ONE SIZE DOES NOT FIT ALL:
MULTIPLE DIMENSIONS OF ABILITY, COLLEGE ATTENDANCE AND WAGES

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NBER Working Paper No. 20752
December 2014
JEL No. C38,J24

ABSTRACT

We investigate the role of mechanical ability as another dimension that, jointly with cognitive and socio-emotional, affects schooling decisions and labor market outcomes. Using a Roy model with a factor structure and data from the NLSY79, we show that the labor market positively rewards mechanical ability. However, in contrast to the other dimensions, mechanical ability reduces the likelihood of attending four-year college. We find that, on average, for individuals with high levels of mechanical and low levels of cognitive and socio-emotional ability, not attending four-year college is the alternative associated with the highest hourly wage (ages 25-30).

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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, multiple studies have shown that both dimensions *positively* affect the acquisition of skills and education as well as labor market productivity as measured by wages. (See Cawley, Heckman and Vytlacil, 2001; O'Neill, 1990; Neal and Johnson, 1996; Herrnstein and Murray, 1994; Bowles, Gintis and Osborne, 2001; Farkas, 2003; Heckman, Stixrud and Urzua, 2006; Urzua, 2008, among others).

But ability is multidimensional in nature and thus, it is reasonable to expect that other dimensions may also affect individual's decisions and outcomes. In fact, economists have recognized that this multidimensionality must be at the "center stage of the theoretical and empirical research on child development, educational attainment and labor market careers" (Altonji, 2010). Following this idea, recent studies in economics, psychology, and other social sciences have explored different components of socio-emotional ability, generally in the form of personality traits (Borghans et al., 2008; Heckman and Kautz, 2013), but the exploration of other facets had received less consideration, especially those that might be related to cognition. Furthermore, there is no theoretical reason to expect that all dimensions affect outcomes in the same direction.

This paper investigates a dimension of ability that has been overlooked by economists when analyzing schooling decisions and adult 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 mechanical 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, Hansen and Heckman (2003) and Heckman, Stixrud and Urzua (2006), so we follow their identification strategy. In particular, we augment our Roy model with a set of test scores (measurement system) from which we identify the distribution of a three-dimensional vector of latent abilities: cognitive, socio-emotional and mechanical. The analysis is carried out using data from the National Longitudinal Study of Youth of 1979 (NLSY79) and we identify mechanical ability from a subset of the

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[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, unlike this paper, the literature does not simultaneously analyze multiple abilities, schooling decisions and labor market outcomes.

Armed Services Vocational Aptitude Battery (ASVAB).

This paper contributes to the literature by documenting that mechanical ability matters. We show that it affects schooling decisions and labor market outcomes differently than other, more conventional dimensions. In particular, we show that mechanical, like socio-emotional and other cognitive dimensions, has positive returns on wages, but in contrast to them, it predicts the choice of low levels of schooling. Specifically, it reduces the probability of attending four-year college. In this context, we expand the set of abilities that explain differences in human capital and wages in the population.[2]

In addition, our study provides insight into the schooling choices and labor market outcomes 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, after obtaining a high school degree, not attending four-year college implies a higher expected hourly wage compared to the alternative of doing so. This has important implications for public policies promoting general enrollment in four-year colleges.

The document also presents an alternative use of the ASVAB that has been historically used by the military to determine qualification for enlistment in the United States armed forces. Despite its popularity, the literature has investigated only a subset of these questions, the battery of tests used to calculate the Armed Forces Qualification Test (AFQT) score, which is commonly interpreted as a proxy for cognition. This paper highlights the importance of using the technical composites of the ASVAB to capture another facet of ability.

The paper has six sections. Section 2 describes mechanical ability and discusses the tests used to identify it. Section 3 describes the data used, explores the relation between mechanical ability test and other more conventional tests, and finally presents reduced-form estimates of the implied effect of mechanical ability tests on schooling choices and wages, conditional on observed measures of the cognitive and the socio-emotional dimensions. Section 4 contains the details of our augmented Roy model and the estimation strategy. Section 5 presents the main results. Section 6 concludes.

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[2]Conceptually, mechanical ability might well be another dimension of ability or a different dimension of cognitive ability. The conceptual definition goes beyond the purpose of this paper but we decided to use a model of three abilities to highlight the differential effect of mechanical ability on choices and outcomes.

2 Beyond Conventional Taxonomy: Mechanical Ability

A large proportion 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, Stixrud and Urzua (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, Christopher, 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 the label, defining mechanical ability is a complex task. In fact, the term mechanical ability has never been rigidly and unambiguously defined, although it has been an expression for the abilities required for creditable work with tools and machinery (Wittenborn, 1945). Cognitive and vocational psychologists as well as neuroscientists have utilized concepts such as mechanical aptitude, mechanical reasoning, and mechanical sense to describe this dimension.[3] Nevertheless, two distinctive components emerge from the 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

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

fueled the interest in identifying the underlying traits leading to success in specific careers and occupations.[4]

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 information about mechanisms and machines.[5] 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.[6] 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, Just and Morrison, 1988; Carpenter and Just, 1989; Hegarty, 1992).[7]

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. In addition,

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[4]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).

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

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

[7]The degree to which these abilities can be classified as cognitive is relative and it strongly depends on the theory of intelligence accepted. Some studies classify mechanical ability tests in the same category of other cognitive or intelligence test (Carroll, 1993), while other studies recognize the presence of two separate components: one highly correlated with cognition (spatial visualization and perception) and the other more related to motor abilities such as dexterity, movement, steadiness and psychomotor abilities (Wittenborn, 1945) and others. While the specific classification of mechanical ability is beyond the scope of this paper, the interest of the paper is to highlight this dimension of ability, that might well be a dimension of cognitive ability but different from the ability measured by conventional cognitive tests such as the ASVAB, and present its particular behavior in predicting outcomes.

Hartog and Sluis (2010), Boehm (2013), and Prada (2014) use a measure of mechanical ability similar to the one analyzed here 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, Levy and Murnane (2003) has influenced this research. 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 schooling decision model with counter factual adult wages, we continue and extend 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.[8]

The literature has extensively analyzed the ASVAB, but typically focusing on the computation of the Armed Forces Qualification Test (AFQT). This construct 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.[9]

The questions from the *mechanical comprehension* section are intended to capture the ability to

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[8]The ASVAB is administered by the United States Military Entrance Processing Command and it has been used since 1976 to determine qualification for enlistment in the United States Armed Forces.

[9]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.

solve simple mechanics problems and understand basic mechanical principles. The set of questions 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, these 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. 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.

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 also for wood and metal shop practices, requiting an understanding of how the combination of several components work together to perform a specific function. The test covers topics commonly included in most high school auto and shop courses, such as automotive components, 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. As for the *automotive and shop information section*, these topics are commonly covered in high school science classes. As we discuss below, this represents a concern for our identification strategy, since it could potentially generate reverse causality between human capital accumulation and abilities. We follow Hansen, Heckman and Mullen (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 in Section 5.

The technical composites of the ASVAB have been proven to measure abilities and skills im-

portant 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, Kucinkas and Curran, 1990; Wise et al., 1992). Furthermore, according 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.[10] Thus, 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).

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.[11]

[Figure 1 about here.]

3   Data and Exploratory Analysis

This section presents a description of our source of information, a 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 tests on schooling choices and wages, conditional on standard tests of cognitive and socio-emotional ability.

The insights from the descriptive analysis are used in two ways. First, to document that mechanical ability is correlated with schooling decisions differently than standard measures of ability. Second, to motivate the use of a model to capture the effect of mechanical ability overcoming the main problems associated with the reduced-form estimates.

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[10] 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.

[11] We present a list of sample questions for the three sections in Section 1 in the Web Appendix.

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 attending school at the time of the survey. We chose to analyze white males in order to have a benchmark to compare our results with previous studies (Willis and Rosen, 1979; Heckman and Sedlacek, 1985; Keane and Wolpin, 1997; Gould, 2002; Cunha and Heckman, 2007, etc). Additionally, we want to abstract from influences that operate differently on various demographic groups. 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. Moreover, the five-year window is useful to get a smooth average of the first part of the wage profile of the individuals.

We restrict the sample further to concentrate on individuals meeting the minimum entrance requirements for a four-year college because that is the margin of interest in the paper. In consequence, we do not include high school dropouts. As a result, our analysis is specific and cannot be generalized to the whole population.

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 and fall of 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. The sample is further reduced because we eliminate 244 observations corresponding to high school dropouts and individuals with no information on schooling. The final sample contains 1,466 individuals. Table 1

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

presents the description of the variables used.

[Table 1 about here.]

We analyze one schooling choice, 4 year college attendance. The variables used to determine college attendance are the maximum degree attained by the age of 25 and the 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] These questions are used to compute the AFQT, a measure 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 tests 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.

