What Makes a Leader? The Impact of Cognitive and Noncognitive Abilities*

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Abstract

We estimated the effect of human capital on leadership. Our human capital measures included not only the traditional measures of education and on-the-job learning but also measures of cognitive and noncognitive abilities. The measures of cognitive abilities included numeracy, literacy, and problem solving, and the noncognitive abilities measures included perseverance, openness to learning, and social trust. Our data came from the Programme for the International Assessment of Adult Competencies (PIAAC) survey for the United States. The results indicated that, in addition to education and on-the-job learning, both cognitive and noncognitive abilities were significant and substantial determinants of leadership. More specifically, out of the cognitive abilities, the most important factor was problem-solving ability; and among noncognitive abilities included, perseverance was most important.

Keywords: Human capital, Leadership, PIAAC

JEL Codes: I26, J24

I. Introduction

An integral characteristic of managers and supervisors is their leadership, which is essential for the development of businesses, governments, and numerous other groups and organizations. Thus, it should not be surprising that firms are increasingly investing in developing their employees' leadership skills. Similarly, colleges and other institutions of higher education are starting to use leadership as an important admission criterion. Despite the importance of leadership, only a few studies have looked at the impact of various human capital measures on leadership. We aim to fill this gap by using detailed measures of cognitive and noncognitive abilities, to investigate how they affect leadership.

Human capital has traditionally been measured through education and on-the-job learning (Mincer 1974). However, these indicators do not fully represent an employee's human capital. As more comprehensive measures of individual human capital become available, direct indicators of human capital, for instance, cognitive ability, have recently drawn more attention. In fact, many researchers have recognized the importance of cognitive ability, commonly measured by the intelligence quotient (IQ), for individuals' future development (Murnane et al. 1995; Cawley et al. 2001; Ree and Carretta 2002).

Although the importance of cognitive ability constructs (i.e., intelligence) is well established, noncognitive abilities that represent personality, behaviors, and attitudes (e.g., perseverance and self-discipline) have often been neglected in economic studies. This is surprising when considering that, along with cognitive abilities, noncognitive abilities are increasingly recognized as important factors for determining academic and career outcomes (Heckman et al. 2006). For instance, some individuals with a high level of intelligence do not succeed at work due to low levels in noncognitive abilities such as a lack of persistence, reliability, or self-discipline (Heckman and Rubinstein 2001). Moreover, it is possible that noncognitive abilities are correlated with other human capital measures such as education. Ignoring such noncognitive aspects will result in a bias caused by unobserved heterogeneity in estimating models of labor market outcomes when investigating the effects of human capital.

In addition to earnings and occupations, whether a person is in a leadership position is an important aspect of labor market outcomes, reflecting an individual's market value and success. In this study, we utilized newly available data from the Programme for the International Assessment of Adult Competencies (PIAAC) survey to investigate the impact of individual human capital on an individual's chance of being a leader. We adopted three measures of cognitive ability (i.e., numeracy, literacy, and problem-solving abilities) and three measures of noncognitive ability (i.e., perseverance, openness to learning, and social trust) to study their impact on whether or not a person held a leadership position. We checked the robustness of our results to alternative estimation techniques and model specifications.

The contributions of this study include the following: First, we conducted a thorough economic analysis of leadership as a labor market outcome from the human capital perspective; second, our human capital measures contained not only traditional measures of human capital (i.e., education and on-the-job learning) but moved considerably beyond them by incorporating other important aspects of human capital (i.e., cognitive and noncognitive ability).

Our leadership study has been inspired by the extensive research by specialists in organizational behavior and psychology (Stogdill 1948; Barrow 1977; Yukl 1989; House et al. 1997; Zaccaro 2007). Among different leadership theories proposed in these studies, the concept of trait theory is most closely related to our study. Traits are defined as relatively stable and coherent integrations of personal characteristics, and certain traits are important predictors of leadership (Zaccaro et al. 2004). According to trait theory, important categories of leadership traits include (1) cognitive abilities, (2) personality, (3) motivation, (4) social appraisal and interpersonal skills, (5) leader expertise, and (6) tacit knowledge.[1] Even though the trait theory of leadership has been empirically tested in many psychological experiments and studies, leadership studies from an economic point of view are scarce.

This paper is organized as follows. Section II sets up a theoretical framework for human capital and leadership. Section III introduces the data, different human capital measures, and their relations. Section IV presents basic results from the estimation of the impact of human capital on leadership. Section V further investigates the issue of the endogeneity of ability measures. Section VI presents the core conclusions of this study.

II. A theoretical framework for human capital and leadership

To model our understanding of leadership, we followed Gibbons and Waldman's (2006) conceptualization of job assignment and human capital but with much more detailed measurements of individual human capital. More specifically, we defined a job on the basis of its complexity, and leaders were defined as those who took complex jobs. Assume that all firms have two kinds of jobs denoted by index j: managerial jobs ($j = 1$), which are relatively more complex, and ordinary jobs ($j = 0$), which are less complex. A leader will, by definition, have a managerial position.

The output of worker i assigned to job j is y_{ij}:

$$y_{ij} = d_j + G_j(S_i) + c_j h_i + u_{ij},$$

[1] Tacit knowledge here means the type of knowledge one needs to have to succeed in the labor market; this knowledge is usually not explicitly taught.

where d_j is the output of job j that is independent of the worker's human capital. S_i represents individual i's level of education. $\mathrm{G}_j(S_i)$ is a function of education, and the impact of education on the output depends on the individual's job assignment. $\mathrm{G}'_j(S_i) > 0$ for $\mathrm{j} = 0$ or 1. h_i represents individual i's human capital in addition to education. We will refer to h_i as on-the-job human capital, including on-the-job learning ($Learn_i$), cognitive ability (Cog_i), and noncognitive ability ($NonCog_i$). c_j is the sensitivity of the output of job j to the individual's on-the-job human capital. u_{ij} is the error term. Job characteristics include c_j and d_j, and we assume $d_0 > d_1$ and $c_0 < c_1$. h^* is the critical level of on-the-job human capital at which a worker is equally productive at jobs 0 and 1 (i.e., $E(y_{i0}) = E(y_{i1})$).

Given a fixed schooling level, Figure 1 displays the relationship between on-the-job human capital and output, where ${h_i}^* = \frac{d_1 - d_0 + G_1(S) - G_0(S)}{c_0 - c_1}$. Note that when an individual has zero on-the-job human capital (i.e., $h_i = 0$), he/she will be more productive at ordinary jobs. That is, $d_0 + \mathrm{G}_0(S) > d_1 + \mathrm{G}_1(S)$. In addition, as h_i increases, the productivity growth in managerial jobs is faster than in ordinary jobs ($c_1 > c_0$). To be a leader, an individual must generally be more productive in a managerial job than in an ordinary job. That is, an individual must have an on-the-job human capital higher than h^*. According to Figure 1, given $h_i > h^*$, at a particular school level, the higher the on-the-job human capital, the larger the difference between productivities between a managerial and an ordinary-level job, and, thus, the higher the person's probability of being a leader. As education level increases, the productivities are expected to increase (shift upwards), too.

