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

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Abstract

This paper investigates the role of mechanical ability as a determinant of schooling decisions and labor market outcomes. Using a Roy model with multiple unobserved abilities and longitudinal data from the NLSY79, we find that this ability has a positive effect on overall earnings. However, in contrast to cognitive and socio-emotional, mechanical ability reduces the likelihood of attending a four-year college. The rationale for this asymmetry comes from its large estimated impact on earnings conditional on not attending four-year college. Our findings highlight the importance of moving beyond the one-size-fits-all discourse to offer individuals alternative educational pathways to successful careers.

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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 past decades, multiple studies have shown that both dimensions *positively* affect education as well as labor market productivity as measured by earnings or wages (see Cawley et al., 2001; O'Neill, 1990; Neal and Johnson, 1996; Herrnstein and Murray, 1994; Bowles et al., 2001; Farkas, 2003; Heckman et al., 2006; Urzua, 2008, among others). But ability is multidimensional in nature (Altonji, 2010), and thus other dimensions should also affect individual's outcomes and, in principle, not necessarily in the same direction as cognitive and socio-emotional traits.

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 other facets had received less consideration especially those that might be related to cognition. This paper investigates a dimension of ability that has been overlooked by economists when analyzing schooling decisions and adult outcomes. It 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 conventional dimensions), we implement a Roy model of college decisions and counterfactual adult earnings with unobserved heterogeneity. This framework is similar to that in Carneiro et al. (2003); Heckman et al. (2006) and Heckman et al. (2016b); so we follow their identification strategy. In particular, we augment the 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 1979 (NLSY79), and we identify mechanical ability from a subset of the Armed Services Vocational Aptitude Battery (ASVAB) available in the sample.

This paper contributes to the literature by documenting that mechanical ability matters. In particular, like socio-emotional and cognitive dimensions, we show that it has positive returns on

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

overall earnings. However, mechanical ability has a distinctive effect on schooling decisions. In contrast to conventional constructs, it reduces the probability of attending four-year college. In this way, we expand the set of abilities explaining the differences in human capital and labor income observed in the population.

In addition, this 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 receiving a high school degree, attending four-year college might not lead to higher ex-post earnings compared to the alternative of not doing so. This has important implications for public policies promoting general enrollment in four-year institutions.

Our analysis also highlights the importance of using the technical composites of the ASVAB to measure other ability dimensions. Despite being widely used, most of the literature has investigated only a subset of these questions, namely the battery of tests used to calculate the Armed Forces Qualification Test (AFQT) score, which is commonly interpreted as a proxy for cognition (e.g., Neal and Johnson, 1996). We document the empirical relevance of the technical composites both in the context of reduced-form results and the Roy model's estimates.

2 Beyond The Conventional Taxonomy

A large fraction of the literature examining the effects of ability on schooling and labor market outcomes has concentrated on the role of cognitive ability: traits that are related to the mechanisms behind learning, remembering, and problem-solving. In recent years, however, social scientists have successfully incorporated socio-emotional abilities (e.g. persistence, grit, self-control, and self-esteem) into the analysis (see Borghans et al., 2008, for a review of this literature). Nonetheless, further research is needed as other relevant dimensions could potentially affect human capital accumulation and labor market productivity.

In this paper we study mechanical ability. Although there is no consensus on its definition, we conceptualize it as the ability to perceive and understand how objects, mechanisms, and machines move and work, alone and in relation with other objects. It is also related to visual-spatial relations, motor skills, manual dexterity, and in general, to the skills required for creditable work with tools and machinery.

Neuroscientists as well as cognitive and vocational psychologists have studied multiple constructs of mechanical ability. The research from cognitive psychology, for example, has provided insights into how the brain acquires, processes, and uses information about mechanisms and machines (Blauvelt, 2006). This literature defines mechanical ability in relation to the rules and skills used by individuals to accomplish specific goals and also to the traits contributing to explain individual differences in performance (Hegarty et al., 1988; Hegarty, 1992; Carpenter and Just, 1989; Sternberg and Frensch, 1991).[2]

Neuroscientific research, on the other hand, has examined the association between brain processes and performance on specific tasks, linking mechanical abilities and visuospatial reasoning to mental rotation, motor, and psychomotor abilities (Moreau, 2012). Vocational/industrial psychologists have identified underlying traits leading to success in specific careers and occupations. In particular, this research associates mechanical ability with skills required for occupations involving intensive use of tools and machinery, as well as jobs involving the operation, maintenance, and repair of complicated machinery and other technically oriented jobs (Stenquist, 1923; Cox, 1928; Paterson et al., 1930; Wittenborn, 1945). Importantly, despite the interest on the subject, this literature has not formally examined the predictive power of mechanical ability.

In economics, only a handful of studies have directly analyzed mechanical ability (or related constructs) as determinant of schooling decisions and labor market outcomes. Willis and Rosen (1979), for instance, show that mechanical test scores and manual dexterity reduce the probability of attending tertiary education.[3] Yamaguchi (2012) includes a measure of motor skills in his analysis of occupational choices throughout the life cycle. He shows that it explains a large fraction of the observed wage variance and, for high school graduates, also a large fraction of wage growth. Hartog and Sluis (2010) and Boehm (2013), on the other hand, use a measure of mechanical ability similar to the one analyzed here to study the determinants of sorting across occupations (entrepreneurship

[2] The literature identifies two distinctive components of mechanical ability. The first component, commonly referred to as mechanical reasoning, is related to the abilities needed to perceive and understand the movement or function of a mechanism either from interacting with it or by observing it. The second component, mechanical comprehension, is related to the skills used to describe a mechanism that, when given some specific input, will produce a desired output. See Blauvelt (2006) for a detailed literature review and Jeffrey et al. (1990) for a study relating mechanical test scores to various criterion domains.

[3] Our results are consistent with this finding, although it is not possible to compare the two papers due to differences in data sources and empirical approaches.

and middle-skills occupations, respectively). However, none of these studies analyzes mechanical ability jointly with cognitive and socio-emotional dimensions. Furthermore, they all assume test scores are perfect proxies for abilities, an assumption challenged by the evidence (Heckman et al., 2006), and omit potential sources of endogeneity.[4]

In this context, we extend the economic literature by simultaneously modeling schooling decisions and labor market outcomes in the context of a multidimensional set of unobserved abilities, which includes mechanical ability. We do not enter the debate on its specific definition or nature, including whether it can be conceptualized as a distinctive dimension of ability or another dimension of cognition. Instead, we propose an empirical model that highlights its differential and independent effects, and allows for its interaction with conventional dimensions.[5]

3 Data and Exploratory Analysis

This section presents our data source, including a detailed description of the available cognitive, socio-emotional and mechanical ability measures. It also documents the relationships among these measures, and their reduced-form impacts on schooling choices and adult earnings. The insights from this analysis motivates our Roy model framework.

[4] The idea of mechanical ability also emerges from the research agenda pioneered by Autor et al. (2003). In particular, this literature has provided the theoretical foundations for analysis of the complex assignment problem of workers with heterogenous talents across occupations requiring multiple tasks. Here, mechanical ability can be loosely related to the type of skills needed to perform tasks in occupations classified as manual (e.g., technicians in laboratories or electricians) (Acemoglu and Autor, 2011). However, the empirical strategy followed by this literature does not necessarily identify causal effects of abilities on outcomes as the characteristics of occupations are used to infer worker's abilities. In contrast, as described below, we identify workers' ability by examining pre-labor market information from multiple test scores. Finally, Prada (2014) analyzes the role of mechanical ability using a similar approach to the one in this paper. However, she focuses on early occupational choices instead of the choice of attending a four-year college.

[5] The degree to which mechanical ability can be classified as a cognitive trait strongly depends on the considered theory of intelligence. Some studies classify mechanical ability tests in the same category as other cognitive or intelligence tests (Carroll, 1993), while others recognize the presence of two separate components: one highly correlated with cognition (e.g., spatial visualization and perception) and one closely related to motor abilities such as dexterity, movement, steadiness, and psychomotor abilities (Wittenborn, 1945).

3.1 The NLSY79 Study

We analyze data from the National Longitudinal Survey of Youth (NLSY79).[6] In particular, we use the cross-sectional sample of white males who were not attending school at the time of the survey.[7] With respect to the schooling decision, we focus our analysis on four-year college attendance by age 25, and define average annual earnings between ages 25 and 35 as the outcome of interest. The ten-year window provides a smooth average of the first part of the individuals' labor market income profiles. A table with summary statistics is presented below.

To examine cognitive and mechanical ability measures we rely on the Armed Services Vocational Aptitude Battery (ASVAB) available in the NLSY79. This 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, automotive and shop information, electronics information, and mechanical comprehension. It was administrated during the summer and fall of 1980, and results are available for over 90% of the sample of individuals originally interviewed in round 1.