Following the literature, we use two constructs to measure socio-emotional ability: 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 measures self-esteem, i.e., the degree of approval or disap-

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[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.

[14]These measures have been used in the literature as proxies of socio-emotional ability (Heckman, Stixrud and Urzua, 2006).

[15]Extracted from http://www.nlsinfo.org/nlsy79/docs/79html/79text/attitude.htm.

proval 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 0.87 (Menaghan, 1990) to 0.94 (Strocchia-Rivera, 1988), depending on the nature of the NLSY79 sample selected.[16]

3.2 Measurement of Mechanical Ability

In order to establish the relationship between our measure of mechanical ability and standard measures of ability, we first show the correlation between all the different measures.

In particular, Table 2 shows the correlation matrix between the three technical composites of the ASVAB (mechanical comprehension, auto and shop information and electronics information), four tests used to compute AFQT (arithmetic reasoning, word knowledge, paragraph comprehension and numerical operations), mathematics knowledge, coding speed, 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 2 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]

We also present the results from an Exploratory Factor Analysis (EFA) that confirms the presence of one factor that is captured by the technical composites, but it is not captured by the other tests. The results from the Exploratory Factor Analysis on nine subsections of the ASVAB (the three technical composites, the four set of questions used to create the AFQT plus mathematics

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[16]Ibid.

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

knowledge and coding speed) confirm that at least two factors are needed to explain the correlation among the scores in the nine questions.[18]

[Figure 2 about here.]

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. 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, the loadings are close to zero.[19] Figure 2 (Panel a) presents the original estimated loadings for each factor, i.e., the estimated coefficients associated with each factor.

The suggested structure persists after several forms of rotation. In Figure 2 (panel b) we present the loadings after a rotation that maximizes the variance of the squared loadings between variables (simplicity within factors).[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. [21]

We label the first factor, shared by all components of the ASVAB, as cognitive ability. This factor affects the three technical composites of the ASVAB. This is expected as several of their questions require a certain degree of reading or verbal comprehension and basic mathematics skills associated with cognition. The second factor, which is only present for the technical composites, can be interpreted as mechanical ability. The part of ability that is related to understanding how

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[18]The factor analysis performed under the assumption of orthogonal factors that allows for some unique components in the equation keeps the first four 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. We focus only on the first two factors because they account for all the shared variance. The first factor accounts for 84.8 percent of the variance and the second factor for 14.9 percent the second factor.

[19]Numerical Operations is an exception because the loading 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 0.30 or greater is considered significant (Diekhoff, 1992; Sheshkin, 2004, among others).

[20]Rotation is important because of the indeterminacy of the factor solution in the exploratory factor analysis.

[21]Other studies have found the presence of two components when analyzing separate components of the ASVAB. See Welsh, Kucinkas and Curran (1990) for a review of several factor analysis studies.

things work but it is not captured by the AFQT. We incorporate these ideas in our empirical model. See section 4 for more details.

3.3   Sorting into College

As previously discussed, the set of scores can be used to create a composite measure for each type of ability. For cognitive ability this measure is constructed using the average of the standardized scores for arithmetic reasoning, mathematical knowledge, paragraph comprehension, word knowledge, numerical operations, and coding speed. Mechanical ability measurement is constructed as the average of the standardized scores in mechanical comprehension, electronics information, and auto and shop information. Finally, for socio-emotional ability the measure is created as the standardized sum of the average of Rotter and Rosenberg scores.[22]

We use these composite measures to document the sorting into college. In particular, we analyze the association between each of these observed measures and the probability of attending four-year college after graduating from high school (or after obtaining a GED). Figure 3 shows the cumulative distribution function (cdf) of each measure of ability by schooling choice -attending four-year college or not. Panel (a) corresponds to the cognitive measure, panel (b) depicts the case for the socio-emotional measure and panel (c) corresponds to the mechanical measure. For all three measures of ability, the cdf for people with high education stochastically dominates the cumulative density function 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 pattern.

[Figure 3 about here.]

To further analyze the effect of the observed tests on schooling choices we estimate probit models for the probability of attending four-year college. All regressions include a set of family background controls, cohort dummies and dummies for region and urban location. Table 3 presents the marginal effects evaluated at the mean (MEM).

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[22]We use the four-item abbreviated version of the Rotter Internal-External Locus of Control Scale and the 10-item Rosenberg Self-Esteem Scale. We take the average of each measure before adding them because they measure two different socio-emocional traits.

Column (1) displays the results controlling for cognitive and socio-emotional measures while column (2) presents the results controlling for mechanical and socio-emotional measures. 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. Cognitive and mechanical tests show a similar pattern in terms of the positive impact on schooling attainment but the effect of AFQT is more than four times 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 figure 3.

Column (3) displays the results controlling for the three measures of ability simultaneously. In this case, the effect of the mechanical test on educational attainment is reversed. In particular, a one standard deviation increase on the mechanical test decreases the probability of attending a four-year college in 6.23 percentage points (keeping cognitive and socio-emotional measures constant). The same increase on the cognitive test increases college attendance by 20.6 percentage points. These effects are large considering that in the sample the probability of attending college is 32 percent. The impact of socio-emotional ability on four-year college attendance is positive but non-significant.

[Table 3 about here.]

3.4 Reduced-form Results: Hourly Wages

To estimate the association between wages and measures of skills we estimate the following Mincer-type regression:

$$\ln w_i = \alpha + X_i\beta_x + \beta_c Cog_i + \beta_s Soc_i + \beta_m Mec_i + u_i$$

Where w_i corresponds to hourly wages, X_i basic individual characteristics including schooling, Cog, Soc and Mec are the observed measures of cognitive, socio-emotional and mechanical skills and u_i the error term.

Table 4 presents the results. The "return" to the mechanical composite is positive and high, even when compared to the return to AFQT. In particular, after controlling for education, one unit increase in the mechanical test is associated with a 0.0358 increase in the log hourly wages. The effect is similar to the effect of our socio-emotional composite test score, although less precise. The

effect of the cognitive test on wages more than doubles this value.

[Table 4 about here.]

The reduced-form results show that mechanical abilities are rewarded by the labor market and, opposed to standard measures of ability, reduces the probability of attending four-year college. However, those regressions are problematic because: 1) schooling choices are endogenous and that must be controlled for to estimate the returns to ability and 2) test scores are just proxies of abilities and they are influenced by schooling at the time of the test, age and family background variables, among other 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 here deals with two of the main problems that arise when computing the effect of abilities on wages: the endogeneity of schooling choices and the fact that test scores are just proxies for abilities.

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, Stixrud and Urzua (2006), Urzua (2008) and Heckman et al. (2014) 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 net benefits across each feasible choice and chooses the alternative that yields the highest payoff.

We present each of the components of the model in a separate subsection. The model estimated considers one schooling choice (attending a four-year college or not), two potential outcomes for hourly wages, and three dimensions of ability (three latent factors). The factor are identified from the distribution of the scores in six cognitive tests, three tests on mechanical ability, and two tests on socio-emotional abilities.

4.1 Model of Schooling Choice and Wages

The latent utility of getting education is given by:

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

Where D denotes a binary variable that takes the value of 1 if the individual chooses to attend a four-year college and 0 otherwise.[23] And,

$$I_i = X_i\beta + \boldsymbol{\theta_i}\lambda'_D + e_i \text{ for } i = 1,...N \tag{1}$$

where X_i is a matrix of observed variables that affect schooling, β is the vector of coefficients. $\boldsymbol{\theta_i} = [\theta_{c,i}, \theta_{m,i}, \theta_{s,i}]$ is the vector of latent abilities where subscript c is used to denote cognitive ability, m mechanical ability and s socio-emotional ability. $\lambda_D = [\lambda_D^c, \lambda_D^m, \lambda_D^s]$ are 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_i and $\boldsymbol{\theta_i}$.

Conditional on X_i and $\boldsymbol{\theta_i}$ 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.

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

$$\ln w_{D,i} = X_{w,i}\beta_{w,D} + \boldsymbol{\theta_i}\lambda'_{w,D} + e_{w,D,i} \tag{2}$$

for $D = \{0,1\}$, where $\lambda_{w,D} = [\lambda_{w,D}^c, \lambda_{w,D}^m, \lambda_{w,D}^s]$ and $e_{w,D,i}$ is the error term assumed to be orthogonal to X_i and $\boldsymbol{\theta_i}$.

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[23]Through all the paper we use the indicator function $\mathbf{1}[]$. This function takes a value of one if the condition inside the parentheses is satisfied.