Therefore, based on the theoretical framework above, the probability of being a leader can be written as a function of human capital. That is,

$$Prob(leader)_i = f(S_i, h_i) + u_{ij} = f(S_i, Learn_i, Cog_i, Noncog_i\ ) + u_{ij}.$$

Traditionally, most studies have used education and on-the-job learning as the sole measures of human capital when evaluating the impact of human capital on individual career outcomes. However, an individual's cognitive and noncognitive abilities, to the extent that they are not fully reflected by education and on-the-job learning, are crucial aspects of human capital that are often left in the error term. In this study, we included a number of cognitive and noncognitive ability measures in our model, in addition to education and on-the-job learning.

III. Data, human capital measures, and their relations

Our data originated from the Programme for the International Assessment of Adult Competencies (PIAAC) survey that was initiated by the OECD.[2] The PIAAC survey collects internationally comparable data about key cognitive and workplace skills of adults between the ages of 16 and 65 in OECD countries and other participating countries. In the first round, which took place in 2012 and was published in 2013, 24 countries participated. Nine additional countries implemented PIAAC in the second round, which took place in 2014, and there will be an upcoming third round soon. In each country, the PIAAC surveyed more than 5,000 individuals with a high response rate (i.e., the minimum response rate was 50%).[3] Compared with other adult ability surveys, the PIAAC has several advantages: It provides recent and, thus, up-to-date data, covers a large number of countries, provides substantially larger sample sizes per country, and offers several in-depth measures of cognitive and noncognitive abilities including the ability to solve problems in technology-rich environments.

[2] The link provides access to the PIAAC data: http://www.oecd.org/site/piaac/publicdataandanalysis.htm

[3] The PIAAC is different from the Programme for International Student Assessment (PISA) such that PISA measures the skills of 15-year-old students in mathematics, reading, and science, whereas the PIAAC measures the skills of adults in numeracy, literacy, and problem solving in technology-rich environments.

In our study, we used United States survey data. We focused our study on the manufacturing, trade, and service industries.[4] Moreover, we included only full-time paid employees. We also limited the age range to 25 to 54 years (thus excluding those younger than 25 and older than 54) in order to avoid including participants who were in the earliest stage of their career and those who were close to retirement. As a result, our final sample consisted of 970 observations.

However, measuring leadership on a quantitative level is challenging because there are many definitions of what potentially constitutes a leader. In general, leadership contains a process of motivating and influencing the activities of other individuals or a group of individuals toward a common goal in a given situation (Hersey and Blanchard 1988). By developing missions, setting strategies, and motivating others, an effective leader disaggregates a complex project into relatively easy tasks and then assigns them to individual employees. Since the process of being a leader is complicated, the demonstration of leadership requires a group of employees that are led by the leader. Therefore, we defined an individual as a leader if he/she supervised more than five employees and as a non-leader if the individual did not supervise anyone.[5][6] As a result, we had 249 leaders and 721 non-leaders, with leaders accounting for 25.67% of the sample.[7]

[4] Other industries that were included in the PIAAC survey were agriculture and the military. These industries involve different mechanisms for becoming a leader. Therefore, they were not considered in the current study.

[5] Our leadership variable was based on two PIAAC questions: "Do you manage or supervise other employees?" and "How many employees do you supervise or manage directly or indirectly?" The response options for the first question included "Yes" and "No" and for the second question included "1 to 5 people," "6 to 10 people," "11 to 24 people," "25 to 99 people," and "100 or more people." If an individual responded "no" to the first question, then he/she would automatically be treated as a non-leader.

[6] We excluded individuals who supervised one to four employees in order to have a clear cut difference between leaders and non-leaders.

[7] In this study, we treated leader as a binary variable. It is possible to use the number of people who are supervised as a quantitative measure of leadership and then apply the Ordered Probit model to study the extent of leadership. One concern with this approach is that the smaller differences between the numbers of people who are supervised may not directly reflect the complexity of leadership.

As robustness checks, we also constructed two additional leadership measures: "Lead10" and "Manager." Lead10 defined leaders as those who led more than ten employees. With this definition, we had 151 leaders and 721 non-leaders, with leaders accounting for 17.32% of the sample. In addition, we defined a leader variable on the basis of the occupational classification of the respondent's job at the 2-digit level as defined by the International Standard Classification of Occupations (ISCO-08). If the occupation was "Manager," then the individual was defined as a leader.[8] With this definition based on "Manager," we had 159 leaders and 1,166 non-leaders, with leaders accounting for 12% of the sample. The correlation between Manager and Lead5 was 0.44, between Manager and Lead10 was 0.45, and between Lead5 and Lead10 was 1.00 (as Lead10 was a subset of Lead5).

In the literature, commonly used measures of cognitive ability include, amongst others, IQ tests, the Armed Forces Qualification Test (AFQT), and reading, writing, mathematics, and science tests administered by educational institutions. The PIAAC survey is used to collect information on each individual's cognitive abilities in three domains: numeracy (*NUM*), literacy (*LIT*), and problem solving in technology-rich environments (*PS*).[9] Each of the three skill domains measures related and yet somewhat distinct dimensions of an individual's skill set and is represented by a 500-point scale (ranging from 0 to 500) with higher points denoting a higher level of desirable skills.[10]

[8] Individuals were defined as managers if they belonged to one of these occupational groups: administrative and commercial managers (ISCO=12), production and specialized services managers (ISCO=13), hospitality, retail, and other services manager (ISCO=14).
[9] In the PIAAC, problem-solving ability is measured in technology-rich environments, representing a special type of problem solving. However, we believe it still reflects general problem solving ability.
[10] When presenting descriptive statistics and regression analyses, we divided all cognitive ability scores by 100. Thus, the numeracy, literacy, and problem solving scores ranged from 0 to 5 in the analyses that we applied (instead of from 0 to 500).

The definitions of each of the three domains provided by the PIAAC are as follows (OECD 2013):

- Numeracy: the ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;
- Literacy: the ability to understand, evaluate, use, and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential;
- Problem solving in technology-rich environments: the ability to use digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks.

