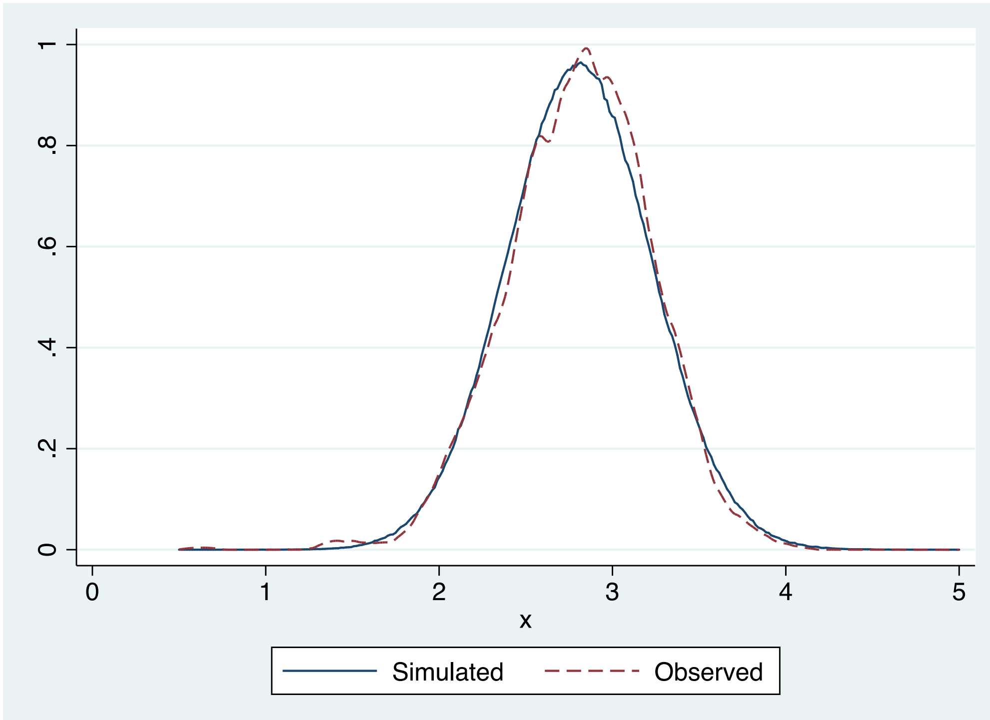
Table 16: Goodness of Fit: Schooling (Ho:Model=Data)

	3 factors	**2 factors**
χ^2	0.40	0.02
p-value	0.53	0.87
Critical at 90%	2.71	2.71
Critical at 95%	3.84	3.84

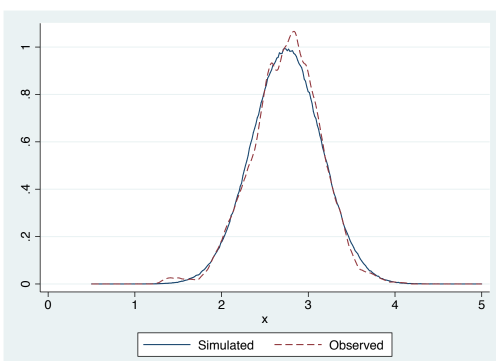
Note: The table presents a Chi-squared test.

9.4 Appendix 4: Additional Tables and Figures

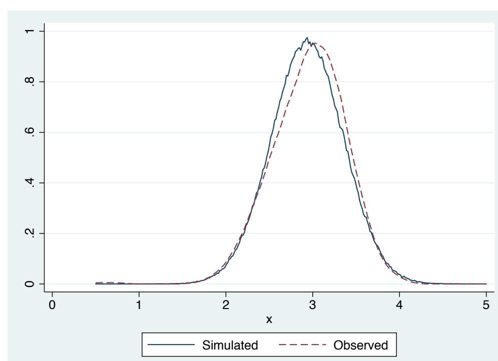
Figure 16: Simulated versus Observed Wages



(a) Overall



(b) No college



(c) College

Note: The dashed line depicts the actual distribution of log hourly wage in the data while the solid line is computed after simulating a sample of over 1'000.000 individuals using the structure and estimates of the model.