4.2 Test Scores as a Measurement System and Latent Factors

To deal with the fact that ability is latent rather than observed by using test scores as an auxiliary measurement system to identify cognitive, socio-emotional and mechanical ability.[24]

The empirical strategy relies on the assumption of a linear relation between the latent ability and the observed variables. We treat observed cognitive, socio-emotional, and mechanical test scores as the outcomes of a process that has as inputs unobserved abilities and individual observable characteristics such as family background, schooling at the time of the test, among others. Motivated by the findings of the Exploratory Factor Analysis performed in Section 3, the model allows each cognitive and socio-emotional test scores 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:

$$C_{j,i} = X_{C_j,i}\beta_{C_j} + \lambda_{C_j}^c \theta_{c,i} + e_{C_j,i} \tag{3}$$

for $j = \{1, ..., 6\}$. The model for the mechanical measure M_k is:

$$M_{k,i} = X_{M_k,i}\beta_{M_k} + \lambda_{M_k}^c \theta_{c,i} + \lambda_{M_k}^m \theta_{m,i} + e_{M_k,i} \tag{4}$$

for $k = \{1, ..., 3\}$. And the model for the socio-emotional measure S_l is:

$$S_{l,i} = X_{S_l,i}\beta_{S_l} + \lambda_{S_l}^s \theta_{s,i} + e_{S_l,i} \tag{5}$$

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

In addition, 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 $D = \{0, 1\}$ 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 (ability).

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[24]More precisely, we follow use the measurement system jointly with data on educational choices to non-parametrically identify the parameters of the distribution of the latent factors and then we draw from these distributions the realizations of the latent factors used in the model. Appendix 1 describes in detail the identification of the model that follows Carneiro, Hansen and Heckman (2003) and Hansen, Heckman and Mullen (2004).

Latent Factors. Latent factors, $\boldsymbol{\theta_i}$, are assumed to be known by the individual but unknown to the researcher. The levels of latent factors may be the result of a combination of inherited ability, the quality of the family environment in which individuals were raised, cultural differences, among other dimensions. In the context of our model, they are assumed to be fixed by the time the individual is choosing whether or not to enroll in a four-year college.

We assume that cognitive and socio-emotional factors are independent. This assumption has been used in the literature (Heckman, Stixrud and Urzua, 2006) and table 2 provides its empirical justification. The correlations between cognitive and socio-emotional test scores are small, and they reduce even more once family background characteristics are controlled for (results available upon requests from the authors). The correlations between technical composites and socio-emotional measure are even smaller. Consequently, we also assume that mechanical and socio-emotional factors are independent. On the other hand, given their conceptual and empirical associations, we allow cognitive and mechanical ability to be correlated.

4.3 Estimation Strategy

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

In addition to the independence assumptions on the error terms, we assume that the error terms are normally distributed. Specifically, we assume $e_i \sim N(0,1), e_{w,D,i} \sim N(0, \sigma^2_{w,D})$ for $D = \{0,1\}$, $e_{C_j,i} \sim N(0, \sigma^2_{C_j})$ for $j = 1, ..., 6$, $e_{M_l,i} \sim N(0, \sigma^2_{M_k})$ for $k = 1, ..., 3$, $e_{S_l,i} \sim N(0, \sigma^2_{S_l})$ for $l = 1, 2$.

For latent factors (abilities) we use mixtures of normal distributions. These provide enough flexibility, imposing a minimum number of restrictions on the underlying distributions of $[\theta_c, \theta_m, \theta_s]$ (Ferguson, 1983). In particular, we use mixtures of two-normal distributions and assume $E[\theta_c] = E[\theta_m] = E[\theta_s] = 0$. Appendix 1 presents a detailed description of the empirical and identification strategies.

Our likelihood function is:

$$L(X|\delta_0) = \prod_{i=1}^{N} f(D_i, \ln w_{D,i}, T_i|X_i, X_{w,i}, X_{T,i}; \delta_0)$$

where δ_0 denotes the vector of parameters. Given that conditional on unobserved abilities all the error terms are mutually independent, and denoting by $F_{\boldsymbol{\theta}}(\cdot)$ the joint distribution of $\boldsymbol{\theta} \in \Theta$, our likelihood can also be expressed as:

$$L(X|\delta_0, \delta_1) = \prod_{i=1}^{N} \int_{\tau \in \Theta} f(D_i, \ln w_{D,i}, T_i|X_i, X_{w,i}, X_{T,i}, \tau; \delta_0) dF_{\boldsymbol{\theta}}(\tau; \delta_1)$$

where δ_1 denotes the vector of parameters defining the factors' distribution. 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 (Gourieroux and Monfort, 1995). Our statistical inference uses the Bernstein-von Mises Theorem, which establishes that the variance of the posterior is the asymptotic variances of the estimates. See Hansen, Heckman and Mullen (2004), and Heckman, Stixrud and Urzua (2006) and Appendix 2 for more details.

5 Main Results

5.1 Test Scores vs. Latent Abilities

Table 5 presents the estimated coefficients from Equations 3 to 5.[25] The table with the full set of results is presented in the Web Appendix (Section 3). 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, Hansen and Heckman, 2003, and Appendix 1). The selected numeraires are mathematics knowledge, 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 4 presents the variance decomposition of the measurement system. The results show the contribution

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[25]We present evidence on the goodness of fit of the model in Appendix 3. Also, we demonstrate that our proposed three-factor model does a better job predicting log wages than a two-factor model that does not include the mechanical factor.

of observed variables, latent abilities and error terms as determinants of the variance of each test score.

The variance decomposition confirms the critical role of latent ability. they explain between 11% and 80% of the overall variance depending on the test score. On the other hand, the contribution of observed variables to the variance of the test scores is never more than 20 percent. Notice that 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.[26]

[Figure 4 about here.]

5.2 Distribution of Abilities

Observed test scores and unobserved abilities differ in many dimensions. We use the estimated parameters for the distribution of each ability to estimate the distribution of cognitive, socio-emotional, and mechanical abilities. Table 6 displays the mean and the standard deviation of the simulated distribution for each ability.

[Table 6 about here.]

We use these results to show that the distribution of abilities and the distribution of test scores are not the same. For mechanical ability, these differences have profound implications in terms of the implied sorting into schooling.

Figure 5 presents the marginal cumulative distribution functions of the latent factor by schooling level. For cognitive (in panel (a)) and socio-emotional ability (in panel (b)) the cumulative distribution of the ability for people that attended college stochastically dominates the cumulative distribution for those who did not (see Figure 5). Although the distributions between observed and latent abilities are different, the sorting into schooling is similar. In particular, for both observed test scores and unobserved abilities, the distribution from more educated people with high education first-order stochastically dominates those from people with low schooling (see Figures 5 and 3).

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[26]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 between a third and two thirds, depending on the test, compared with the model in which both factors are used as explanatory variables.

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 levels of education. The marginal cumulative distribution function of the latent ability for more educated individuals is first-order stochastically dominated by distribution obtained from those who did not attend college (see Figure 5 panel (c)). As a consequence, for mechanical ability, the sorting to schooling implied by the estimated factor and the observed test scores is different.[27]

[Figure 5 about here.]

5.3 Effect of Abilities on Schooling Choice

Figures 6 to 11 present the main results of the model. Figures 6 and 7 present the joint distributions of the probability of attending a four-year college 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, although the positive effect of cognitive is always stronger. In order to understand the underlying magnitude in these figures we compare the effect of moving individuals across deciles of both cognitive and mechanical ability on the probability of going to college. Given that cognitive has a positive effect and mechanical a negative effect this exercise shows 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.

In fact, the estimated probability of attending four-year college for an individual at the bottom of the distribution of both cognitive and mechanical ability is 11.3 percent, that probability increases to 30.8 percent for an individual with cognitive and mechanical abilities in the median of the respective distribution and it increases to 51.2 percent for individuals at the top of both distributions.[28]

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

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[27]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).

[28]The estimated probabilities for all the combinations between the first, fifth and tenth deciles cognitive and mechanical ability are presented in the Web Appendix (Section 3).

of mechanical and socio-emotional ability (see Figure 7). Moving someone from the bottom to the top of both distributions changes the probability of attending four-year college from 29.6 percent to 39.7 percent.[29]

The marginal effect of cognitive ability integrating out the effect of mechanical is presented in panel (a) of Figure 8, while panels (b) and (c) present analogous results for socio-emotional and mechanical ability, respectively.

[Figure 6 about here.]

[Figure 7 about here.]

[Figure 8 about here.]

Finally, Table 7 presents the effect on college attendance associated with a one standard deviation increase in each of the factors. According to the estimates, a one standard deviation increase in cognitive ability is associated with an increase of 22.9 percentage points in the probability of attending four-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.[30]

[Table 7 about here.]