Numeracy tasks require, for instance, calculating the number of layers of tea candles packed in a box given other information or calculating the cost of a trip from a motor-vehicle logbook. The literacy test contains questions that require finding the right contact information in a simulated website, identifying the name of the author of a particular book in a simulated library website, and extracting certain information from given paragraphs or tables. Problem-solving questions include tasks such as reserving a meeting room on a particular date using a reservation system, organizing a family get together, and locating information on a spreadsheet and then e-mailing the requested information.

The sample statistics for the three cognitive abilities are reported in Table 1. Leaders had higher average cognitive ability scores in all three domains than non-leaders. The average scores for leaders in numeracy, literacy, and problem solving were 2.78, 2.88, and 2.88, respectively, whereas the scores for non-leaders were 2.73, 2.86, and 2.81, respectively; and the difference in problem solving between leaders and non-leaders was statistically significant. [11] In addition to this, the standard deviations of the measured cognitive abilities of the leaders were smaller than those of the non-leaders, except for numeracy.

Similar to cognitive ability, there are different ways to measure noncognitive ability. Some commonly used indices of noncognitive ability include Rotter's measure of locus of control (Rotter 1966), the Rosenberg self-esteem scale (Rosenberg 1965), the Five-Factor Model of Personality (Muller and Plug 2006), and emotional intelligence (Goleman 2000). Specifically for our study, the PIAAC obtained its noncognitive ability measures from a background questionnaire. This information allowed us to obtain noncognitive ability measures including perseverance, openness to learning, and social trust, which were hypothesized to be important predictors of leadership.

Perseverance was measured with the question "I like to get to the bottom of difficult things." The respondents selected their response from a 5-point scale with the anchor points "not at all," "very little," "to some extent," "to a high extent," and "to a very high extent." In order to be categorized in the high-perseverance group, the response had to be "to a very high extent."[12] Thus, if a person responded to the statement "to a very high extent," and none of the situations listed in Footnote 12 occurred, we set *Perse=1.* Otherwise, *Perse=0*. We placed a strict rule on defining a high level of perseverance because the responses per se were subjective, and a person may be more likely to be overly positive in a self-evaluation. Similarly, openness to learning was

[11] The average scores for the three measures in the whole sample (i.e., 970 observations) were 2.74, 2.86, and 2.83, with standard deviations of 0.47, 0.41, and 0.41, respectively.

[12] Due to the highly subjective nature of responses to this question, we double checked the individual's choice with additional information that was based on the actions and the activities that happened during the interview: (1) the respondent held a conversation with someone else in the house besides the interviewer; (2) the respondent engaged in domestic tasks such as washing or cooking; (3) a television set, radio, game console, or music player was in use in the immediate vicinity of the respondent. We argue that people with strong perseverance would not conduct any of the above activities during the interview.

measured with the response to the statement “I like learning new things.” We set *Learn=1* if an individual responded “to a very high extent.” Otherwise, *Learn=0*.

Social trust was measured with two statements: “There are only a few people you can trust completely” and “If you are not careful, other people will take advantage of you.” Responses to the statements were again measured on a 5-point scale with the anchor points “strongly agree,” “agree,” “neither agree nor disagree,” “disagree,” and “strongly disagree.” We argue that individuals had good social trust (i.e., *Strust=1*) if they answered “disagree” or “strongly disagree” to at least one of the statements; otherwise, *Strust=0*.[13]

Table 1 presents the descriptive statistics for the noncognitive abilities of leaders and non-leaders. Among leaders, individuals with strong perseverance, openness to learning, and good social trust accounted for 32%, 47%, and 31%, respectively. The percentages dropped to 24%, 45%, and 26% for non-leaders. The largest difference in percentage points was observed in perseverance. This can be explained by the notion that leaders generally need a high level of perseverance to solve complex problems when completing their work duties.

In addition, we controlled for other human capital measures such as education and on-the-job learning (measured by years of experience). We also added several control variables in our models such as gender, parental education, and so forth. Education was measured by obtaining individuals’ highest academic degrees such as high school diplomas, bachelor’s, master’s, and Ph.D. degrees. Similar to the patterns of cognitive and noncognitive abilities,

[13] As a robustness check, we also defined the noncognitive measure in a less conservative way. For example, if we first relaxed perseverance (i.e., defined as *Perse=1* if the response was #4 or #5), the estimation results showed that perseverance was the only significant noncognitive ability measure with a smaller magnitude. If we relaxed both perseverance and openness to learning (i.e., defined as *Perse=1* and *Learn=1* if the responses to the corresponding questions were #4 or #5), the results showed that openness to learning was the only significant noncognitive ability.

leaders had higher levels of education than non-leaders. Among leaders, 52% had bachelor's degrees or higher, whereas among non-leaders, only 48% had a similar level of education.

The survey data did not provide the exact age of the respondents but reported 5-year age categories. We estimated the age of the individuals by taking the median of these categories. Further, we defined experience as age minus years of schooling minus six, a common practice in the literature.[14] Table 1 shows that leaders generally had more years of work experience. In addition, men were more likely to be a leader. That is, 57% of the leaders were male. The family background variables included marital status, number of children, and parental education. If one of the parents received tertiary education, then parental education equaled one; otherwise, it equaled zero.

We expected that the sets of human capital measures would be related to each other. A comprehensive analysis of such relations is integral to the understanding of their impact on leadership. Table 2 shows the correlations between the cognitive ability measures and the correlations between the noncognitive ability measures. In particular, the cognitive ability measures were highly correlated with each other (all correlations > .82). The correlation between numeracy and literacy was the highest. It is possible that comprehending a numeracy task requires good literacy ability. Table 2 further indicates that cognitive and noncognitive abilities were positively correlated too, but the correlations were much smaller (all correlations < .20) than those within the cognitive abilities.

Figure 2 depicts the distributions of the three cognitive ability measures separated by education level. Clearly, as education level increased, the mean ability levels increased for all cognitive ability measures as well. On average, individuals with master's or Ph.D. degrees had

[14] This calculation provides an upper bound for experience because we did not have information on unemployment.

the highest abilities, and those with no high school diploma had the lowest. The largest increase was observed for numeracy. Individuals with master's or Ph.D. degrees had a 38.7% higher average score in numeracy than those with below a high school education. It is interesting that problem-solving scores showed the smallest gap between different educational levels.

For noncognitive abilities, as shown in Table 3, the percentage of individuals with good noncognitive abilities was higher for individuals with college or graduate degrees compared with those with a high school education or below. For instance, for those with graduate degrees, the proportion with high perseverance was 8.1 percentage points higher than for those with less than a high school education. A similar pattern was found for openness to learning, and the difference between graduate education and below a high school education was 10 percentage points. Social trust, which might be an important noncognitive ability for being a leader, also showed a positive relation to education, and the gap between the higher and lower educational levels was even larger. According to Hooghe et al. (2012), individuals with an attitude of trust are likely to develop good social relationships and a clear academic orientation, which in turn leads to higher education.