The literature has extensively analyzed the ASVAB, but typically focuses on the Armed Forces Qualification Test (AFQT). The AFQT scores are computed using four of the available subsets (arithmetic reasoning, word knowledge, paragraph comprehension, and numerical operations), and are widely used as a measure of cognitive ability 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).[8]

To measure mechanical ability we use the following three sections of the ASVAB, commonly referred as the technical composites: the mechanical comprehension, the automotive and shop information, and the electronics information sections. These sections are not used to compute

[6] The National Longitudinal Survey of Youth (NLSY79) is a panel data set of 12,686 individuals who were born between 1957 and 1964. This survey is designed to represent the population of youth aged 14 to 21 as of December 31, 1978, who were living in the United States on January 1, 1979. Data is collected on an annual basis from 1979 to 1994 and biannually until the present day.

[7] We chose to analyze only white males to ensure comparability of 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, this sample allows us to abstract from factors that might operate differently across demographic groups.

[8] The ASVAB has been used since 1976 to determine qualifications for enlisting in the United States Armed Forces. It has evolved over time to reflect advancements in the measurement of mental aptitude and the findings from the extensive validation research. In consequence, any comparison between different versions is not trivial. See Mayberry and Hiatt (1992) for a detailed history of the main changes of the tests over time, Segall (1997) for a comparison between the paper and pencil test with the CAT versions, and Altonji et al. (2012) for a careful discussion on how to treat differences when computing and comparing the AFQT for the NLSY79 and NLSY97 samples.

the AFQT; instead, they are designed exclusively to compute the Military Occupational Specialty (MOS) scores.[9]

In fact, it has been documented that they capture abilities and skills important in predicting occupational choices, training success, job satisfaction, and job performance in the following career fields within the military: combat operations, general maintenance, mechanical maintenance, and surveillance and communications (Welsh et al., 1990; Wise et al., 1992). Furthermore, these tests are viewed as good 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).

The analysis of each of the sections indicate that the questions from the *mechanical comprehension* segment are intended to capture the ability to solve simple mechanics problems and understand basic mechanical principles. They deal with pictures demonstrating basic machinery such as pulleys, levers, gears, and wedges, asking the test taker to visualize how the objects would work together.[10]

The questions from the other two sections share the same objective, but apply to specific contexts. In particular, 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, requiring an understanding of how the combination of several components work together to perform a specific function.

The *electronics information section* requires additional knowledge of the principles of electronics and electricity. For example, knowledge of electric current, circuits, how electronic systems work, electrical devices, tools, symbols, and materials is tested.

These subsets of the ASVAB, particularly the last two, include topics commonly covered in high school (e.g. auto and shop courses and science classes). As we discuss below, this represents a concern for our identification strategy since it could potentially generate reverse causality from human capital accumulation to abilities. To deal with this potential source of bias, we follow Hansen et al. (2004) and control for the highest grade attended by the time of the test. Furthermore, we

[9] These composites have been used by other authors, and in some instances, they have been included in the analysis as measures of cognitive ability (see Cawley et al., 2001; Black and Smith, 2006, for examples).

[10] 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. We present a list of sample questions in the Web Appendix (Section 1).

restrict our analysis to the youngest cohort of individuals in the sample, reducing the potential impact of reverse causality. We describe the sample selection in detail later in this section.

As measures of socio-emotional ability, we examine the Rotter Locus of Control Scale, the Rosenberg Self-Esteem Scale and, following recent literature, a measure of adolescent reckless behavior (Heckman et al., 2014a, 2016b).[11]

The Rotter Locus of Control Scale was collected during the first round of the NLSY79. The 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 (i.e. chance, fate, or luck) control their lives (external control). It is constructed from four questions adapted from the original 60-item Rotter Adult I-E scale developed by Rotter (1966), and its scored in the external direction. In other words, the higher the score, the less control an individual feels he has on his life.

The Rosenberg Self-Esteem Scale was collected in three rounds of the NLSY79 (1980, 1987, and 2006), but for the purpose of this paper we only study the earliest measure. The scale is designed to quantify the degree of approval or disapproval towards oneself (Rosenberg, 1965), and it is constructed using using a ten item Likert scale (strongly agree, agree, disagree, or strongly disagree) with statements of self-approval or disapproval. It has been widely used in the literature and there is accumulated evidence of its validity and reliability.[12]

The measure of adolescent reckless behavior comes from a self-reported delinquency scale given to all test takers in 1980. Specifically, we use the variable "times seriously threatened to hit or hit someone in the past year" which, according to the literature, is associated with self-control preventing the incidence of aggressive behaviors (DeWall et al., 2011). The question has an expanded response scale to differentiate high levels of aggression from occasional moments of self-control failure. For the analysis we use the reversed scale.[13] This measure complements and extends the dimensions of socio-emotional ability that could potentially affect performance and earnings.

[11] The first two measures have been proved relevant when explaining schooling choices and labor market outcomes (Heckman et al., 2006; Heineck and Anger, 2010; Coleman and DeLeire, 2003; Osborne-Groves, 2004).

[12] 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. For further details about the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale see http://www.nlsinfo.org/nlsy79/docs/79html/79text/attitude.htm

[13] The original scale ranges from 0 to 6 measuring aggression levels where 0, 1, 2 and 3 correspond to the number of times the event happened during the past year; 4 corresponds to 6 to 10 times; 5 is 11 to 50 times; and 6 denotes more than 50 times.

Why four-year college attendance? The focus on four-year college enables us to discuss the differential effects of the three dimensions of ability on the choice between academic and technical career paths. Both cognitive and socio-emotional ability have been associated with academic success in the type of careers that require a bachelor's degree (Heckman et al., 2006). However, mechanical ability could influence the choice towards careers that generally do not require a bachelor's degree but instead could be performed by individuals with associates degrees, professional certificates, or high school diplomas. In addition, given that most of the literature studying post-secondary schooling decisions has examined four-year college, we can compare our findings to the existing evidence.[14]

On the other hand, we examine enrollment rather than completion due to our interest in understanding and quantifying the ex-post economic returns associated with the decision of attending college. College completion is not necessarily the natural final stage following enrollment and, given the high college dropout rates, attendance and completion are two different events. For example, in our sample only 66% of those who ever attended a four-year college graduate with a bachelor's degree by the age of 25. In fact, dealing with enrollment allows us to account for continuation values, given the dynamic nature of education (Heckman et al., 2016b). Furthermore, college completion is influenced by a number of factors that are not independent from individual ability, which imposes the need of a more complex model dealing with new levels of selection.[15]

Sample selection. Given the schooling decision motivating our analysis, we restrict the sample to concentrate on individuals meeting the minimum entrance requirements for a four-year college. Therefore, we do not include high school dropouts.

In addition, in order to avoid potential correlations due to reverse causality from education to test scores, we exclude individuals with college experience by the time they take the ASVAB. To

[14]Nevertheless, we recognize the importance of considering other post-secondary alternatives. To this end, the Web Appendix presents the empirical consequences of extending our binary decision model to other post-secondary alternatives: four-year college completion and college attendance including two- and four- year institutions. It also presents results for a schooling decision model with three alternatives: graduating high school/no college, attending a two-year college, and attending a four-year college. Even though our small sample prevented us from estimating the full model with three schooling decisions, we document the distinctive role of abilities on the decision to attend a four-year college versus the other two options. These findings confirm our main results are robust to different specifications.

[15]For example, Audrey and Strayer (2000) find evidence using the National Longitudinal Survey of Youth that both college quality and student ability affect the likelihood of college completion; and Bound et al. (2010) find consistent evidence that increases in student-faculty ratios reduce completion. In this context, studying only one margin allows us to directly address the main question of the paper.

prevent reverse causality from labor market experience on test scores, we further exclude individuals who obtained their high school degree more than one year before the test date. Moreover, for those who received a high school degree during the test year, we exclude those who reported employment in the period between graduation and test date. These restrictions on the sample allow us to interpret observed cognitive, socio-emotional and mechanical test scores as proxies for pre-labor market abilities.

All in all, from the original sample of 12,686 individuals, 11,406 are civilians, and 6,111 belong to the cross-section sample. Nearly 40% are white males (2,438 individuals), 1,928 had less than high school education by the time the ASVAB test was conducted, and only 1,481 obtained that degree less than one year before the time of the test or, if obtained the degree the year before, had no work experience. The sample is further reduced because we exclude 426 observations corresponding to high school dropouts and individuals without information on schooling or test scores. The final sample contains 1,022 individuals. Table 1 presents summary statistics for the key variables.

3.2 Exploratory results

To establish the relationship between observed mechanical ability and other ability measures, we first compute the correlation matrix of all the ASVAB test scores, and composite measures for cognitive and socio-emotional ability.[16] Table 2 presents these results.

The three technical composites of the ASVAB are highly correlated with the other ASVAB subsets (correlations range between 0.24 and 0.67) but display relatively low correlations with observed socio-emotional ability (between 0.15 and 0.22). This is consistent with modern psychological theory which views ability as a multidimensional construct with facets that are positively correlated with each other (Dickens, 2008). Consequently, the positive correlation across measures could be a manifestation of a general ability, sometimes referred to as the "Spearman g" or g-factor (Spearman, 1904), or the result of overlapping knowledge required for the different tests such as certain degrees of reading and verbal comprehension or basic mathematics skills.