5.4 Effect of Abilities on Hourly Wages

Figures 9 and 10 present the average (log) wages by deciles of cognitive and mechanical ability and by deciles of socio-emotional and mechanical ability, respectively. Importantly, the overall effect of ability on wages includes the direct effect on log wages holding schooling constant, the effect of ability on the decision to attend college and the implied effect of attending college or not on log wages. This overall effect is positive for all three dimensions of ability.

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[29]The Web Appendix (Section 3) contains a Table with the estimated probabilities for the first, fifth and tenth deciles of socio-emotional ability and for the first, fifth and tenth deciles of the distribution of mechanical ability.

[30]As a robustness check we compare our results from the results obtained using a subsample of males that have not attended any elective course related to mechanical skills by the time of the tests according to their high school transcript information. The results are qualitatively the same for the schooling decision and the measurement system. However, we cannot compute labor market returns due to the small size of this very specific sample. Results are available upon request.

As in the case of Figures 6 and 7 we can analyze the overall impact of latent ability on (log) hourly wages by examining the changes on averages across deciles. Moving someone from the bottom to the top of the distribution in both cognitive and mechanical ability increases the average (log) wage from 2.59 to 2.96 which implies more than a 40 percent increase in hourly wages. The analogous exercise for mechanical and socio-emotional ability implies an increase in average on the same order of magnitude.[31]

[Figure 9 about here.]

[Figure 10 about here.]

The marginal effect of mechanical ability is considerable small compared with the effect of cognitive and socio-emotional ability (Figure 11).

[Figure 11 about here.]

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. These results are presented in Table 8.

[Table 8 about here.]

The conclusions change when analyzing the returns to ability conditional on college attendance. In the case of not attending a four-year college, the returns to cognitive and mechanical ability are very close, 0.047 and 0.044, respectively. While in the case of attending college the returns to cognitive ability is 0.108 compared to the -0.031 for mechanical ability.[32] For socio-emotional ability the difference in the returns is smaller although the returns are higher in the scenario of college attendance.

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[31]Tables with the estimated averages for the combination between the first, fifth and tenth deciles of the distribution in each pair of dimensions of ability can be found in the Web Appendix.

[32]The negative return to mechanical ability for those attending four-year college might seem unconventional; however, other authors have reported similar results when analyzing abilities related to mechanical dimensions. Willis and Rosen (1979) find evidence of negative returns to manual dexterity. They utilize a specific sample of 3,611 high ability male World War II veterans who applied for the Army Air Corps and then responded the NBER-Thorndike-Hagen survey of 1968-71. The negative effect, although not significant, affects mainly college attendees which is interpreted in the paper as supporting evidence for the comparative-advantage hypothesis. In addition, Yamaguchi (2012) using the NLSY79 also finds a negative effect of "motor ability" on wage growth only for individuals with college education.

5.5 Implications

We now analyze the wage gains associated with four-year college attendance for individuals with different 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 (log) hourly wages conditional on the schooling choice and the respective counterfactual wage, i.e. $E[Y_1 - Y_0|D = 0]$ and $E[Y_1 - Y_0|D = 1]$.

Table 9 presents our results. On average, the mean of (log) hourly wages conditional on college attendance is 0.102 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 average of (log) hourly wages is 0.038 lower than the average of the counterfactual wage. These results suggest that, on average, attending four-year college is associated with higher wages even for individuals that, given their observable characteristics and latent abilities, ended up deciding not to attend four-year college.

[Table 9 about here.]

However, these results are computed for the average and may 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 of the table correspond to the bottom, middle and top quintiles of mechanical ability. 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 fifth quintile of the distribution of socio-emotional ability); the third row presents the opposite case, i.e., 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 average (log) hourly wage when cognitive ability is low. This result holds for both low and high levels of socio-emotional ability. In consequence, for individuals with high levels of mechanical ability and low levels of cognitive ability, not attending four-year college is associated with the highest expected hourly wage.[33]

[Table 10 about here.]

Finally, we analyze the ability profile of the individuals who benefit from not attending four-year college which accounts for 21.5 percent of the population.[34] As expected, a large proportion of them are individuals with high levels of mechanical ability. More specifically, we find that 65 percent of the individuals who benefit from not attending four-year college are individuals above the median of the distribution of mechanical ability, which accounts for a 14 percent of the total population. However, as Figure 12 shows the individuals who benefit from not attending four-year college do not come disproportionately from the group of individuals with low levels of cognitive and socio-emotional ability.

[Figure 12 about here.]

Although the absolute percentages are useful, it is important to take into account that the fraction of the population in each specific profile varies. More specifically, the positive correlation between mechanical and cognitive ability implies that the number of individuals with high levels of both abilities is always higher that the number of individuals with low levels of one and high levels of the other. For this reason it is useful to analyze the fraction of individuals in each specific profile

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

[34]In this section we compare hourly wages of individuals early in their careers, between ages 25-30. As a result, the statement on who benefits from not attending college only applies to hourly wages at this early stage. We also calculate the model using the log of average annual earnings between ages 25-30 and the result holds. See Section 2 in the Web Appendix for details on this result. In addition, as a robustness check we calculate the log of the present value at age 25 of annual earnings from 25 to 55 years old. The results are qualitatively similar and we find a larger percent of the population for whom the present value of earnings associated with not attending four-college is higher than the present value of earnings associated with attending four-year college. Results are available upon request. It is important to note that the results obtained using annual earnings include various margins besides the returns to different dimensions of ability such as the effect of ability on hours worked, differential periods of unemployment, accumulation of experience among others. For that reason we concentrate on hourly wages at a relative early age leaving the study of the other margins for future research.

who benefits from not attending four-year college. At the aggregate we find that 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 13 presents the fraction of individuals who benefit from not going to college in eight different ability profiles. These profiles are created by classifying individuals as high or low ability depending on their relative position with respect to the median of the distribution of each of the three dimensions of ability. The figure shows that 40 percent of the individuals with low cognitive, low socio-emotional and high mechanical ability benefits from not attending four-year college. This fraction decreases progressively for the individuals as we look at profiles with higher levels of ability. But even among the individuals with the highest level of ability in all dimensions, we find a high fraction, 21 percent, that benefits from not attending four-year college.

[Figure 13 about here.]

6 Conclusions

This paper investigates the role of mechanical ability in explaining schooling decisions and labor market outcomes. We show that this dimension is positively rewarded by the labor market, but in contrast to the more 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, at least in an early stage in their careers.

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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. Our results compare log hourly wages between the ages of 25 and 30 but they hold when we compare log annual earnings in the same range of ages and also when using the present value of the stream of annual earnings from 25 to 55 years old.

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.[35] 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.

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[35]NCES (2013) and Rosenbaum, Stephan and Rosenbaum (2010).

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Appendix

Appendix 1: Identification of the Model

Carneiro, Hansen and Heckman (2003), Hansen, Heckman and Mullen (2004) and Heckman, Stixrud and Urzua (2006) provide the formal non-parametric identification arguments of models with similar characteristics to the one used here. Consequently, in this section we discuss the main assumptions securing the model's identification and refer the interested readers to the aforementioned papers or our web-appendix for further details.[36]

The distribution of cognitive ability. From the set of six cognitive measures, we normalize the loading associated with mathematics knowledge to 1. This anchors the scale of the cognitive factor. The main identification argument relies on Klotarski's Theorem.

The distribution of socio-emotional ability. For the identification of the distribution of socio-emotional ability we normalize the loading associated with Rosenberg Self-Esteem Scale to 1. This anchors the scale of the cognitive factor. We rely on the orthogonality of θ_s with respect to (θ_c, θ_m) to ensure the non-parametric identification of the distribution of θ_s.

The distribution of mechanical ability. Mechanical measures depend on both θ_c and θ_m, which are allowed to be correlated. We generate this correlation imposing the following linear association between θ_c and θ_m:

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

where θ_2 is an additional factor, which is assumed to be independent of θ_c. Thus, we can rewrite the equation for the k-th mechanical test score using two independent factors as follows:

$$
\begin{aligned}
M_k &= \lambda^c_{M_k} \theta_c + \lambda^m_{M_k} \theta_m + e_{M_k} \\
&= \lambda^c_{M_k} \theta_c + \lambda^m_{M_k} (\alpha_1 \theta_c + \theta_2) + e_{M_k} \\
&= a_k \theta_c + \lambda^m_{M_k} \theta_2 + e_{M_k}
\end{aligned}
$$

where $a_k = \lambda^c_{M_k} + \lambda^m_{M_k} \alpha_1$. In practice, we use three mechanical test scores so $k = 1, ..., 3$.