IV. Human capital and leadership

On the basis of the theoretical framework for the impact of human capital measures on the probability of being a leader that we introduced in the section above, we specified our empirical model as,

$$y_i = \delta_0 + \beta_1 Educ_i + \beta_2 Experience_i + \theta Ability_i + \delta Control_i + e_i,$$

where y_i indicates whether an individual is a leader (yes $= 1$); $Educ_i$ represents education level ($Educ_i = 1$ indicates college); and $Experience_i$ represents years of experience on the job market, a measure that captures the amount of human capital accumulated via on-the-job learning. $Ability_i$ represents an individual's set of cognitive and noncognitive abilities; $Control_i$ is a vector of control variables, including gender, marital status, number of children, parental education, and industry dummies; and e_i denotes the error term.

This model was estimated using linear probability models (LPM) with robust standard errors. The advantage of LPM is that it does not require any assumptions about the underlying distribution of the error term, and it is robust to heteroskedasticity. In addition, we applied weighted least squares (WLS) estimation to obtain more efficient estimates of the LPM model, and we applied the Probit model in the estimation as well.[15]

As cognitive ability is one of the most frequently studied leader attributes, we first included the three cognitive ability measures in the model (Stogdill 1948). The literacy component of cognitive ability was specified as that its potential peaking effect on leadership is in its midrange. We conjectured hat individuals who have very high literacy scores may also have personality traits associated with exceptional erudition that mitigate against their being chosen as leaders.

The results are reported in Table 4. Model 1 shows that out of the three cognitive ability measures, only problem-solving ability was positively and significantly related to leadership.[16] The coefficient of problem solving was 0.306. This indicates that when problem-solving scores increased by 1 unit, the probability of being a leader increased by 0.306 (30.6 percentage points). Because a 1-unit increase represents a 100-point increase in the problem-solving test score, it

[15] In WLS, in order to obtain more efficient standard errors, $1/(\hat{y}*(1-\hat{y}))$ is used as the weight, where $\hat{y}$ is the predicted value of the corresponding OLS estimation.

[16] We also ran this model with cognitive ability measures added to the model separately. We found that education was always a significant predictor of being a leader. In addition, problem-solving skills remained positive and significant, whereas numeracy and literacy remained insignificant in these models.

then means that a 10-point increase in the problem-solving score increased the probability of being a leader by 3.06 percentage points.[17]

Leadership comes along with the need for problem solving on a regular basis at different occasions and in a variety of circumstances. The problems a person faces at work are often complex or intransparent, involve numerous constraints, and consist of large sets of variables. A high level of problem-solving ability can help leaders define exactly what the problem is and help them to generate appropriate solutions for the specific problem at hand (Mumford et al. 2000). In fact, problem-solving ability has been considered an important precursor of lifelong learning and later success in life.[18]

The relevance of problem solving for leadership has also been recognized in the recent literature. For instance, Connelly et al. (2000) found that complex problem-solving skills, together with social judgment skills and leader knowledge, accounted for significant variance in leadership even after controlling for general intelligence, motivation, and personality. In a similar vein, Danner et al. (2011) reported that problem-solving ability predicted supervisory ratings of job performance above and beyond simple reasoning abilities.

Moreover, we found that if an individual had a college degree, his or her probability of being a leader increased by 9.3 percentage points. In fact, the importance of education for leadership has been recognized by many previous studies (e.g., Murphy and Johnson 2011). Experience also had a significant positive impact on leadership. This finding is in line with previous findings on the relation between experience and leadership. Using a sample of about

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[17] We also included interaction terms between problem-solving ability and industry dummies in the analyses. None of these interaction terms were significant.

[18] For this reason, problem solving was included as a transversal skill in the arguably most important international educational large-scale assessment ever conducted, the Programme for International Student Assessment (PISA), in its 2012 cycle, involving 15-year-old students in over 40 countries across the globe (OECD 2014).

5,000 graduates of the Stanford MBA program in the late 1990s, Lazear (2010) showed that the number of previous positions held by individuals significantly increased their probability of being a manager.

In summary, we found that when all human capital measures were included along with the control variables, the probability of being a leader was significantly increased by education, problem-solving skills, and experience.

Model 1 also shows that, after controlling for the human capital measures, males had a nearly 10 percentage points higher chance of being a leader than females. Parental education did not seem to influence a person's chance of being a leader, and marital status and number of children did not show any significant effects either.

Models 2 to 3 in Table 4 present the results of the alternative estimation methods. The results of the Probit estimation in Model 2 were consistent with the OLS estimation of the LPM model (Model 1). In fact, the magnitudes of the marginal effects for the significant variables were almost identical to those from the LPM estimation. The human capital measures, including problem solving, education, and experience, remained significant. The WLS estimation (Model 3), which is presumed to yield more efficient estimates than OLS estimation, exhibited results that were similar to the OLS estimates as well, although the marginal effects for almost all variables were somewhat smaller on a descriptive level. The change for the effect of education seemed to be the largest with a drop from 0.093 in the LPM model to 0.065 in the WLS model.

In order to provide an additional check of the robustness of our results in Models 1 to 3, we ran models using the different definitions of being a leader: supervising at least ten people (Lead10 in Table 4) or being a manager (Manager in Table 4). With the somewhat stricter definition of leadership (i.e., leading more than ten employees), the results of the LPM remained generally consistent. However, in this alternative model, the effects of the human capital measures became larger and more pronounced, which was to be expected given that we were more selective in defining what constituted a leader and what did not. That is, as the level of leadership increased (supervising more people), so did the role of individual human capital. In particular, the coefficient of problem solving increased to 0.447, a marked increase of 46% compared with the model with a more lenient definition of leadership (i.e., supervising more than five employees).

When a leader was defined by the occupation “Manager,” the results (Model 5 in Table 4) were again generally consistent with those that were obtained with the two other definitions of leadership, Lead5 and Lead10, and, generally speaking, exhibited the same pattern of results even though some coefficients changed in magnitude. These changes in the sizes of the coefficients were mixed; for example, the effect of education became larger, whereas the effects of problem solving and experience became smaller. A notable change was observed for numeracy, which was positive and significant only when “Manager” was used as the dependent variable. More specifically, if the numeracy scores increased by 10 points, the probability of being a manager increased by 1.11 percentage points, so even in this model, the effect remained rather small. The explanation for this change is that the position of a manager can vary a great deal in terms of the number of people the manager supervises. Thus, the “Manager” definition is relatively loose in defining a leader, leading to a less distinct pattern of results than found in the previous models. In addition, because of the loose definition, problem solving decreased in importance.