We explore the correlation matrix even further by performing an Exploratory Factor Analysis

[16] The composite measure of cognitive ability is the standardized average over mathematics knowledge, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations and coding speed. The standardized socio-emotional ability measure is computed using the scores from the Rosenberg Self-Esteem scale, the Rotter Internal Locus of Control scale, and adolescent reckless behavior.

(EFA) using the nine subsections of the ASVAB, i.e., the three technical composites and the six components used to compute the cognitive measure.[17] Under the assumption of orthogonal factors, the EFA delivers four factors with positive eigenvalues (4.75, 0.80, 0.22, and 0.17). We focus only on the first two because they explain almost all the shared variance (84.8% and 14.9% of the variance, respectively). This result confirms that at least two factors are needed to explain the correlations among these scores.[18] Our model takes this finding into account.

For the purpose of this paper, it is interesting to note that the EFA suggests a specific factor structure: The first factor is important in linearly reconstructing all the scores, whereas the second factor is only relevant for the scores of the three technical composites. More precisely, the estimated coefficients (factor loadings) associated with the first factor are positive and statistically significant, ranging between 0.62 and 0.83. In contrast, the loadings for the second factor are high and statistically significant only for the three technical composites, ranging between 0.31 and 0.48, while they are close to zero for most of the other tests.[19] Figure 1 presents the estimated loadings and illustrates the distinctive characteristics of the two factors.

Given these results, we could interpret the first factor as cognitive ability. Intuitively, it represents a common trait determining all test scores, which emerges, in part, because they all require a certain degree of reading, verbal comprehension and basic mathematics skills. On the other hand, we could interpret the second factor as a manifestation of mechanical ability, defined as a trait that is related to understanding how things work, and which is not captured by the non-mechanical tests. We incorporate these ideas in our empirical Roy model.

Reduced-form estimates. We can use the composite measures constructed for each ability dimension to understand how individuals sort into college.[20]

Table 3 presents the results from probit models for the probability of attending a four-year

[17]This technique is commonly used in the literature to identify the number of latent constructs and the underlying factor structure of a set of variables (Diekhoff, 1992).

[18]Other studies have also documented the presence of two components when analyzing the subsets of the ASVAB. See Welsh et al. (1990) for a review of several factor analysis studies.

[19]Numerical operations and coding speed are two exceptions because the loadings for the second factor are negative and relatively large (-0.38 and -0.31, respectively). 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). The suggested structure persists after several forms of rotation. Rotation is important because of the indeterminacy of the factor solution in the EFA. Our Web Appendix presents the loadings after a rotation that maximizes the variance of the squared loadings among variables (simplicity within factors).

[20]As previously discussed, we use the set of scores to create composite measures for cognitive and socio-emotional ability. The measure for mechanical ability is constructed as the standardized average of the three technical composites of the ASVAB.

college by age 25 (conditional on obtaining a high school diploma or a GED) as a function of cognitive, socio-emotional and mechanical measures.

All regressions include a set of family background controls, cohort dummies, and dummies for region and urban location. 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. Cognitive and mechanical measures have positive impacts on schooling attainment but the effect of the former is more than four times the effect of the latter. This result is expected given the sorting implied by the distribution of each measure of ability (scores on the tests).[21]

Column (3) presents the specification that controls simultaneously for the three measures of ability. In this case, the effect of the mechanical measure on educational attainment is reversed. In particular, a one standard deviation increase in the mechanical measure decreases the probability of attending a four-year college by 5.5 percentage points (keeping cognitive and socio-emotional measures constant). The same increase in the cognitive measure increases college attendance by 20 percentage points. These effects are large considering that in the sample the overall probability of attending four-year college is 42%.

To document the empirical association between earnings and ability measures, we estimate different versions of the following Mincer-type regression:

$$\ln w_i = \alpha + X_i\beta_x + \beta_D D_i + \beta_c \text{Cog}_i + \beta_s \text{Soc}_i + \beta_m \text{Mech}_i + u_i,$$

where w_i corresponds annual earnings (the average between ages 25 and 35), X_i includes a set of individual characteristics, including cohort dummies as well as geographical controls; and D_i is a dummy variable taking a value of one if the individual attended four-year college by age 25, and zero otherwise. Cog_i, Soc_i and Mech_i are the individual's observed measures of cognitive, socio-emotional and mechanical abilities, respectively, and u_i is the error term.

Table 4 presents the results. Column (1) displays the estimates controlling for cognitive and socio-emotional measures, column (2) for mechanical and socio-emotional measures, and column

[21] For all three measures of ability, our Web Appendix documents that the cumulative distribution function for people who attended a four-year college stochastically dominates the cumulative function for people who did not. As a consequence, people who score higher in these measures of ability tend to sort into four-year colleges.

(3) for the three measures simultaneously.

The estimated regression coefficients of the mechanical composite are positive and have non-negligible relative magnitudes. In particular, after controlling for education and the other two abilities, one standard deviation increase in the mechanical test score is associated with a 0.0412 increase in (log) annual earnings, whereas the estimated effect of the socio-emotional composite is 0.0697 (column 3). Moreover, consistent with the literature, the estimated impact of the cognitive construct on earnings is almost three times larger than the effect of socio-emotional ability (e.g., Heckman et al., 2006). Finally, the estimated return to four-year college attendance on adult (log) earnings is 0.144, and it appears robust to whether or not the regression includes mechanical ability as a control. All estimates are statistically significant at one percent.

In summary, the reduced-form results suggest that mechanical ability is rewarded by the labor market and, unlike standard measures of ability, it reduces the probability of attending a four-year college. However, these findings are problematic not only because schooling choices are endogenous, but also because test scores are proxies of abilities and might be influenced by schooling at the time of the test, age, and family background variables, among others. These concerns need to be considered when estimating the returns to ability (and education) on earnings. The next section presents our model which is proposed to more accurately measure the effect of mechanical ability on schooling decisions and labor market outcomes.

4 Augmented Roy Model with Latent Abilities

The model presented here integrates endogenous schooling decisions and adult earnings under the presence of unobserved heterogeneity. It follows and extends the framework presented in Heckman et al. (2006), Urzua (2008) and Heckman et al. (2014b), where a vector of low dimensional latent abilities is used to generate the distribution of potential outcomes. In the spirit of this literature, we analyze unobserved cognitive, socio-emotional and mechanical abilities. Conditioning on observables, these latent dimensions account for all of the dependence across choices and outcomes.

The theoretical model is static and does not consider the exact timing of the schooling decision (attending a four-year college or not). As a result, the schooling choice model is evaluated when the individual is 25 years old. Agents choose their maximum level of schooling before this age given the information they have at the time. We assume that abilities are unobserved by the econometrician, but that the individual has full information about them, as well as knowledge of how they affect potential earnings at each education level. The agent compares the net benefits across each alternative and chooses the one yielding the highest payoff. Thus, our model analyzes one schooling choice, two potential outcomes for annual earnings, and three dimensions of latent ability.

4.1 College Enrollment and Annual Earnings

In the context of our framework, agents decide to enroll (or not) in a four-year college depending on the perceived valuations of attendance. In principle, these valuations are determined by their perceptions of future earnings, schooling costs, preference shocks, socio-economic variables, unobserved heterogeneity, and other idiosyncratic shocks. Thus, if we let I_i be the net latent utility associated with individual i's decision of enrolling in a four-year college, we can write:

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

where D_i denotes a binary variable that takes the value of one if the individual chooses to attend a four-year college, and zero otherwise.[22] We use a linear approximation for the latent utility of the form:

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

where X_i is a vector of observed variables, and β is the associated 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, m mechanical, and s socio-emotional ability, respectively. $\lambda_D = [\lambda_D^c, \lambda_D^m, \lambda_D^s]$ is the vector of coefficients associated with these abilities (or 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 equation produce a standard discrete choice model.

Armed with this framework, we model (log) earnings under $D_i = 0$, $Y_{0,i}$, and $D_i = 1$, $Y_{1,i}$.

[22] The indicator function $\mathbf{1}[]$ takes a value of one if the condition inside the brackets is satisfied.

Specifically, we assume a linear specification of the form:

$$Y_{D,i} = X_{Y,i}\beta_{Y,D} + \boldsymbol{\theta_i}\lambda_{Y,D} + e_{Y,D,i} \text{ for } i = 1, ...N, \tag{2}$$

where $\lambda_{Y,D} = [\lambda^c_{Y,D}, \lambda^m_{Y,D}, \lambda^s_{Y,D}]$ and $D = \{0, 1\}$. $X_{Y,i}$ represents a vector of observed controls and $e_{Y,D,i}$ is the error term assumed to be orthogonal to X_i and $\boldsymbol{\theta_i}$.