In this context, the identification argument is straightforward. First, given that the variance of

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[36]Cooley, Navarro and Takahashi (2011) present an alternative identification strategy for the case in which the distributions of all factors are asymmetric.

the cognitive factor and the factor loadings in the system of cognitive measures are already known, from the covariance $COV(C_j, M_k) = \lambda^c_{C_j} a_k \sigma^2_{\theta_c}$, where C_j denotes the j-th cognitive test score, we recover a_k for any mechanical test score k. Second, following the aforementioned literature, we normalize one of the factor loadings $\lambda^m_{M_k}$ to one. In particular, we impose this normalization in the equation for the mechanical comprehension score, i.e. $\lambda^m_{M_3} = 1$. This secures the identification of the other factor loadings in the mechanical test score system. We can then apply Klotarski's Theorem to secure the non-parametric identification of the distributions of θ_2 and e_{M_k}, with $k = 1, ..., 3$. Finally, since the system of equations for (a_1, a_2, a_3) contains four unknowns, we need to impose a final normalization. Specifically, we normalize $\lambda^c_{M_1} = 0$, where M_1 denotes the automotive and shop information section of the ASVAB.[37] This implies that the cognitive factor θ_c affects the first mechanical test score only indirectly, through its correlation with the mechanical factor θ_m. In other words, M_1 is a dedicated measure of θ_m.

Our empirical model is implemented assuming that θ_c and θ_2 are distributed as mixture of normal distributions:

$$\theta_{s,i} \sim \sum_{l=1}^2 p_l N \left(\mu^l_s, \left(\sigma^l_s \right)^2 \right)$$

$$\theta_{c,i} \sim \sum_{k=1}^2 p_k N \left(\mu^k_c, \left(\sigma^k_c \right)^2 \right)$$

$$\theta_{2,i} \sim \sum_{j=1}^2 p_j N \left(\mu^j_2, \left(\sigma^j_2 \right)^2 \right)$$

and, consequently, the distribution of θ_m is the convolution of the densities of θ_c and θ_2:

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

Appendix 2: Statistical Inference

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

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[37] We selected this measure because it has the lowest loading on the cognitive factor in the preliminary factor analysis (see Figure 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, $f(Y) = \int L(Y|\theta)f(\theta)d\theta$. Using the Bayes' rule we obtain:

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

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

The mean of the posterior distribution is:

$$\bar{\theta} = \int \theta f(\theta|Y)d\theta \tag{6}$$

Since, we rely on Bayesian methods only to ease the computational burden of the estimation, we analyze $\bar{\theta}$ from a classical perspective, i.e., as an estimator that has the same asymptotic sampling distribution as the maximum likelihood estimator.[38] Therefore, we need to find the sampling distribution of the statistic $\bar{\theta}$. Following the Bernstein-von Mises Theorem, the variance of the posterior is the asymptotic variance of the estimates.[39] In consequence, estimation can be performed by using the moments of the posterior where the mean of the posterior provides a point estimate and the standard deviation of the posterior provides the standard errors.

In this paper we use MCMC as a method to obtain draws from the posterior distribution. We generate 1,000 draws from the posterior distribution of the parameters to compute the mean, which we denote by $\breve{\theta}$, and the standard errors reported in the text. To calculate the standard errors of functions of $\breve{\theta}$, we follow Gelman and Shirley (2011) and carry out simulation-based inference using a collection of 1,000 simulations of the parameter vector, summarized by a mean and standard deviation, and 95% interval using the empirical distribution of the simulations that have been saved.

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[38]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.

[39]The Bernstein-von Mises Theorem establishes the properties of the sampling distribution of $\bar{\theta}$ in three statements: 1. $\sqrt{N}(\theta - \bar{\theta}) \to^d N(0, (-H)^{-1})$; 2.$\sqrt{N}(\bar{\theta} - \theta^{MLE}) \to^p 0$ and 3.$\sqrt{N}(\bar{\theta} - \theta^*) \to^d N(0, (-H)^{-1})$. See Train (2003) for details.

Appendix 3: Goodness of Fit and Comparison with a Two-Factor Model

Table 11 presents the results of the chi-squared goodness of fit test on the simulated distribution of hourly wages. The first column presents a formal goodness of fit test for log wages using the three-factor model, whereas the second column presents the results for a two factor-model (only cognitive and socio-emotional).

For the three-factor model, the chi-squared tests cannot reject the null hypothesis that the simulated distribution of hourly wages is statistically equivalent to the actual distribution. On the other hand, the null hypothesis for the model of two factors is rejected.[40] Consequently, our three-factor model does a better job predicting the distribution of (log) hourly wages than a two-factor model that does not include the mechanical factor.

[Table 11 about here.]

Finally, in Table 12 we compare the performance of our model and a model of two factors in predicting four-year college attendance. In both cases the tests cannot reject the null hypothesis.

[Table 12 about here.]

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[40]Heckman, Stixrud and Urzua (2006) find similar results when computing the Chi-squared test on the sample of four-year college graduates.

Figure 1: **Sample question from the mechanical comprehension section**

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.
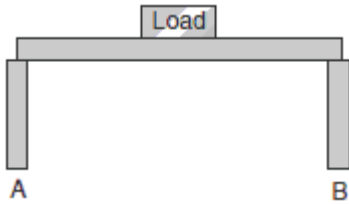
2. The diagram shows a class 1 lever. Which of the following is the same kind of lever?

    (a) A pair of tweezers
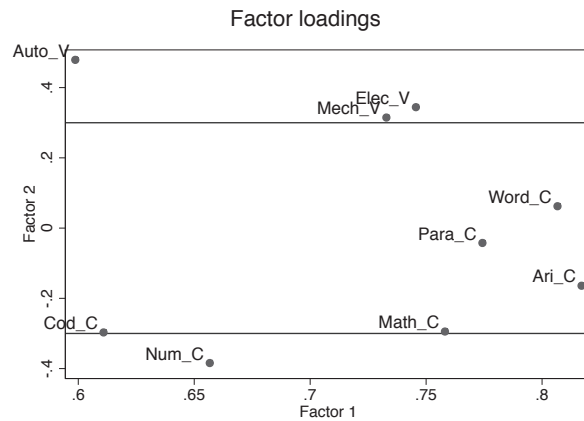
    (b) A pair of scissors

    (c) A wheelbarrow

    (d) A pair of tongs
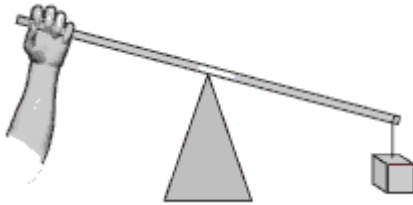
3. Which of the following would feel hottest to the touch if one end were placed in a pot of boiling water?

    (a) A wooden spoon

    (b) A metal fork

    (c) A plastic knife

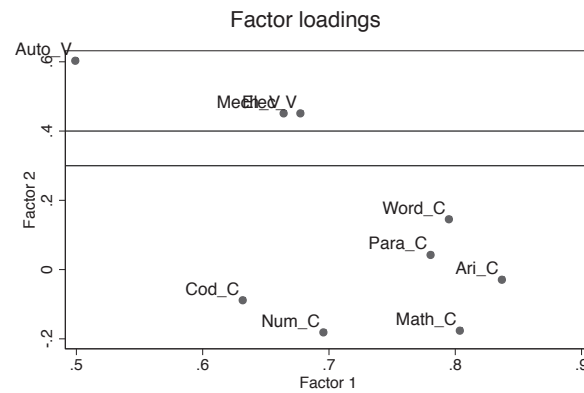   (d) A plastic cup

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Figure 2: Loadings from Factor Analysis-Orthogonal Factors

### Factor loadings

(a) Unrotated

Factor loadings

Rotation: orthogonal quartimax
Method: principal factors

(b) Rotated

Note:"mechanical" is computed by using 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. The magnitude of the loading is critical because any factor loading with an absolute value of 0.30 or greater is considered significant (Diekhoff, 1992; Sheskin, 2004, among others).
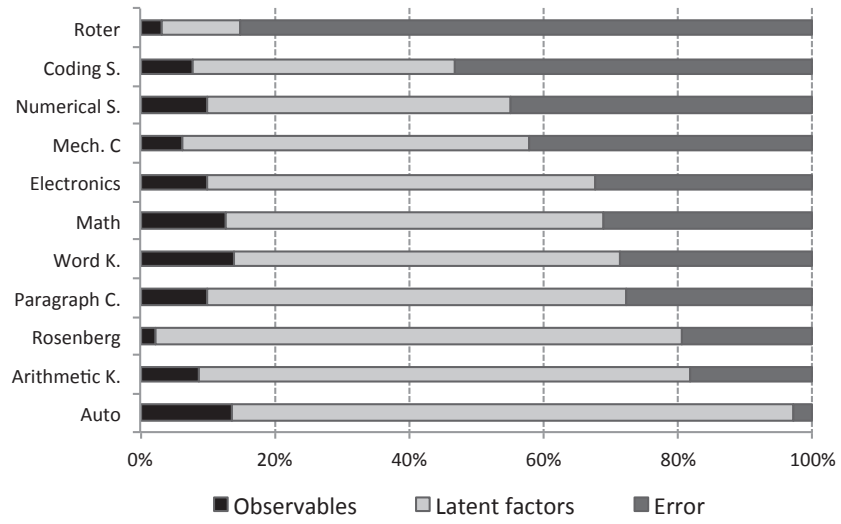
39