After evaluating the impact of the cognitive ability measures, we then added noncognitive ability measures to the models. Noncognitive ability is considered crucial for important economic outcomes such as leadership. In fact, noncognitive ability measures as indicators of human capital have drawn increasing attention in recent years (Kickul and Neuman 2000; Zaccaro et al. 2004). Moreover, some human capital variables that were included in the models (e.g., education) might have been correlated with noncognitive ability measures (e.g., perseverance). This, in turn, could have created an omitted variable problem.

The results are reported in Table 5. Model 1 in Table 5 shows the results when both cognitive and noncognitive abilities were included. Out of the noncognitive ability measures, only perseverance showed a positive and significant effect. More specifically, a high degree of perseverance increased the probability of being a leader by 9.0 percentage points.[19] The importance of perseverance on leadership has been emphasized in previous studies (Dries and Pepermans 2012). Perseverance (i.e., maintaining high energy levels even in difficult circumstances) is an essential trait for leaders. Leaders, who oftentimes face unexpected difficulties, obstacles, and discouragement, need strong perseverance to lead the team and work toward the goal that is to be achieved. Thus, consistent with the literature, our study showed that perseverance, the ability to continue and to move forward, is fundamental for effective leadership.

The results for education and the other human capital measures were similar to those reported in Table 4 for Model 1. However, due to the inclusion of additional human capital variables, the magnitudes of the coefficients were somewhat smaller. This is consistent with our hypothesis that the noncognitive abilities might have been positively correlated with education and problem-solving skills and thus may have resulted in a positive omitted variable bias when omitted. Other studies (e.g., Segal 2013) have reported that a significant portion of the impact of

[19] If we included the noncognitive measures in the model separately, the results were similar; that is, perseverance was the only significant predictor out of the noncognitive abilities.

cognitive ability on earnings could be attributed to noncognitive ability. Again, the results did not change much when we applied Probit estimation or WLS estimation as shown in Table 5.

When leadership was defined more rigorously as Lead10, perseverance was still the only significant noncognitive ability measure, but its absolute impact was somewhat smaller. When leadership was defined more loosely as "Manager," perseverance became insignificant. Again, all the other human capital variables were similar in sign but smaller in magnitude when the noncognitive measures were included.

V. Further investigations

In our previous estimations, we assumed that the cognitive and noncognitive measures adequately represented individual ability. However, as is true for all ability measures, the test scores we employed may have suffered from measurement error, so they were not perfect proxies for ability. To deal with this problem, some studies have used reliability ratios to mitigate the problem of measurement error (Mueller and Plug 2006, Lindqvist and Vestman 2011, Eren and Ozbeklik 2013). Other studies have used repeated measures so that the same cognitive or noncognitive measure was observed more than once, and one measure then served as an instrument for another (Bound et al. 2001, Eren and Ozbeklik 2013).[20] Some studies (e.g., Heckman et al. 2006) have constructed latent cognitive and latent noncognitive abilities to control for the endogeneity problem and measurement error. They then used Bayesian Markov Chain Monte Carlo methods to compute the sample likelihood and estimate the coefficients. Their results showed a significant impact of latent cognitive and noncognitive abilities on a large array of behaviors such as schooling and employment.

[20] Eren and Ozbeklik (2013) used both the reliability ratio method and the repeated measure specification to solve the measurement error problem.

In the current study, due to the highly complex nature of human intellect and human personality, the cognitive and noncognitive measures were not likely to capture the entire range of human ability. For instance, cognitive ability is assumed to be composed of a number of hierarchically ordered abilities with a very general cognitive ability factor at the top of the hierarchy (McGrew, 2009). Numeracy, literacy, and problem solving are probably strongly related to this general factor, but they do not capture all aspects of human intellect. Thus, numeracy, literacy, and problem solving might still be correlated with uncaptured ability in the error term and, through this, they might become endogenous variables. In addition, since education is highly correlated with ability, it might also be an endogenous variable that is correlated with the remaining "portion" of the ability left in the error term.

To solve this potential endogeneity problem, we applied the instrumental variable (IV) approach. Specifically, we constructed instruments for the endogenous variables on the basis of the PIAAC background questionnaire. The first group of IVs was related to language proficiency and cultural involvement, which might have affected the test scores and the level of education. However, because those variables are beyond the control of the individual him/herself, they should be exogenous to the individual's inner ability. Specifically, the IVs we defined were: (1) whether both parents were foreign born, (2) whether the test language was the same as the language usually spoken at home, and (3) the number of years spent in foreign countries before immigrating to the United States.[21] The IVs in the first group were likely to be correlated, but the

[21] Literacy was entered into the model along with its squared term, which was also endogenous. In general, it would have been possible to include all quadratic terms and interaction terms for all instruments as additional instruments for this squared term. However, because most of the instruments were represented as dummy variables, we included only one interaction term as an additional instrument, which was the interaction between "years spent in other countries" and "whether both parents were foreign born." Such an interaction can capture the difference (e.g., if both parents were born outside the US but the years the individual spent in other countries were different). Such a difference is likely to affect people's language proficiency and cultural engagement and subsequently their test scores and education.

correlation was not high. For example, the highest correlation occurred between whether both parents were foreign born and years spent in a foreign country (r = 0.730).

The second group of IVs was constructed on the basis of whether the participants were interrupted by any other activities during the survey, including (1) whether an individual was looking after children and (2) whether an individual was interrupted by some other activity, task, or event. These activities might have distracted individuals from concentrating on the tests, and, thus, might have negatively affected their test scores. However, because these interruptions were likely to be beyond the individual's control, they were exogenous to the person's real ability. Thus, in total, we had six IVs, including one interaction term explained in Footnote 21 and five endogenous variables.

The descriptive analyses of the IVs indicated that individuals whose parents were born in foreign countries accounted for 15% of the sample, and those who usually spoke the test language at home accounted for 93%. The average number of years spent in foreign countries before immigrating to the United States was 2.24. In addition, 10% of the participants were looking after children during the interview, and 11% were interrupted by some other activity, task, or event.

Table A1 in the Appendix lists the first stage estimation results. Our analyses indicated that the IVs were correlated with the endogenous variables. In particular, if English (the test language) was the language usually spoken at home, the scores for all three cognitive abilities were generally higher. This held also for the level of education (i.e., attending college). As discussed in Footnote 21, the interaction between foreign-born parents and years spent outside the US before immigration was negative and significant for literacy, problem solving, and education.