Importantly, as discussed in Heckman et al. (2016a), in schooling choice models where the precise content of the information sets and preferences are not imposed, the set of dimensions affecting individual valuations of the different alternatives may or may not be anticipated (or known) by the agent at the time of the decision. This is the case of our model. Consequently, from a financial perspective, agents could regret the irreversible decision of enrolling in four-year institutions made many years in the past.

4.2 Test Scores as a Measurement System and Latent Abilities

To allow abilities to be latent rather than observed, we follow Carneiro et al. (2003) and connect an auxiliary measurement system of multiple test scores to our framework. As described in Appendix 1, this structure secures the identification of the model.

Formally, the empirical strategy relies on the assumption of a linear relation between the latent and observed abilities. We treat test scores as the outcomes of a process that has as inputs unobserved abilities and individual observable characteristics (e.g., family background variables, schooling at the time of the test, among others). Furthermore, motivated by the findings of the EFA performed in Section 3, our model allows each ASVAB test score (six non-mechanical and three mechanical) to be a function of the cognitive latent ability. Additionally, the technical constructs are also a function mechanical latent ability.[23] The three socio-emotional constructs are assumed to depend on cognitive and socio-emotional ability.

In this context, the model for the cognitive measure C_j can be written as:

$$C_{j,i} = X_{C_j,i}\beta_{C_j} + \lambda^c_{C_j}\theta_{c,i} + e_{C_j,i} \text{ for } i = 1, ...N, \tag{3}$$

[23] A potential source of concerns is the presence of additional unobserved variables resulting in correlations among the error terms on the ASVAB test scores. However, only two empirically relevant sources of unobserved heterogeneity are identified from a factor analysis decomposition of the ASVAB test scores (see Section 3.2). This is consistent with the findings in Cawley et al. (2001) and Black and Smith (2006).

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

$$M_{k,i} = X_{M_k,i}\beta_{M_k} + \lambda^c_{M_k}\theta_{c,i} + \lambda^m_{M_k}\theta_{m,i} + e_{M_k,i} \text{ for } i = 1, ...N, \tag{4}$$

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

$$S_{l,i} = X_{S_l,i}\beta_{S_l} + \lambda^c_{S_l}\theta_{c,i} + \lambda^s_{S_l}\theta_{s,i} + e_{S_l,i} \text{ for } i = 1, ...N, \tag{5}$$

where $l = \{1, ..., 3\}$.

In addition, all error terms $\{e_i, e_{Y,0,i}, e_{Y,1,i}, e_{C_1,i}, ..., e_{C_6,i}, e_{M_1,i}, ..., e_{M_3,i}, e_{S_1,i}, ..., e_{S_3,i}\}$ are mutually independent, independent of the factors and of all observable characteristics. This assumption implies that all correlations between observed choices and measurements are captured by latent unobserved factors (ability). Table 5 describes the empirical specification of our measurement system, schooling choice model and earnings regressions.

Latent Abilities. The vector of latent abilities, $\boldsymbol{\theta_i}$, is assumed to be known by the individual but unknown to the researcher. We interpret the levels of latent factors as result of a combination of inherited ability, the quality of the family environment in which individuals were raised, and cultural differences, among other dimensions. In the context of our model, each of the components of $\boldsymbol{\theta_i}$ is assumed to be fixed by the time the individual is choosing whether or not to enroll in a four-year college. Finally, we follow the literature, and assume they are independent of the set of variables used as exogenous controls (Heckman et al., 2006).

We allow latent abilities to be correlated. This relaxes the independence assumption used previously (Hansen et al., 2004; Urzua, 2008), and it is consistent with recent studies using similar empirical strategies (Heckman et al., 2016b). As shown in Appendix 1, the parameters in equations 3, 4, and 5, as well as the distributions of unobserved abilities, are identified if we assume at least one socio-emotional construct exclusively dedicated to socio-emotional ability, at least one mechanical construct dedicated to mechanical ability, and a set of standard normalizations.[24]

[24]Formally, we use the measurement system to non-parametrically identify the distribution of the latent abilities. Appendix 1 describes in detail the identification of the model. See also Carneiro et al. (2003) and Hansen et al. (2004).

4.3 Identifying the effects of abilities and college attendance on earnings

As argued in Heckman et al. (2016a), the causal interpretation of the estimated effects generated from models like ours follows from an identification strategy, which combines arguments typically used in structural and reduced-form approaches.[25] Specifically, by examining pre-college information from test scores and a joint model of schooling choices and labor market outcomes, we take into account the role of unobserved abilities as potential determinants of disparities in labor market outcomes, a major source of concern in the literature dealing with the identification of the causal effect of education. This logic relies on specific functional forms and conditional independence assumptions about unobserved sources of heterogeneity (see also Heckman et al., 2014a).

On the other hand, reduced-form approaches avoid structural assumptions at the price of imposing matching conditions and/or using exclusion restrictions. These sources of identification, although conceptually more transparent, do not necessarily deliver economically meaningful parameters. Our empirical strategy incorporates exclusion restrictions, but in the context of a framework which allows for the identification of a causal effect at a well-defined margin: attending a four-year college or not. Furthermore, in order to secure the identification of causal effects of education, we control for both observed variables and unobserved endowments (matching conditions). Finally, by adjoining a measurement system to the Roy Model, our approach neutralizes the potential impact of family background characteristics, schooling at the time of the test, and measurement error problems on our proxy variables.

Therefore, using the structure of the model, we can define different average effects of four-year college attendance on ex-post annual earnings. We focus our analysis on two treatment parameters: The effect for those who attended (average effect on the treated or $E[Y_1 - Y_0|D = 1]$) and the effect for those who did not attend (average effect on the untreated or $E[Y_1 - Y_0|D = 0]$). The empirical strategy also allows us to report these parameters by levels of unobserved ability.

4.4 Estimation Strategy

Let $\boldsymbol{T_i} = [C_{1i}, ..., C_{6,i}, M_{1i}, ..., M_{3,i}, S_{1i}, ..., S_{3,i}]$ be the vector of test scores for individual i, and let $\boldsymbol{X_{T,i}} = [X_{C,i}, X_{M,i}, X_{S,i}]$ denote the matrix of associated exogenous controls. Thus, the model's

[25] Heckman et al. (2016b) present a similar identification argument but in the context of a dynamic setting with multiple schooling levels and two unobserved latent abilities

likelihood function can be written as:

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

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

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

where δ_1 denotes the vector of parameters characterizing the ability distribution.

In addition to the independence assumptions on the error terms, for the empirical implementation of the model we assume that the error terms are normally distributed. Specifically, we assume $e_i \sim N(0,1)$, $e_{Y,D,i} \sim N(0, \sigma^2_{Y,D})$ for $D = \{0,1\}$, $e_{C_j,i} \sim N(0, \sigma^2_{C_j})$ for $j = \{1, ..., 6\}$, $e_{M_k,i} \sim N(0, \sigma^2_{M_k})$ for $k = \{1, ..., 3\}$, and $e_{S_l,i} \sim N(0, \sigma^2_{S_l})$ for $l = \{1, ..., 3\}$. For latent factors (abilities), on the other hand, 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 $E[\theta_c] = E[\theta_m] = E[\theta_s] = 0$.

The model is estimated using MCMC techniques, avoiding the computation of a high order integral. In consequence, we focus primarily on the mean of the posterior distribution, viewing it from a classical perspective and interpreting it 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 variance of the estimates. See Hansen et al. (2004), and Heckman et al. (2006) and Web Appendix (Section 2) for more details.

5 Main Results

5.1 Characterizing Latent Abilities

Table 6 presents the estimated coefficients from equations (3), (4) and (5). In general, our findings confirm the role of latent cognitive, socio-emotional and mechanical ability as determinants of observed ability measures.[26]

To analyze the relative importance of each ability in explaining test scores, Figure 2 presents the variance decomposition of the measurement system. The results show the contribution of observed variables, latent abilities, and error terms to the variance of each test score.

The variance decomposition confirms the critical role of cognitive, socio-emotional, and mechanical latent ability. Depending on the specific ASVAB test or socio-emotional construct, latent abilities explain between 5% and 74% of the overall variance. The contribution of observed characteristics is always below 20%. And the analysis of the results from the mechanical comprehension, automotive, and electronics information sections confirms that both cognitive and mechanical ability explain a significant proportion of their variances.[27]

Figure 2 also illustrates the relevance of measurement error in the analysis of ability measures. More than 90% of the variance of the Rotter locus of control test and the measure of adolescent reckless behavior can be attributed to the error terms, whereas the percentage is approximately 20% in the case of the Rosenberg Self-Esteem Scale. For cognitive test scores, on the other hand, the percentage ranges from 64% (coding speed) to 33% (arithmetic knowledge), confirming that conventional ability measures suffer from measurement error problems. Across the three test scores used to identify mechanical ability, the error terms explain between 30% and 37% of the overall variance. Although the consequences of measurement error are not obvious in the context of multivariate regression models, its presence implies that estimates from reduced-form models, as those in table 4, should be interpreted with caution.