Figure 3: Measurement of Cognitive, Socio-emotional and Mechanical Ability

(a) Cognitive

(b) Socio-emotional

(c) Mechanical
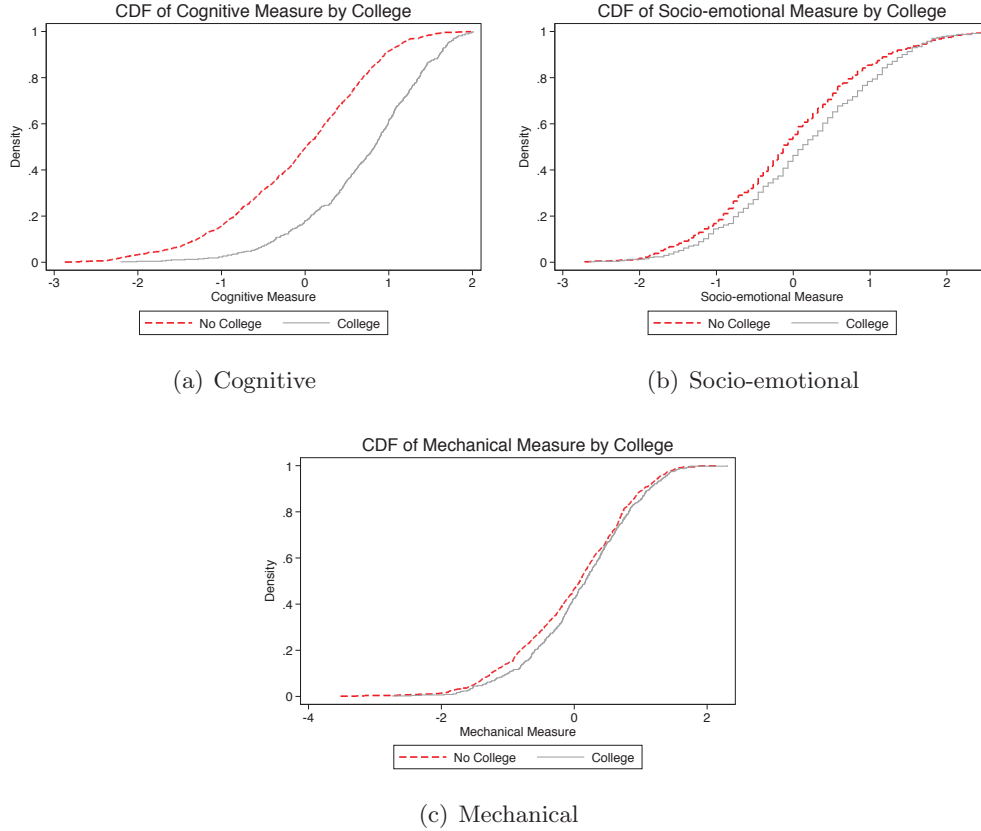
Note: The figure shows the cumulative distribution function (cdf) of each measure of ability by schooling choice, attending four-year college or not. The red dashed line corresponds to individuals who chose not to attend four-year college while the grey solid line is the marginal cdf for individuals that decided to attend four-year college. Panel (a) corresponds to the cognitive measure, panel (b) depicts the case for the socio-emotional measure and panel (c) for mechanical. The sample of individuals under "College" includes those with at least one year of enrollment in a four-year college institution before age 25. "No college" includes all those individuals in our sample who have not attendended four-year college but excludes high school dropouts and individuals with no information on schooling.

Figure 4: Variance Decomposition

Note: The figure presents the variance decomposition of the measurement system.

Figure 5: Marginal CDF: Cognitive, Socio-emotional and Mechanical Ability
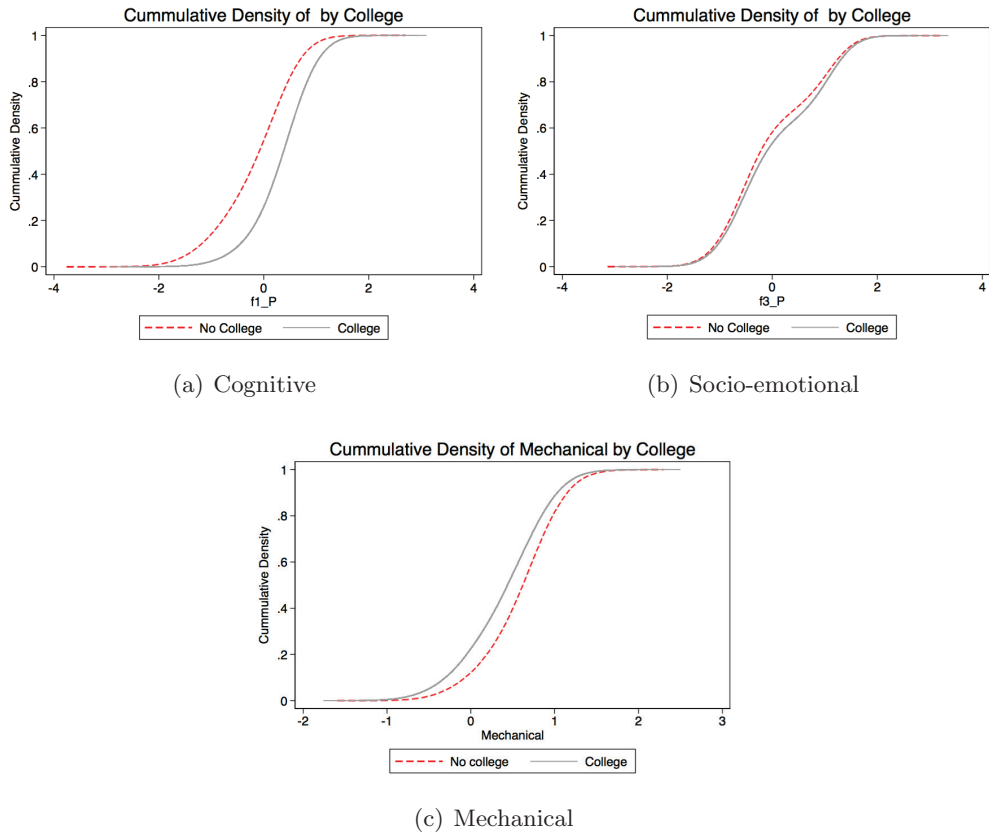
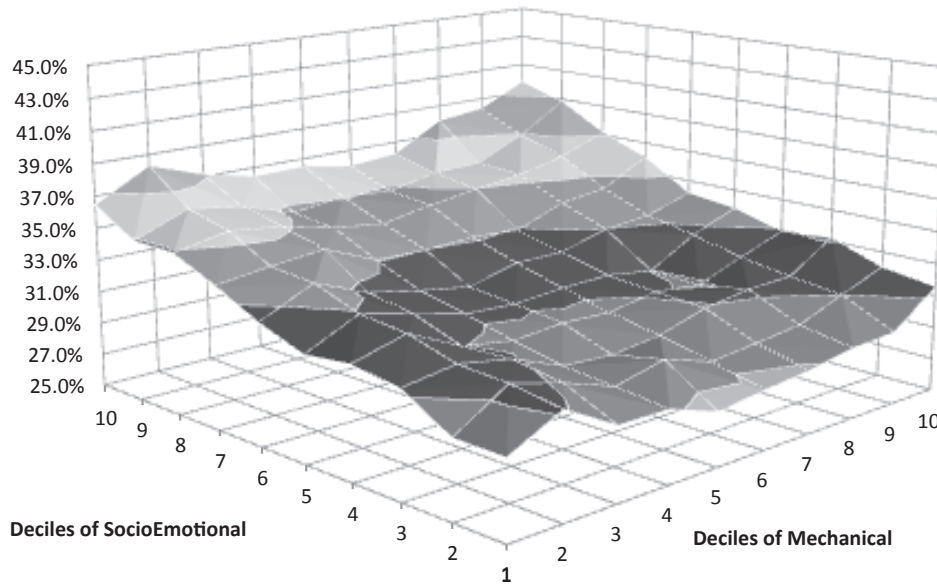(a) Cognitive

(b) Socio-emotional

(c) Mechanical

Note: The data are simulated from the estimates of the model and our NLSY79 sample. The figure presents the marginal cumulative distribution functions of each latent factor by schooling level, attending four-year college or not. The red dashed line corresponds to individuals who chose not to attend four-year college while the grey solid line is the marginal cdf for individuals that decided to attend four-year college. Panel (a) corresponds to cognitive ability, panel (b) to socio-emotional ability and panel (c) to mechanical ability.