The results of the IV estimation are reported for Model 1 in Table 6. The over-identification test could not be rejected, indicating that there was no evidence against the validity of our instruments. Consistent with the previous estimations, the IV approach showed that education and perseverance were significant. In particular, the probability of being a leader increased by 0.503 if an individual had a college degree (or a higher degree) relative to those without a college degree. This coefficient was much higher than the coefficient in our previous estimation of 0.085 (Table 5, Model 1).[22] In addition, the results of the IV analyses indicated that individuals with strong perseverance had a higher probability of being a leader of 0.094, which was similar to the previous LPM estimation of 0.090 (Table 5, Model 1). In the IV estimation, problem solving did not show any significant impact on leadership, though. However, based on the Hausman Test, the null hypothesis of exogeneity could not be rejected (p = 0.307). That is, according to this test, OLS estimation of LPM was preferable to IV estimation due to the relative efficiency of OLS.

Considering that the endogenous variables included one nonlinear term (i.e., the squared literacy term), we also applied the control function (CF) estimation to further improve efficiency. When there are nonlinear endogenous regressors, CF is generally more efficient than IV estimation.[23] The CF estimation results are reported for Model 2 in Table 6. In general, they were similar to the pattern of results for the IV estimation with regard to education and perseverance,

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[22] Many studies in the literature of omitted ability bias, especially those based on the Mincer equation, found that IV estimates are much higher than OLS estimates, although they are supposed to be smaller due to the removal of the positive ability bias. A common explanation is that the attenuation bias caused by measurement error dominated the omitted ability bias (Card 1999). Our results here seem to be in line with this finding.

[23] In the CF approach, we employed the estimated equation $y_1 = \boldsymbol{z_1\delta_1} + \alpha_1 G(y_2) + u_1$, where y_1 is the dependent variable, y_2 is the endogenous variable, $G(y_2)$ is a function of the endogenous variable, $\boldsymbol{z_1}$ is a $1 \times L_1$ sub-vector of $\mathbf{z}$, and $\mathbf{z}$ is a $1 \times$ L vector of exogenous variables. The reduced form of y_2 is $y_2 = \boldsymbol{z\pi_2} + v_2$. In addition, $u_1 = \rho_1 v_2 + e_1$. Assume $\mathbf{z}$ is independent of u_1 and v_2, $\mathrm{E}(y_1|\boldsymbol{z}, y_2) = \boldsymbol{z_1\delta_1} + \alpha_1 G(y_2) + E(u_1|\boldsymbol{z}, y_2) = \boldsymbol{z_1\delta_1} + \alpha_1 G(y_2) + E(u_1|\boldsymbol{z}, v_2) = \boldsymbol{z_1\delta_1} + \alpha_1 G(y_2) + \rho_1 v_2$. Then, the model could be estimated by OLS with v_2 added, whereas v_2 could be estimated with the residual from the reduced form of y_2 (i.e., $\widehat{v_2}$).

both in sign and magnitude. The CF further showed that literacy had positive and significant effects on being a leader. Similarly, however, the Hausman type test based on CF estimation was not significant and, thus, the OLS method of estimation could not be rejected.

In addition, in the IV and CF approaches, we used numeracy, literacy, and problem solving to measure different aspects of cognitive ability. However, these three could also be viewed as indicators of one underlying cognitive ability. Therefore, we also applied Indicator Estimation to solve the omitted ability problem. Because an indicator represents the "full" omitted ability, we did not need to specify which independent variables were correlated with the omitted ability.

More specifically, in this approach, all three cognitive ability measures served as indicators of one underlying cognitive ability. When multiple indicators of one underlying ability exist, one cognitive measure serves as the indicator included in the model, and the other indicators serve as instruments, and therefore, we applied the Multiple Indicator (MI) estimation method.[24] In theory, the roles of all three indicators, numeracy, literacy, and problem solving are interchangeable in MI estimation. However, we argue that problem solving provides a more comprehensive measure of the underlying cognitive ability, as supported by the regression results discussed above. Therefore, we used problem-solving ability to indicate cognitive ability and the other two indicators, numeracy and literacy, as instruments for problem-solving ability.

The results of the MI estimation are reported for Model 3 in Table 6. Of note, the MI results were generally consistent with the IV and CF results. In particular, both education and

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[24] In the indicator approach, suppose the original equation is $y = \alpha_0 + \mathbf{x\beta} + \gamma q + v$, where q represents the omitted ability variable. Suppose we have multiple indicators of q from q_1 to q_n, indicator q_1 can be written as $q_1 = \delta_0 + \delta_1 q + a_1$, where $\text{cov}(q, a_1) = 0$ and $\text{cov}(\mathbf{x}, a_1) = \mathbf{0}$. If we rewrite q as a function of q_1 and then substitute it back into the original equation, we then have $y = \alpha_1 + \mathbf{x\beta} + \gamma_1 q_1 + v - \gamma_1 a_1$, where $\gamma_1 = \frac{\gamma}{\delta_1}$. If we express each of the rest of the indicators (i.e., q_2 to q_n) as a function of q and also assume the error terms are not correlated with a_1, then q_2 to q_n become valid instruments for q_1.

perseverance showed positive and significant relations with leadership.[25] In fact, the estimated perseverance coefficient was almost identical to the IV and CF estimates. The effect of education was smaller than that of IV and CF estimation but still closely in line with the OLS estimation that was applied in Model 1 in Table 5. In addition, experience became a significant predictor, consistent with the OLS estimation.

VI. **Conclusion**

In this study, we investigated the effects of individual human capital on the probability of being a leader. Unlike in traditional studies, in addition to the commonly used measures of human capital such as education and on-the-job learning, we employed more detailed measures of individual human capital (i.e., literacy, numeracy, and problem solving as cognitive abilities; perseverance, openness to learning, and social trust as noncognitive abilities).

With the newly available data from the PIAAC, we estimated the model using LPM estimation, WLS estimation, and Probit estimation to study the effect of individual measures of human capital on leadership. Moreover, we also applied IV estimation, CF estimation, and MI estimation to check the sensitivity of our results under various assumptions about individuals' ability.

We found that the commonly used human capital measures such as education and experience had positive and significant effects on being a leader. That is, a college degree increased a person's chance of being a leader by 7.2 to 8.5 percentage points compared with not having a college degree after controlling for other human capital measures. With regard to

[25] When we changed the order of the indicators, education became insignificant.

experience, one additional year of work experience increased the probability of being a leader by 0.5 to 0.6 percentage points.

Moreover, out of the three cognitive measures, problem-solving skills showed the strongest effect on leadership, which was positive and significant, whereas literacy and numeracy did not show a robust significant effect. However, in some cases, for example, when leadership was defined in a looser way or in alternative estimation methods, literacy and numeracy showed positive and significant effects.

Out of the noncognitive ability measures, perseverance consistently exhibited a positive and significant effect on being a leader. Individuals with high levels of perseverance relative to those with low levels had an 8.4 to 9.0 percentage points higher chance of being in a leadership position. Finally, the effect of human capital became even stronger when the dependent variable of leadership was defined in a more rigorous way, especially for the effects of problem-solving abilities and education.