With respect to the distributions of unobserved cognitive, socio-emotional, and mechanical abilities; Table 7 displays the estimated means and standard deviations of the marginal distributions

[26] The full set of results are presented in the Web Appendix (Section 3). The Web Appendix also documents the model's within-sample goodness of fit. We demonstrate that our proposed three-factor model does a better job characterizing the distributions of (log) earnings than a two-factor model, which excludes the mechanical dimension.

[27] For these tests, latent variables explain between 53 and 60% of the variance. In a model that does not include mechanical ability, the fraction explained by the latent variables ranges between 22 and 41%, depending on the test. See Web Appendix for further details.

as well as the underlying correlations.

The estimated correlation between cognitive and mechanical ability is 0.46, between mechanical and socio-emocional is 0.10, and between cognitive and socio-emotional is 0.21. These findings highlight the importance of allowing general correlations among unobserved abilities.

We use these results to document the differences between the distributions of latent abilities and test scores. Our Web Appendix presents and compares the cumulative marginal distribution functions of test scores and unobserved abilities by schooling level. The analysis confirms that for cognitive and socio-emotional ability, the distributions of those who attended college stochastically dominate the distributions of those who did not. Interestingly, although the distributions between observed and latent abilities are different, the sorting patterns that emerge are similar.

However, for mechanical ability the results are different. In this case, the distribution function of latent ability for four-year college attendees is first-order stochastically dominated by distribution obtained from those who did not attend four-year college. This implies that people with high levels of mechanical ability choose lower levels of education. Importantly, this result challenges what one could conclude from the sorting patterns based on observed mechanical ability, which mimic those based on cognitive and socio-emotional dimensions. As a consequence, for mechanical ability, the sorting into four-year college implied by latent ability and the observed test score differs.[28]

5.2 The Effects of Abilities on Outcomes

Four-year College Enrollment. Figure 3 presents the main results of the schooling choice model. The figure displays the probability of attending a four-year college by deciles of cognitive and mechanical ability (panel a) and by the deciles of socio-emotional and mechanical ability (panel b).

In order to illustrate the magnitudes of the estimated effects, we compare the consequences of moving individuals across deciles of both dimensions of ability on the probability of attending college. Given that cognitive has positive and mechanical negative effects, this exercise shows which effect prevails.

Starting at the lowest extreme of both distributions and moving to the next deciles across both

[28] The sorting implied by the estimated factor explains why after controlling for the three test 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).

dimensions at the same time, the estimated probability of attending to college always increases. In fact, the estimated probability of attending a four-year college for an individual with cognitive and mechanical ability levels at the bottom 10% of the respective distribution is 16.6%, increasing to 41.9% for an individual with cognitive and mechanical abilities in the fifth deciles, and reaching 63.7% at the top of the distributions (see Figure 3 panel a).

A similar exercise on the distributions of socio-emotional and mechanical shows a less steep gradiant. Moving someone from the bottom to the top of both distributions changes the probability of attending four-year college from 28.5 to 53.4%. The smaller magnitude of the effects is a consequence of the high correlation of mechanical and cognitive ability, the relatively lower correlation between mechanical and socio-emotional ability, and the opposite effects of mechanical and socio-emotional ability (see Figure 3 panel b).

Overall, the estimates imply that a one-unit increase in cognitive ability is associated with an increase of 30.5 percentage points in the probability of attending a four-year college. The same increase in socio-emotional ability is associated with a 4 percentage point increase in the probability, whereas a one-unit increase in mechanical ability decreases the probability by 17.7 percentage points.[29]

Annual Earnings. Figure 4 presents (log) average annual earnings by deciles of cognitive and mechanical ability (panel a) and by deciles of socio-emotional and mechanical ability (panel b). Importantly, in this case the overall effect of ability on earnings includes the direct effect on earnings holding schooling constant, the effect of ability on the decision to attend college, and the implied effect of attending college (or not) on earnings. This overall effect is positive for all three dimensions of ability.

Following the analysis of Figure 3, we study the overall impact of latent ability by examining the changes in average earnings across deciles of their distributions. The results indicate that moving someone from the bottom 10% to the top 10% of the joint distribution of cognitive and mechanical ability increases the average (log) of annual earnings from 10.15 to 10.80. The analogous exercise for mechanical and socio-emotional ability implies an average increase of similar magnitude.

Nevertheless, despite being informative of the joint effects of abilities on earnings, this analysis

[29] Using the standard deviations of the estimated abilities the effects are 23, -11, and 3.5 percentage points for cognitive, mechanical, and socio-emotional, respectively.

does not fully inform about the distinctive role of each dimension. To identify specific impacts, Table 8 presents the estimated effects by college attendance status.

The overall effects confirm the dominant role of cognitive ability: A one-unit increase in cognitive ability, keeping the other ability dimensions constant, is associated with an increase of 0.252 in (log) annual earnings. For mechanical ability the same exercise produces an estimated effect of 0.105, while for socio-emotional ability the effect is 0.049. However, the conclusion changes when analyzing the effect of ability conditional on college attendance. In the event of not attending a four-year college ($D = 0$), the effect of mechanical ability almost doubles the effect of cognitive ability on adult (log) earnings, 0.13 and 0.06, respectively. Conditional on attending a four-year college ($D = 1$), on the other hand, the effect of cognitive ability is 0.237 compared to -0.029 for mechanical ability.[30] For socio-emotional ability the difference in the effects by college attendance is very small.

5.3 Implications for the Returns to College on Earnings

The previous results have non-trivial implications for the analysis of the returns to college on earnings. To unveil then, we compute the ex-post effects of four-year college attendance on future (log) annual earnings conditional on the schooling choice. Formally, we compute $E[Y_1 - Y_0|D = 0]$ and $E[Y_1 - Y_0|D = 1]$.

Our results imply that, on average, attending a four-year college is associated with higher earnings for all individuals relative to the alternative, even for those who decided not to attend it. Specifically, the estimated average effect on the treated is 0.26 whereas the average effect on the untreated is 0.16 (both statistically significant at one percent).[31]

However, these estimated effects are computed integrating out unobserved abilities over the population and may not hold for all individuals. In particular, by analyzing the earning gains associated with college attendance for individuals with different ability profiles one can reach dif-

[30] The negative effect of 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. In addition, Yamaguchi (2012), using the NLSY79, also finds a negative effect of "motor ability" on wage growth only for individuals with a college education.

[31] Although comparisons with results reported elsewhere are not trivial, our estimates are close in magnitude to the OLS results obtained by Kane and Rouse (1995) using the NLS-72 which range between 0.4 and 0.5 per semester enrolled in college, close to 0.28 for a BA degree. Their IV estimates are 15-50% above the corresponding OLS specifications. However, estimating a comparable result is not possible because the population affected by their instruments is not reported.

ferent conclusions. In fact, our findings suggest that for individuals endowed with high levels of mechanical ability and low levels of any of the conventional dimensions, the decision of not attending four-year college might lead to higher annual earnings than the alternative. Table 9 examines this point. It presents the treatment effect on the untreated for different ability profiles, defined as a combination of high and low levels of cognitive, socio-emotional and mechanical ability.

These results imply that if individuals at the top 20% of the distribution of mechanical ability but with cognitive and socio-emotional abilities in the bottom 20% had attended a four-year college, their adult (log) earnings would have been 0.08 lower than under the alternative of no four-year college experience.[32] And even for those with exceptionally high levels of cognitive and socio-emotional abilities, the estimated difference in favor of four-year college attendance is only 0.22, which is just above the estimated average effect on the untreated.

These findings are consistent with those reported in Heckman et al. (2016b) as these authors conclude that graduating from college might not be a wise strategy for all, particularly for low-ability people who do not benefit.[33] Nevertheless, we complement their argument in two important ways. First, we show that in the group of people traditionally considered low ability, some actually have high levels of mechanical ability. For those individuals, and from a purely financial perspective, not attending four-year college might be the best strategy: On average, it delivers higher relative ex-post annual earnings. Second, we document that some low ability people, in the conventional sense (i.e., individuals with low cognitive and socio-emotional ability), do benefit from attending a four-year college.

In light of this analysis, an obvious question is who benefits from not attending four-year college. Overall, we estimate that 19% of our sample would have had higher annual earnings if they had decided not attending four-year college (i.e., for them $E[Y_1 - Y_0] \leq 0$). As expected, a large proportion of them (57%) are individuals with high levels of mechanical ability.

However, as Figure 5 shows, those 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. In fact, 31% and 47% have cognitive and socio-emotional ability levels above the respective

[32] According to the estimated distributions of abilities, close to 4% of the population have ability levels in the top 20% of the distribution of mechanical ability and the bottom 20% of either cognitive or socio-emotional ability.