Figure 6: Joint Distribution of College Attendance Decision by Deciles of Cognitive and Mechanical Factors
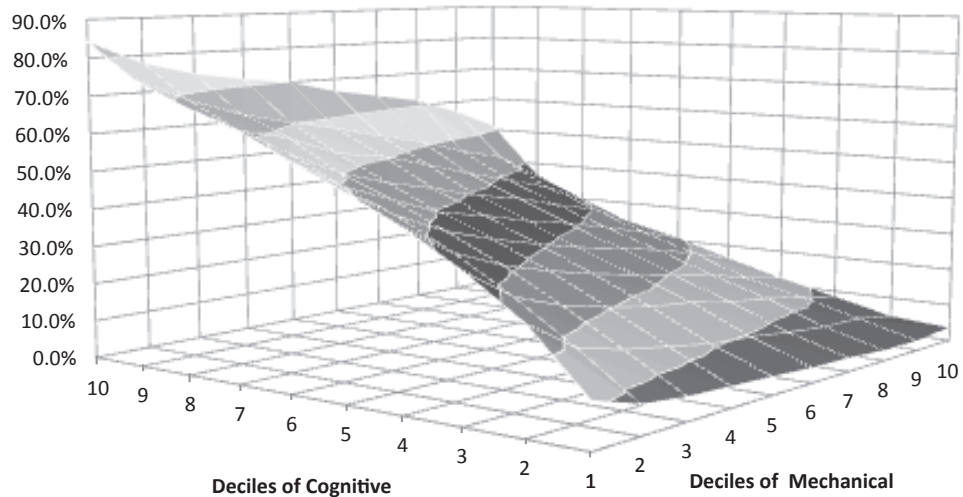
Note: The data are simulated from the estimates of the model and our NLSY79 sample. In the figure we present the joint distributions of the probability of attending a four-year college ($D = 1$) by deciles of cognitive (d_i) and mechanical (d_j) ability. We plot $P_{i,j} = \int \Pr(D = 1|\theta_c \in d_i, \theta_m \in d_j)dF(\theta_s)$ for $d_i = 1,..10$, and $d_j = 1,..10$.

Figure 7: Joint Distribution of College Attendance Decision by Deciles of Socio-emotional and Mechanical Factors
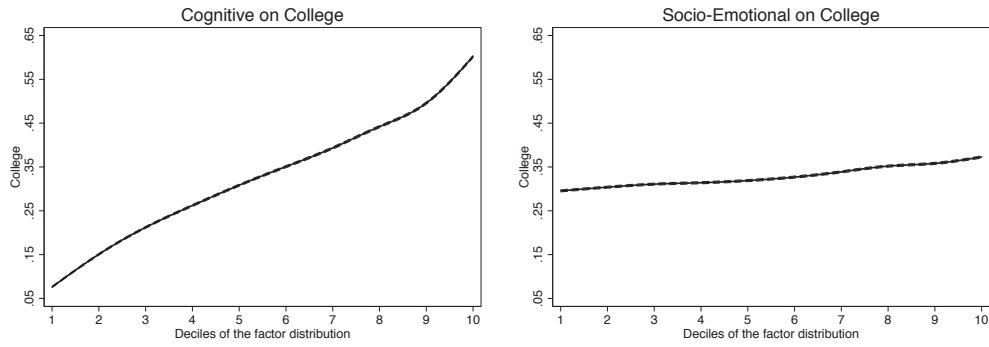

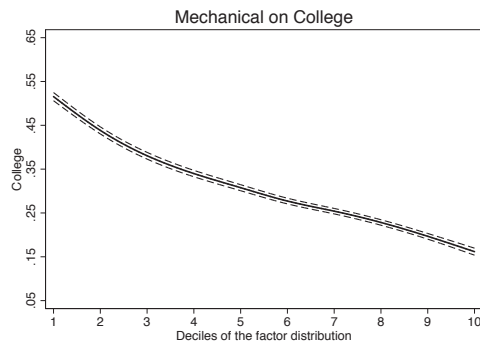Note: The data are simulated from the estimates of the model and our NLSY79 sample. In the figure we present the joint distributions of the probability of attending a four-year college ($D = 1$) by deciles of socio-emotional (d_k) and mechanical (d_j) ability. In particular, we plot $P_{j,k} = \int \Pr(D = 1|\theta_m \in d_j, \theta_s \in d_k)dF(\theta_c)$ for $d_j = 1, ..10$, and $d_k = 1, ..10$.

Figure 8:   The Impact of Ability on Four-year College Attendance

(a) Cognitive

(b) Socio-emotional

(c) Mechanical

Note: The data are simulated from the estimates of the model and our NLSY79 sample. Panel (a) of the figure presents the marginal effect of cognitive ability integrating out the effect of socio-emotional and mechanical ability, while panels (b) and (c) present analogous results for socio-emotional and mechanical ability, respectively. Dashed lines demarcate the 95% confidence interval.

Figure 9: Average (log) Hourly-Wage (ages 25-30) by Deciles of Cognitive and Mechanical Ability

Note: The data are simulated from the estimates of the model and our NLSY79 sample. Figures present the average (log) wages by deciles of cognitive and mechanical ability. The lines capture the overall effect of ability on wages which includes: the direct effect on log wages holding schooling constant, the effect of ability on the decision to attend college and the implied effect of attending college or not on log wages.

Figure 10: Average (log) Hourly-Wage (ages 25-30) by Deciles of Socio-emotional and Mechanical Ability
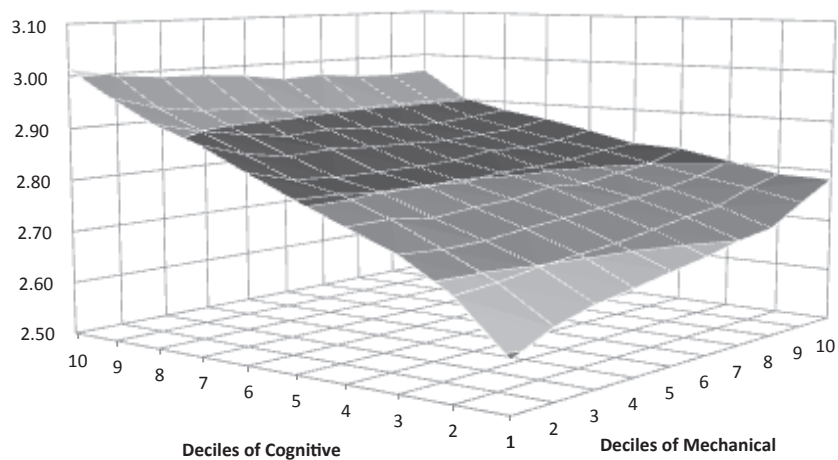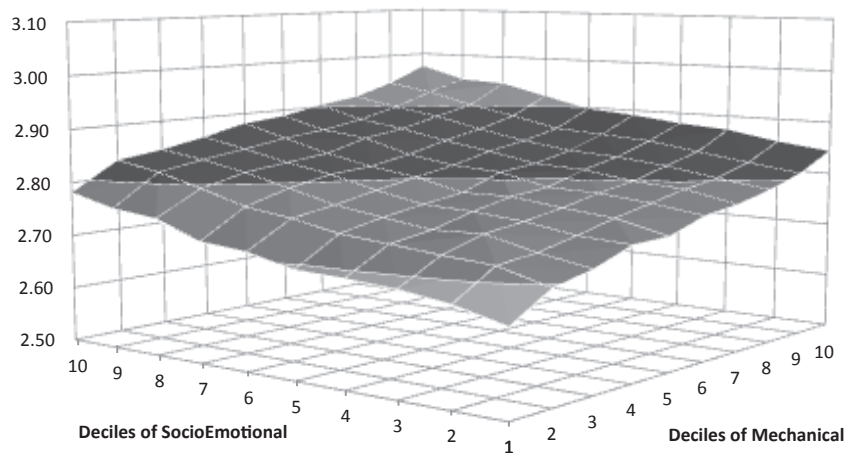

Note: The data are simulated from the estimates of the model and our NLSY79 sample. Figures present the average (log) wages by deciles of mechanical and socio-emotional ability. The lines capture the overall effect of ability on wages which includes: the direct effect on log wages holding schooling constant, the effect of ability on the decision to attend college and the implied effect of attending college or not on log wages.