There are several policy implications that can be derived from the results of this study. For instance, it will be helpful to develop mechanisms for identifying individuals with strong leadership skills as an additional factor in job assignment and promotion. Moreover, government policies and company strategies for providing training for both cognitive and noncognitive abilities, including lifelong learning opportunities, will improve individuals' leadership potential.

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Table 1. Descriptive statistics

	Lead5=1 (Obs=249)			Lead5=0 (Obs=721)			Difference
Variable	Obs.	Mean	SD	Obs.	Mean	SD	
Cognitive skills							
Numeracy	249	2.778	0.468	721	2.729	0.467	1.423
Literacy	249	2.875	0.397	721	2.861	0.412	0.470
Problem solving	249	2.882	0.399	721	2.811	0.413	2.383*
Noncognitive skills							
Perseverance (yes=1)	249	0.321	0.468	721	0.239	0.426	2.459*
Openness to learning (yes=1)	249	0.470	0.500	721	0.452	0.498	0.483
Social trust (yes=1)	249	0.309	0.463	721	0.264	0.441	1.359
Education degree							
Below high school	249	0.056	0.231	721	0.031	0.172	1.610
High school	249	0.422	0.495	721	0.490	0.500	1.862*
Bachelors	249	0.313	0.465	721	0.295	0.457	1.147
Masters or Ph.D.	249	0.209	0.407	721	0.184	0.388	0.824
Others							
Male (yes=1)	249	0.570	0.496	721	0.449	0.498	3.313*
Experience (years)	249	20.133	8.450	721	18.031	8.824	3.346*
Married (yes=1)	213	0.817	0.388	577	0.730	0.445	2.696*
Either parent had a college degree (yes=1)	243	0.407	0.492	694	0.451	0.498	1.185
Number of children	249	1.731	1.213	721	1.422	1.298	3.405*
Industry Dummies							
Manufacturing (yes=1)	248	0.165	0.372	721	0.215	0.411	1.763*
Trade (yes=1)	248	0.278	0.449	721	0.151	0.358	4.035*
Service (yes=1)	248	0.556	0.498	721	0.634	0.482	2.129*

Note: 1. Our final sample of 970 included only individuals with all three cognitive ability measures.
2. * indicates that the difference between leader and non-leader was significant at the 10% significance level.

Table 2. Correlations between abilities

	Numeracy	Literacy	Problem solving	Perseverance	Openness to learning	Social trust
Numeracy						
Literacy	0.886*					
Problem solving	0.824*	0.858*				
Perseverance	0.097*	0.061*	0.065*			
Openness to learning	0.043	0.057*	0.066*	0.354*		
Social trust	0.153*	0.154*	0.187*	-0.011	0.141*	

Note: The numbers are correlation coefficients between different ability measures. * indicates the correlation was significant at the 10% significance level.

Table 3. Noncognitive ability and education level

Education	Perseverance	Openness to learning	Social trust
Below High School	23.5%	45.1%	17.6%
High School	21.5%	41.7%	20.2%
College	32.1%	52.0%	37.0%
Masters or Ph.D.	31.6%	55.1%	39.9%

Note: The percentages represent proportions of individuals with high noncognitive abilities (i.e., perseverance=1 based on the definition explained in the text) at each education level.

Table 4. Cognitive ability and leader

	Lead5			Lead10	Manager
	(1)	(2)	(3)	(4)	(5)
	LPM	PROBIT	WLS	LPM	LPM
Numeracy	-0.031	-0.035	0.007	0.018	0.111**
Literacy	0.153	0.158	0.079	-0.008	-0.339
Literacy^2	-0.068	-0.067	-0.048	-0.069	0.032
Problem solving	0.306***	0.307***	0.283***	0.447***	0.123**
Education	0.093**	0.091***	0.065*	0.118***	0.107***
Experience	0.006***	0.006***	0.005***	0.006***	0.004***
Male	0.097***	0.102***	0.093***	0.030	0.010
Married	0.057	0.067	0.051	0.010	0.025
Either parent had a college degree	0.002	-0.003	-0.009	0.013	-0.009
Number of children	0.021	0.020	0.022*	0.021*	0.006
Constants	-0.667	-3.619*	-0.619	-0.797	-0.022
Industry dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	758	758	758	676	1040
R^2	0.075		0.112	0.120	0.065
Adjusted R^2	0.060		0.098	0.104	0.054
F-statistics	5.248		7.832	6.750	5.347
Pseudo R^2		0.066			

Note: 1. The Probit model presents the marginal effects evaluated at the means of the covariates.
2. *** denotes significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.

Table 5. Noncognitive ability and leader

	Lead5			Lead10	Manager
	(1)	(2)	(3)	(4)	(5)
	LPM	PROBIT	WLS	LPM	LPM
Numeracy	-0.040	-0.046	-0.033	0.013	0.108**
Literacy	0.166	0.177	0.145	-0.012	-0.333
Literacy^2	-0.068	-0.068	-0.053	-0.067	0.032
Problem solving	0.295***	0.300***	0.273***	0.438***	0.122**
Education	0.085**	0.083**	0.072**	0.113***	0.105***
Experience	0.006***	0.006***	0.005**	0.006***	0.004***
Perseverance	0.090**	0.090**	0.084**	0.068*	0.023
Openness to learning	-0.027	-0.028	-0.032	-0.011	-0.001
Social trust	0.034	0.035	0.038	0.011	0.005
Male	0.093**	0.098***	0.090***	0.028	0.009
Married	0.057	0.067	0.048	0.011	0.025
Either parent had a college degree	0.001	-0.004	-0.012	0.013	-0.010
Number of children	0.022	0.020	0.022*	0.021*	0.006
Constants	-0.658	-3.644*	-0.639	-0.779	-0.028
Industry dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	758	758	758	676	1040
R^2	0.083		0.106	0.126	0.066
Adjusted R^2	0.064		0.088	0.106	0.052
F-statistics	4.752		5.862	5.651	4.291
Pseudo R^2		0.072			

Note: 1. The Probit model presents the marginal effects evaluated at the means of the covariates.
2. *** denotes significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.

Table 6. Instrumental variable, control function, and multiple indicator estimation

	(1) IV	(2) CF	(3) MI
Numeracy	-0.745	-0.727	
Literacy	2.305	1.422*	
Literacy^2	-0.234	-0.069	
Problem solving	-0.459	-0.454	0.006
Education	0.503*	0.482*	0.075*
Experience	0.005	0.005	0.004**
Perseverance	0.094*	0.094*	0.095**
Openness to learning	-0.052	-0.052	-0.027
Social trust	0.034	0.022	0.045
Constant	-1.582	-0.478	-0.014
Number of observations	751	751	758
R^2	-	0.089	0.066
F-statistics	-	3.955	-
Endogeneity test (F-test)	1.202 (p=0.307)	1.44 (p=0.219)	
Over-identification test (Chi^2)	0.022 (p=0.989)		

Note: *** denotes significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.