[33] Using a sample of males from the NLSY79, these authors analyze the impact of college decisions on (log) hourly wages. Our estimated treatment parameters are higher because we are analyzing annual earnings and four-year college enrollment.

medians, respectively. This result is explained by the large effect of mechanical ability on earnings conditional on not attending college, which contrast with its small but negative effect conditional on attending (see Table 8).[34]

In conclusion, we find that despite the large average premium associated with a four-year college education, some individuals might actually benefit from not attending. As proved above, those endowed with exceptionally high levels of mechanical ability and extremely low levels of cognitive ability are the ones that benefit the most from not attending four-year college. However, others can also benefit from not attending college depending on their bundle of traits.

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 reduces the likelihood of attending a four-year college. As a consequence, mechanical ability comes to enrich a set of unobserved factors that explain observed disparities in schooling decisions and labor market outcomes.

Beyond simply expanding the range of empirically relevant dimensions of ability. The inclusion of mechanical ability alters the dichotomous paradigm of low and high ability individuals resulting from the symmetry on how abilities impact 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 levels of mechanical ability and greatly benefit from it. In particular, we find that despite the high returns associated with college attendance, these individuals could expect higher earnings by not attending a four-year college, at least in the early stage of their careers. This is a direct result of the large and positive impact of mechanical ability on earnings in the scenario of not attending a four-year college, which contrasts with its small and negative estimated effect under the alternative of attending four-year college.

Overall, our findings highlight the importance of moving beyond the one-size-fits-all discourse on college and exploring alternative pathways for individuals with different ability profiles. This message is relevant not just for the United States, where less than half of the students attempting

[34]We compare annual earnings of individuals early in their careers (ages 25-35). As a result, we can only discuss annual earnings at the early stage.

to get a bachelor's degree succeed and where completion rates are below 20% for students who score low in standardized tests during high school (NCES, 2013; Rosenbaum et al., 2010). The message is important for any country seeking to expand or reform its higher education system. 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 at least three important areas for extensions and future research. First, the analysis of wage growth and the comparison between initial versus late returns to ability. There are many reasons to expect a lower labor income gradient for abilities early in the life cycle and the current model does not account for that. Second, it would be useful to incorporate labor market experience to the analysis, as well as endogenous occupational choices. Third, it would be interesting to examine gender and racial disparities across the three ability dimensions.

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Appendix

Identification of the Model

Carneiro et al. (2003), Hansen et al. (2004) and Heckman et al. (2006) provide the formal non-parametric identification arguments of models with similar characteristics of the one presented in Section 4. 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.[35]

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

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:

$$\theta_m = \alpha_1 \theta_c + \theta_1$$

where θ_1 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:

$$\begin{aligned} M_k &= \lambda^c_{M_k}\theta_c + \lambda^m_{M_k}\theta_m + e_{M_k} \\ &= \lambda^c_{M_k}\theta_c + \lambda^m_{M_k}(\alpha_1\theta_c + \theta_1) + e_{M_k} \\ &= a_k\theta_c + \lambda^m_{M_k}\theta_1 + e_{M_k} \end{aligned}$$

where $a_k = \lambda^c_{M_k} + \lambda^m_{M_k}\alpha_1$ with $k = \{1, ..., 3\}$ as the empirical model considers three mechanical test scores.

In this context, the identification argument is straightforward. First, given that the variance of the cognitive factor and the factor loadings in the system of cognitive measures are already identified (Carneiro et al., 2003), 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

[35] Cooley et al. (2011) present an alternative identification strategy for the case in which the distributions of all factors are asymmetric.

aforementioned literature, we normalize one of the factor loadings $\lambda^m_{M_k}$ to one. 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_1 and e_{M_k}, with $k = 1, ..., 3$. 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.[36] 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. Thus, M_1 becomes a dedicated measure of θ_m.

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 one. This anchors the scale of the socio-emotional latent factor.

The argument follows the same logic used in the case of mechanical ability. Socio-emotional constructs depend on both θ_c and θ_s, which are allowed to be correlated. We impose:

$$\theta_s = \pi_1\theta_c + \theta_2$$

where θ_2 is an additional factor, which is assumed to be independent of θ_c. Thus, we can rewrite the equation for the l-th socio-emotional scale as follows:

$$\begin{aligned} S_l &= \lambda^c_{S_l}\theta_c + \lambda^s_{S_l}(\pi_1\theta_c + \theta_2) + e_{S_l} \\ &= \phi_l\theta_c + \lambda^s_{S_l}\theta_2 + e_{S_l} \end{aligned}$$

where $\phi_l = \lambda^c_{S_l} + \lambda^s_{S_l}\pi_1$ with $l = \{1, ..., 3\}$ as we consider three socio-emotional measures. Finally, we impose $\lambda^s_{S_1} = 1$ and $\lambda^c_{S_1} = 0$ where S_1 denotes Rosenberg Self-esteem scale.

Implications for empirical implementation. Our empirical model is implemented assuming that θ_c, θ_1, and θ_2 are distributed as mixture of normal distributions:

[36] We select this measure because it has the lowest loading on the cognitive factor in the exploratory factor analysis (see Figure 1). Our current results do not depend on this assumption, results are qualitatively similar if we select any section on the technical composites of the ASVAB (mechanical comprehension or electronics information). These results are presented in the Web Appendix.

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

$$\theta_2 \sim \sum_{j=1}^{2} p_j N\left(\mu_1^j, \left(\sigma_1^j\right)^2\right)$$

$$\theta_3 \sim \sum_{l=1}^{2} p_l N\left(\mu_2^l, \left(\sigma_2^l\right)^2\right)$$

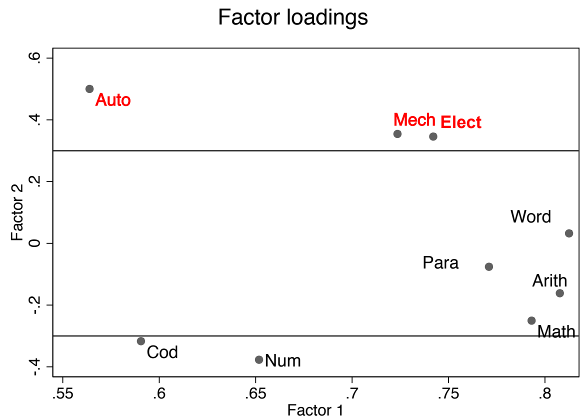
and, consequently, the distribution of θ_m is the convolution of the densities of θ_c and θ_1:

$$f_{\theta_m}(\theta_m) = \int_{-\infty}^{+\infty} f_{\theta_c}(t) f_{\theta_1}(\theta_m - t) dt.$$

Likewise, the distribution of θ_s can be obtained from:

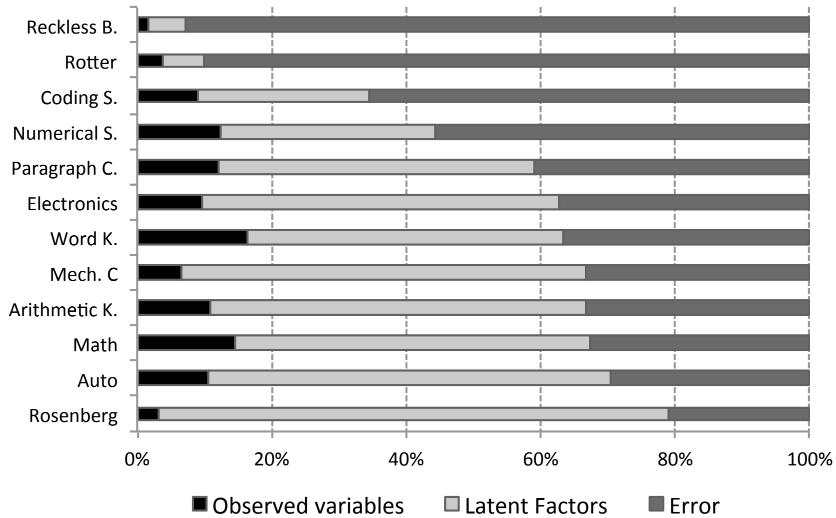
$$f_{\theta_s}(\theta_s) = \int_{-\infty}^{+\infty} f_{\theta_c}(t) f_{\theta_2}(\theta_s - t) dt.$$

Figure 1: Loadings from Factor Analysis (Orthogonal Factors)



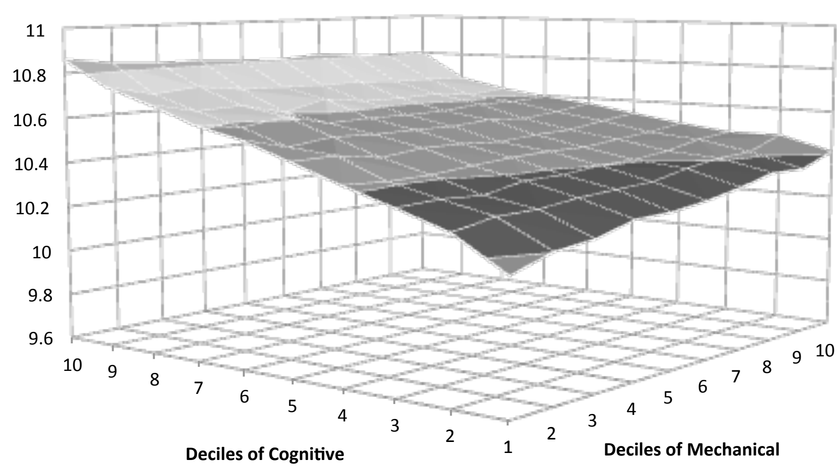
Note: “Auto”: Automotive information and shop information, “Elect”: Electronic information, “Mech”: Mechanical comprehension, “Arith”: Arithmetic reasoning, “Cod”: Coding speed, “Math”: Mathematics knowledge. “Word”: World knowledge, “Para”: Paragraph comprehension, “Num”: Numerical operations. The magnitude of the loading is critical because any factor loading with an absolute value of 0.30 or greater is considered significant in the sense described by (Diekhoff, 1992; Sheskin, 2004, among others).