Figure 11: The Impact of Ability on (log) Hourly-Wages (ages 25-30)

(a) Cognitive

(b) Socio-emotional

(c) Mechanical

Note: The data are simulated from the estimates of the model and our NLSY79 sample. The data are simulated from the estimates of the model and our NLSY79 sample. Each panel presents the effect of ability taking into account: the direct effect on log wages holding schooling constant, the effect of ability on the decision to attend college and the implied effect of attendi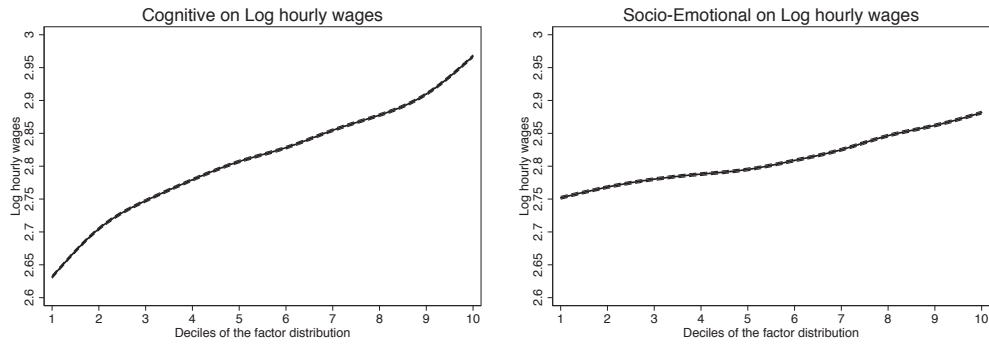ng college or not on log wages. Panel (a) presents the effect 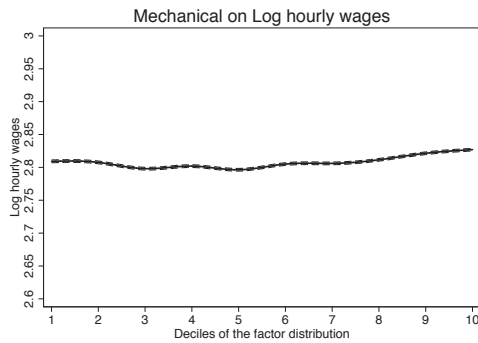of cognitive ability integrating out the effect of the other two dimensions of ability, while panels (b) and (c) present analogous results for socio-emotional and mechanical ability, respectively. Dashed lines demarcate the 95% confidence interval.

Figure 12: Composition of the Individuals Who Benefit from not Attending Four-year College by Ability Profile
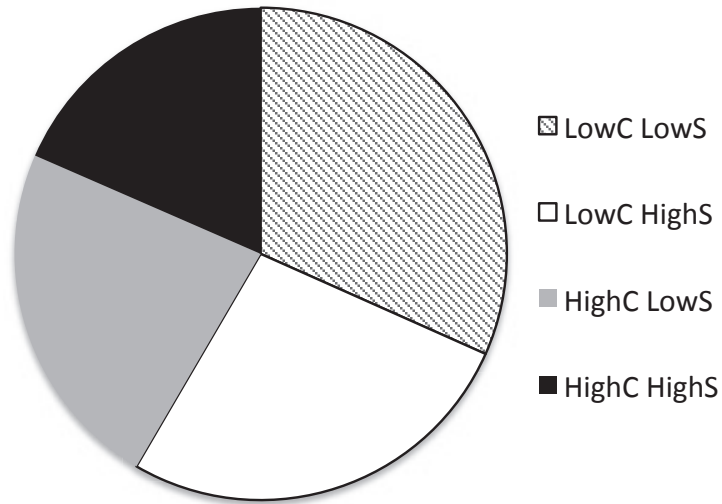
Note: The data are simulated from the estimates of the model and our NLSY79 sample. The figure presents the composition of the group of individuals who benefit from not attending college, i.e., $\Pr(Y_1 - Y_0 | profile = x) \times \Pr(profile = x)$ where Y_1 is the (log) hourly wage corresponding to the scenario of attending four-year college, Y_1 is the analogous in the alternative scenario of not attending four-year college and $x =$ LowC LowS, LowC HighS, HighC LowS and LowC LowS. Given that we classify individuals as high or low depending on whether they are above or below the median of the distribution of each latent ability, the four categories are mutually exclusive and collectively exhaustive.

Figure 13: Proportion of Individuals Who Benefit from not Attending Four-year College in Each Ability Profile Group
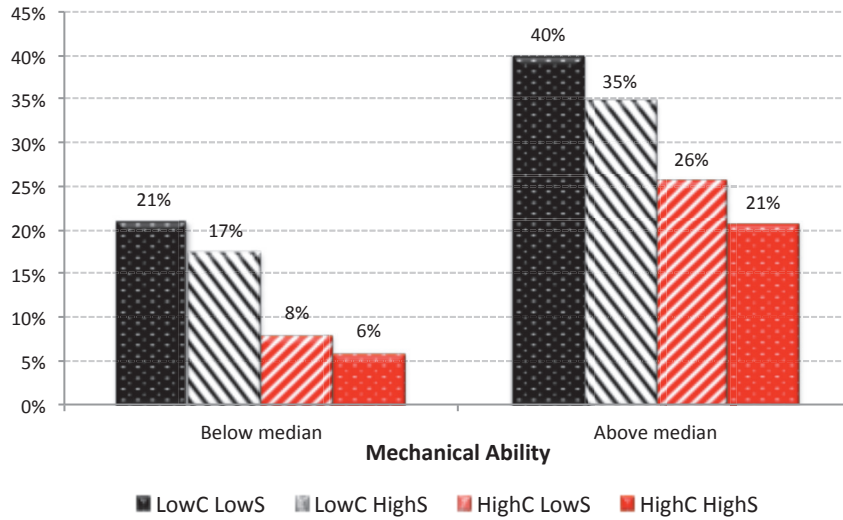
Note: The data are simulated from the estimates of the model and our NLSY79 sample. Figure presents the percentage of people that benefits from not attending college in each category, i.e., $P(Y_1 - Y_0|profile = x)$ where Y_1 is the (log) hourly wage corresponding to the scenario of attending four-year college, Y_1 is the analogous in the alternative scenario of not attending four-year college and $x =$ {LowC LowS LowM, LowC HighS LowM, HighC LowS LowM, LowC LowS LowM, LowC LowS HighM, LowC HighS HighM, HighC LowS HighM, LowC LowS HighM}. Given that we classify individuals as high or low depending on whether they are above or below the median of the distribution of each latent ability, the eight categories are mutually exclusive and collectively exhaustive.

Table 1: 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 2: 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: All the test scores are standardized. 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)
Cognitive (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 4: Reduced-form Results: Returns to Cognitive, Socio-emotional and Mechanical ability

	(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	

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

Notes: The table presents the estimated coefficients from equations 3 to 5. 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	$\mathrm{Covar}(\theta^c,\theta^i)$	$\mathrm{Correlation}(\theta^c,\,\theta^i)$
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: Four-year College Attendance

	Cognitive	Mechanical	Socio-emotional
College $D = 1$	0.229	-0.095	0.024
	(0.002)***	(0.001) ***	(0.000) ***

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

Standard errors in parenthesis

Note: The table presents the effect on college attendance associated with a one standard deviation increase in each of the factors. 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, Overall and by Schooling

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

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

Standard errors in parenthesis.

Note: The table presents the effect on (log) hourly wages associated with a one standard deviation increase in each of the factors. The "Overall" effect of ability on wages includes the direct effect on log wages holding schooling constant, the effect of ability on the decision to attend four-year college and the implied effect of attending college or not on log wages. The effects by schooling comes from the (log) hourly wage equation we have calculated separately for the scenario with no college attendance, $D = 0$, and the scenario with college attendance, $D = 1$. These effects do not include the effect of ability on the decision to attend four-year college. In the (log) wage equations we control for cohort dummies as well as geographical controls for region and urban residence at age 25.

Table 9: The average effect of attending four-year college on hourly wages

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

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

Note: The table presents the calculated average effect of attending four-year college on hourly wages conditional on $D = 1$ (treatment on the treated) and $D = 0$ (treatment on the untreated). Each parameter is constructed using the estimates from our model.

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	0.104	***	0.006		-0.068	***
Low C - High S	0.145	***	0.048	***	-0.039	**
High C - Low S	0.246	***	0.131	***	0.053	***
High C - High S	0.258	***	0.180	***	0.090	***

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

Note: The table presents the estimated gains of not attending college conditional on the decision of not attending, $E[Y_0 - Y_1|D = 0]$, for different ability profiles. The columns of the table correspond to the bottom, middle and top quintiles of mechanical ability. The rows present four extreme ability profiles defined as a combination of different levels of cognitive and socio-emotional ability. "Low" refers to the first quintile of the distribution of Cognitive ability (C) or Socio-emotional ability (S), while "High" refers to the fifth quintile.

Table 11:   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 12:   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.