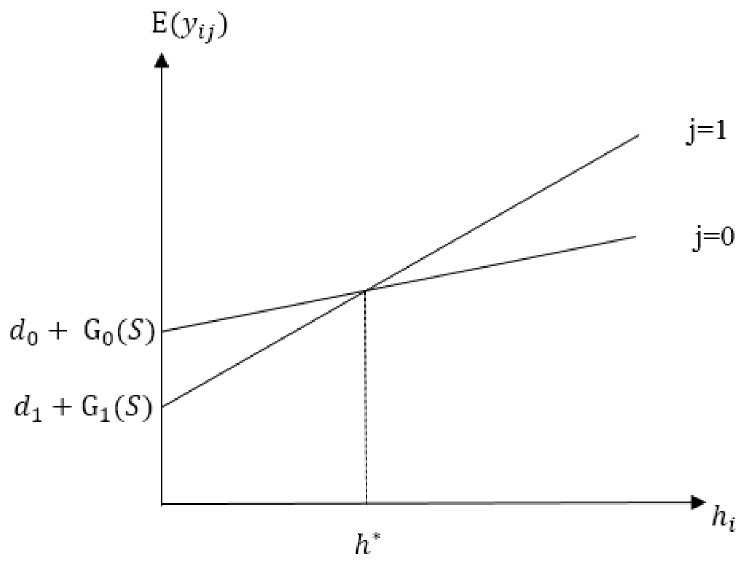

Figure 1. On-the-job human capital and output, given a fixed education level

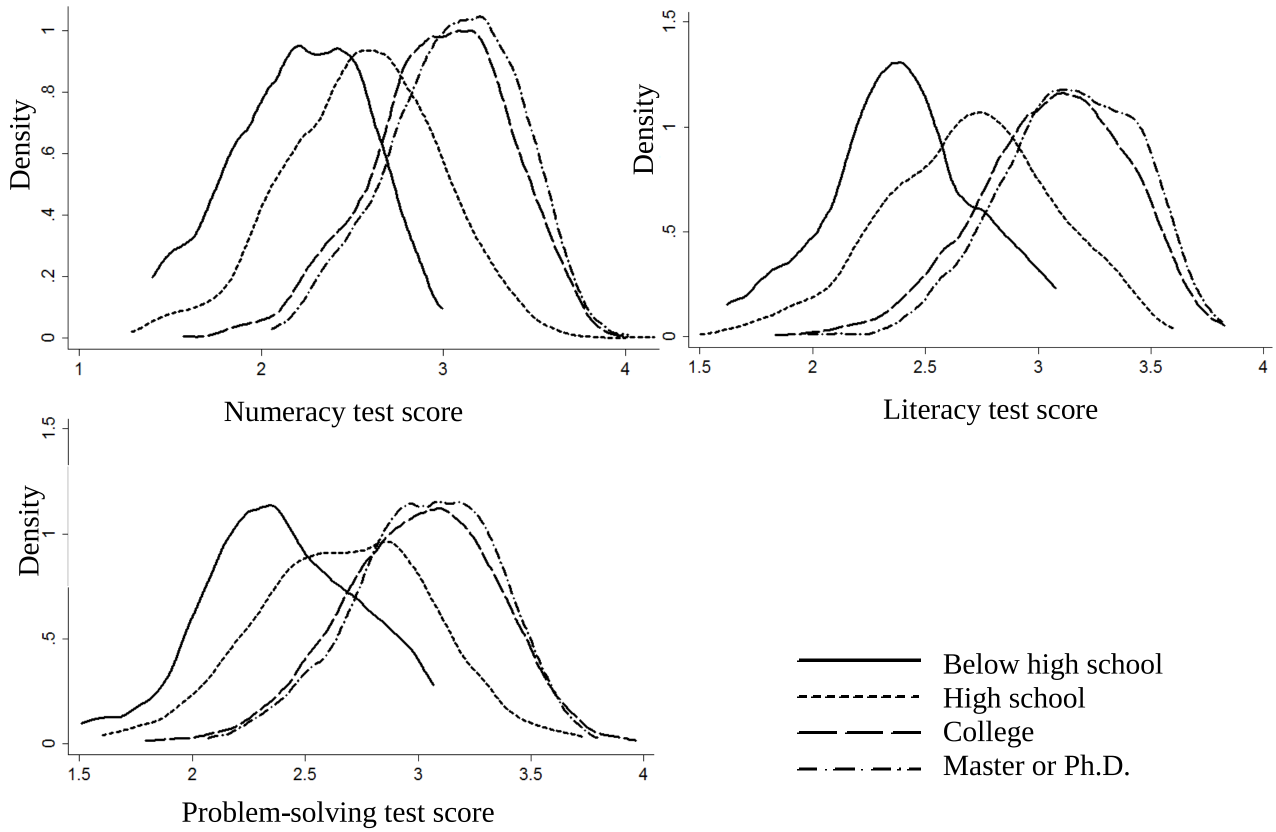

Figure 2. Kernel distribution of the three cognitive abilities by education levels

Appendix

Table A1. First stage IV regression

	Numeracy	Literacy	Problem solving	Education
Male	0.173***	0.022	0.052*	-0.008
Experience	-0.007***	-0.006***	-0.010***	-0.011***
Married	0.164***	0.109***	0.095***	0.096**
Either parent had a college degree	0.192***	0.183***	0.116***	0.189***
Number of kids	-0.038***	-0.031**	-0.021	-0.023
Perseverance	0.065*	0.034	0.044	0.060
Openness to learning	-0.028	-0.013	-0.011	0.024
Social trust	0.124***	0.100***	0.126***	0.170***
Parents foreign born	0.066	0.097*	-0.026	0.045
Test language same as language usually spoken at home	0.280***	0.239***	0.213***	0.195**
Foreign years	-0.004	-0.002	-0.007	0.022**
Foreign years squared	0	0	0	0
Looking after children	0.001	0	-0.043	-0.114**
Interrupted by other activities	-0.019	0	0.009	-0.008
Parents foreign born*Foreign years	-0.004	-0.020***	-0.009*	-0.012*
Constant	2.421***	2.682***	2.761***	0.405***
Number of observations	751	751	751	751
R^2	0.251	0.252	0.247	0.252
Adjusted R^2	0.234	0.235	0.230	0.234
F-statistics	16.861	14.711	13.41	25.308

Note: *** denotes significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%.