Figure 2: Variance Decomposition



Note: The figure presents the variance decomposition of the measurement system. The results show the contribution of observed variables, latent factors, and error terms as determinants of the variance of each test score.

Figure 4: Average (log) Annual Earnings (ages 25-35) by Ability Levels (Deciles)



(a) Cognitive and Mechanical

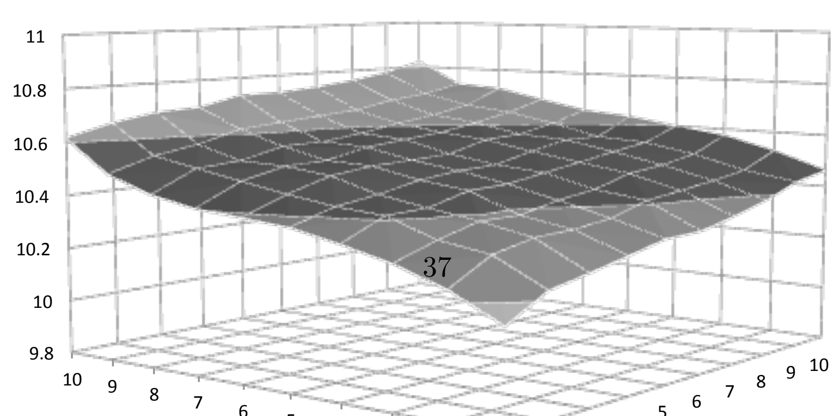
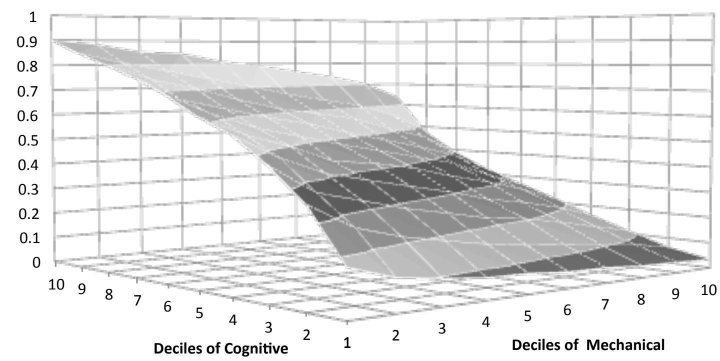
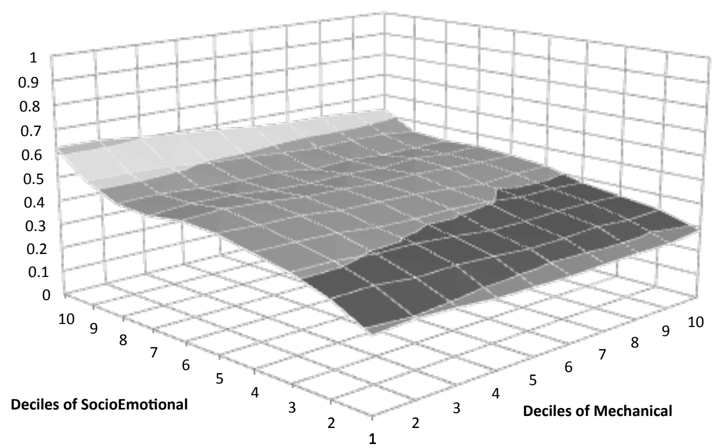


Figure 3: The Probability Attending Four-year College by Ability Levels (deciles)



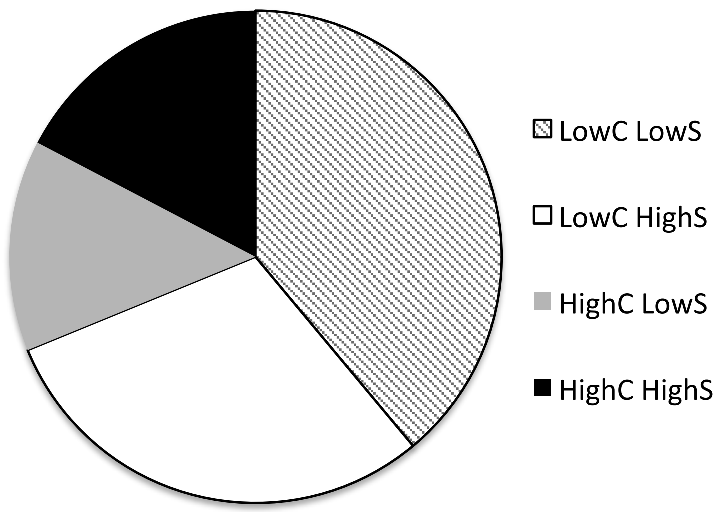
(a) Cognitive and Mechanical



(b) Socio-emotional and Mechanical

Note: The data are simulated from the estimates of the model and our NLSY79 sample. Each panel present the probability of attending four-year college as a function of two abilities: Cognitive and mechanical (panel a), and socio-emotional and mechanical (panel b). Formally, if D is a dummy variable indicating whether or not an individual attended four-year college, and given deciles d and p for abilities i and j, respectively, each panel depicts: $\Pr(D=1|\theta_i \in d, \theta_j \in p) = \int \Pr(D=1|\theta_i \in d, \theta_j \in p, \theta_k) dF(\theta_k|\theta_i \in d, \theta_j \in p)$ for different values of $d = 1,..10$, and $p = 1,..10$.

Figure 5: Composition of the Individuals Who Benefit from not Attending Four-year College by Ability Level



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 four-year college. Formally, if Y_1 denotes the (log) annual earnings corresponding to the scenario of attending four-year college, Y_0 is the analogous in the alternative scenario of not attending four-year college, and x represents a pair of ability levels with x ={(Low Cognitive,Low Socio-emotional), (Low Cognitive,High Socio-emotional), (High Cognitive,Low Socio-emotional),(Low Cognitive,Low Socio-emotional)}, thus the figure depicts the decomposition of $\Pr(Y_1 - Y_0 \leq 0)$ into $\sum_x \Pr(Y_1 - Y_0 \leq 0|profile = x) \times \Pr(profile = x)$. 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 considered are mutually exclusive and collectively exhaustive.

Table 1: Summary Statistics

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Attended four-year college by age 25	0.421	(0.494)	0	1	1022
Log annual earnings 25-35	10.526	(0.716)	5.51	12.036	954
Urban residence at age 25	0.722	(0.448)	0	1	950
Northeast residence at age 25	0.173	(0.379)	0	1	1022
Northcentral residence at age 25	0.312	(0.464)	0	1	1022
South residence at age 25	0.253	(0.435)	0	1	1022
West residence at age 25	0.165	(0.372)	0	1	1022
Cohort1 (Born 57-58)	0.041	(0.199)	0	1	1022
Cohort2 (Born 59-60)	0.062	(0.241)	0	1	1022
Cohort3 (Born 61-62)	0.418	(0.493)	0	1	1022
Cohort4 (Born 63-64)	0.479	(0.5)	0	1	1022
Family Income in 1979	22.23	(12.021)	0	75.001	1022
Number of siblings 1979	2.82	(1.843)	0	12	1022
Mother's highest grade completed	11.62	(3.243)	0	20	1022
Father's highest grade completed	11.817	(4.164)	0	20	1022
Living in urban area at age 14	0.726	(0.446)	0	1	1022
Living in the south at age 14	0.254	(0.436)	0	1	1022
Education at the time of the test	10.996	(1.014)	6	12	1022
Local unemployment	0.049	(0.032)	0.011	0.338	1022
Local four-year College Tuition at age 17	18.75	(6.51)	3.71	50.03	1022
Cognitive	0	(1)	-3.393	2.133	1022
Mechanical	0	(1)	-3.307	2.006	1022
Socio-emotional	0	(1)	-2.887	2.682	1022

Note: Cognitive is an average of standardized scores for arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, numerical operations and coding speed sections of the ASVAB. Socio-emotional is the standardized average of the scores for the Rotter and Rosenberg tests and adolescent reckless behavior. Mechanical is an average of standardized scores for auto and shop information, mechanical comprehension and electronics information sections of the ASVAB. Family income in 1979 is expressed in thousands of 2000's dollars. Local four-year college tuition is the county-level average of in state four-year college tuition costs. It is expressed in hundreds of 2000's dollars. The variables used to determine whether or not an individual has attended four-year college by age 25 include the highest grade completed by the respondent as of each interview date, respondent's enrollment status on May 5 of the survey year, and the type of college attended.

Table 2: Correlations between ASVAB Test Scores, AFQT and a Measure of Socio-emotional Ability

	Auto	**Mech**	**Electr**	**Cognitive**	**Arith**	**Coding**	**Math**	**Word**	**Parag**	**Num**
Auto	1									
Mech	0.66	1								
Electr	0.66	0.66	1							
Cognitive	0.4	0.55	0.56	1						
Arith	0.39	0.58	0.54	0.8	1					
Coding	0.26	0.35	0.33	0.83	0.49	1				
Math	0.26	0.49	0.47	0.79	0.76	0.5	1			
Word	0.5	0.55	0.67	0.74	0.61	0.44	0.59	1		
Parag	0.41	0.52	0.55	0.73	0.62	0.46	0.58	0.73	1	
Num	0.24	0.34	0.35	0.83	0.58	0.64	0.56	0.48	0.5	1
Socio-emotional	0.15	0.22	0.19	0.28	0.24	0.2	0.23	0.27	0.24	0.21

Note: All the test scores are standardized. "Auto": Automotive information and shop information, "Electr": Electronic information, "Mech": Mechanical comprehension, "Arith": Arithmetic reasoning, "Coding": Coding speed, "Math": Mathematics knowledge. "Word": World knowledge, "Parag": Paragraph comprehension, "Num": Numerical operations. Cognitive is the standardized average over mathematics knowledge, arithmetic reasoning, word knowledge, paragraph comprehension, numerical operations and coding speed. Socio-emotional is the standardized average of the scores for the Rotter and Rosenberg scales and adolescent reckless behavior (reversed).

Table 3: Schooling Choice: Four-year College Attendance as a function of Ability Measures (Average Marginal Effects)

	(1)	(2)	(3)
Cognitive	0.172***		0.199***
	(0.014)		(0.015)
Socio-emotional	0.0340**	0.0626***	0.0367***
	(0.013)	(0.014)	(0.014)
Mechanical		0.0346***	-0.0550***
		(0.015)	(0.016)
Observations	1022	1022	1022
Pseudo R^2	0.237	0.151	0.245

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.001$. Standard errors in parentheses. All regressions include family background controls, cohort dummies and geographical controls for region and urban residence at the age of 14. See Table 1 for the detailed list of variables.

Table 4: The impact of Cognitive, Socio-emotional and Mechanical Measures on Earnings

Reduced-form Results

	(1)	(2)	(3)
Attended four-year college	0.137***	0.277***	0.144***
	(0.0516)	(0.0487)	(0.0517)
Cognitive	0.213***		0.190***
	(0.0244)		(0.0287)
Socio-emotional	0.0698***	0.0864***	0.0697***
	(0.0218)	(0.0221)	(0.0217)
Mechanical		0.134***	0.0412*
		(0.0230)	(0.0265)
N. Observations	954	954	954
R^2	0.176	0.140	0.178

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.001$. Standard errors in parentheses. "Attended four-year college" is a dummy variable. It takes a value of one if the individual attended four-year college by age 25. See section 3.1 for a detailed description of the sample. College is dummy variable for four-year college attendance. All regressions include cohort dummies as well as geographical controls for region and urban residence at age 25. See table 1 for the detailed list of variables.

Table 5: Empirical Specification

Variable	**Measurement System**			**College**	**Earnings**
	Cog.	**Socio-emo.**	**Mech.**	**attendance**	
Cohort dummies	YES	YES	YES	YES	YES
Mother's highest grade completed	YES	YES	YES	YES	
Father's highest grade completed	YES	YES	YES	YES	
Living in urban area at age 14	YES	YES	YES	YES	
Living in the south at age 14	YES	YES	YES	YES	
Family Income in 1979	YES	YES	YES	YES	
Number of siblings in 1979	YES	YES	YES	YES	
Education at the time of the test	YES	YES	YES		
Urban residence at age 25					YES
Region of residence at age 25					YES
Local unemployment at age 25					YES
Four-year college tuition (age 17)				YES	
Cognitive ability	YES	YES	YES	YES	YES
Mechanical ability			YES	YES	YES
Socio-emotional ability		YES		YES	YES

Note: Cognitive test scores include arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, numerical operations and coding speed sections of the ASVAB. Socio-emotional test scores include Rotter Locus of Control Scale, Rosenberg Self- Esteem Scale and adolescence reckless behavior (reversed). Technical composites include automotive and shop information, mechanical comprehension and electronics information sections of the ASVAB. Earnings regressions use as dependent variable the (log) of average annual earnings between ages 25 and 35. College attendance is four-year college attendance by age 25. See table 1 for a description of the variables.

Table 6: The Effect of Abilities on Test Scores

	Cognitive		**Mechanical**		**Socio-emotional**	
Automotive	-		1.3	***	-	
	-		(0.09)		-	
Electronics	0.46	***	0.85	***	-	
	(0.04)		(0.06)		-	
Mechanical Comprehension	0.41	***	1		-	
	(0.04)		-		-	
Arithmetic Knowledge	1.02	***	-		-	
	(0.03)		-		-	
Mathematics Knowledge	1		-		-	
	-		-		-	
Word Knowledge	0.93	***	-		-	
	(0.04)		-		-	
Paragraph Comprehension	0.93	***	-		-	
	(0.04)		-		-	
Numerical Operations	0.77	***	-		-	
	(0.04)		-		-	
Coding Speed	0.69	***	-		-	
	(0.04)		-		-	
Rotter Locus of Control	0.23	***	-		0.22	***
	(0.04)		-		(0.04)	
Rosenberg Self-esteem	0.25	***	-		1	
	(0.04)		-		-	
Reckless behavior (reversed)	0.02		-		0.05	
	(0.05)		-		(0.04)	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Notes: The table presents the estimated coefficients from equations 3 to 5. Standard errors in parentheses. 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, geographical controls for region and urban residence at the age of 14 and the highest grade completed at the time of the test. For identification purposes, one loading for each unobserved ability is set to one. The remaining loadings are interpreted in relation to that loading set as the numeraire (see Appendix 1 for details). The selected numeraires are mathematics knowledge, mechanical comprehension, and the Rosenberg self-esteem scale for cognitive, mechanical, and socio-emotional abilities, respectively.

Table 7: Parameters Characterizing the Ability Distributions

	Mean	SD	Correlation(θ^c, θ^i)	Correlation(θ^m, θ^i)
θ^c	-0.001	0.73	1	
θ^m	-0.000	0.60	0.46	1
θ^s	0.000	0.86	0.21	0.10

Notes: θ^c denotes cognitive ability, θ^m mechanical ability and θ^s socio-emotional ability. Results simulated from the estimates of the model and our NLSY79 sample.

Table 8: Estimated Effects of Abilities on (log) Annual Earnings, Overall and by College Attendance

	Cognitive	**Mechanical**	**Socio-emotional**
Overall	0.252	0.049	0.105
	(0.000)***	(0.003) ***	(0.001) ***
$D = 0$	0.061	0.132	0.098
	(0.002)***	(0.001)***	(0.000)***
$D = 1$	0.237	-0.029	0.094
	(0.002)***	(0.001) ***	(0.001) ***

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The table presents the effects on (log) annual earnings associated with one-unit increase in each ability. The "Overall" effect includes the direct effect on earnings holding four-year college attendance constant as well as the effect of ability on the decision to attend four-year college and its consequent impact on log earnings. The effects by schooling comes from the (log) annual earnings equation we have calculated separately for the scenario with no four-year college attendance, $D = 0$, and the scenario with four-year 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: Average Treatment Effect on the Untreated for Different Ability Profiles

Mechanical	**Bottom 20% M**	**Top 20% M**	**Total**
Bottom 20% C-Bottom 20% S	0.12 (0.002)***	-0.08 (0.007)***	0.06 (0.001)***
Bottom 20% C-Top 20% S	0.14 (0.004)***	-0.07 (0.005)***	0.07 (0.002)***
Top 20% C-Bottom 20% S	0.47 (0.020)***	0.21 (0.005)***	0.28 (0.004)***
Top 20% C-Top 20% S	0.48 (0.016)***	0.22 (0.004)***	0.27 (0.003)***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table presents the estimated gains of attending four-year college conditional on the decision of not attending, i.e., the treatment effect on the untreated, for different ability profiles. The columns of the table correspond to the bottom and top 20 percent of mechanical ability. The rows present four extreme ability profiles defined as a combination of different levels of cognitive and socio-emotional ability. "Bottom" refers to the first quintile of the distribution of Cognitive ability (C) or Socio-emotional ability (S), while "Top" refers to the fifth quintile.