Role Of The Non-Cognitive Skills On Labour Market Outcomes

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Abstract

This paper investigates the role of self – confidence or self – assessment that we call non – cognitive skill for labor market outcomes. The key idea is to infer non – cognitive skill from the difference between actual and self-reported skills. In addition, we are able to compare this effect across 11 countries due to the data set that we plan to employ.

I. Introduction

Numerous studies reveal that measured cognitive skills are good predictors for the labor market outcomes. In real life, it is easy to detect that cognitive skills are not only determinants of labor market outcomes. Besides, other factors can account on determining wages or employment status such as, among others, personal traits, and personal preferences. Studying these factors comes along with various problems mostly due to lack of a concrete definition or scope of these factors. Thus, the role of such factors is not comprehensively investigated in the literature. This is partly because it is hard to identify an accurate relation between such factors and labor market outcomes.

One important identification problem may arise is that a potential relationship between personal traits and labor market outcomes is too much sensitive to definition of personal traits. While cognitive skills can be reduced to one dimension, i.e. level of IQ or test results, non-cognitive skills are multidimensional. Therefore, this study does not assert to capture the whole relationship between personality and labor market outcomes. Rather, we will focus on just one dimension of people’s personalities, which is the difference between actual and self-reported numeracy skill. We argue that this difference must explain a significant part of the human characteristics. However, the question of which part will be explained by this variable is not super easy and there are two possible answers: self-confidence and self-assessment. Even these concepts are defined in pretty different ways in psychology literature, we will label the difference between actual and self-reported skills as non-cognitive skill which is likely to affect the labor market outcomes of people.

Self-confidence or self-assessment have impact on labor market outcomes in various ways. For instance, believing oneself to be high skills makes it easier to convince employers that he/she have such qualities. Furthermore, self-confidence may improve the individual’s motivation to succeed his/her job.

The aim of this paper is understanding the relationship between a specific personal characteristic, self – assessment or self – confidence, and labor market outcomes, wage and employment, and showing how this relationship vary across countries. By doing this, we will employ Adult Literacy and Lifeskills Survey (ALL) which contains both cognitive skill measure (numeracy test score) and self – reported numeracy skill, besides a rich set of individual, social, and economic variables for 11 countries across the world. In this vein, this paper will be related to the literature which investigates the relative importance of non-cognitive skills on labor market outcomes.

The contribution to this literature will be its measure of non-cognitive ability. While extant literature considers the psychological tests, which assess the participants’ general psychological wellbeing, we will use participants’ self-assessment level or self-confidence level about a specific cognitive skill. Furthermore, due to cognitive ability measurement, we are able to assess self – confidence about his skill level by considering his/her real skill level. Therefore, we can avoid the measurement errors which arise because of the people’s endowment levels.

More specifically, the difference between the self-confidence level of a physics professor and a high school dropout might stem not only from their personalities but also from their endowments. This dataset constitutes an opportunity to isolate their personalities from their endowments.
Additionally, to best our knowledge, no empirical research exists addressing the question of how the relative importance of non-cognitive skills vary across countries because of the lack of available data who measure the non–cognitive skills of people in more than one country. In this sense, this comparative study may pave the way for new researches which investigate the labor market institutions that determine the importance of non–cognitive skills.

III. Literature Review

The first important point in the literature on the relative importance of non-cognitive skills for labor market outcomes is the taxonomy of non-cognitive skills. Among others, generally accepted taxonomy of non-cognitive skills is the Five – Factor Model. Following by Nyhus and Pons (2005), this model includes the following five factors: agreeableness, conscientiousness, emotional stability, extraversion, and autonomy.

The non-cognitive skill variable that we define above can be considered as a subtitle of emotional stability factor. By using a special data from DNB Household Survey (DHS) that include s items designed to tap psychological concepts, Nyhus and Pons (2005) report that emotional stability is positively associative with the wage of both men and women in Germany. DHS dataset contains list of 20 statements, which respondents answered using a five-point scale. These answers of the respondents to these statements are thought to be measures of emotional stability by psychologists. However, it is not possible to understand which personal traits are rewarded in the labor market by looking at the definition of emotional stability.

More specifically, Heckman et al. (2006) used Rotter Locus of Control Scale as non-cognitive measure. The Rotter scale measures the degree of control individuals feel they possess over their life and measures perception of self – worth, self – motivation, and self – esteem. They propose that noncognitive skills strongly influence schooling decisions and also affect wages, given schooling decisions.

Furthermore, Bowles, Gintis, and Osborne (2001) presents a linkage between personal traits and productivity to answer the question of why some non-cognitive skills have a bearing in the labor markets. They called this linkage as “incentive enhancing preferences”. As a result, they find both aggression and withdrawal have a sizeable negative impact on later earnings.

IV. Data

To investigate the relationship between non-cognitive skills and labor market outcomes, we figure on to employ Adult Literacy and Lifeskills Survey (ALL), which is an international comparative study designed to provide participating countries, including the United States, with information about the skills of their adult populations ages from 16 to 65.

A primary advantage of this dataset is that it provides subjective (self – reported) skill measures besides the objective measures of literacy and numeracy skills. In addition, it includes a rich set of individual, economic, and social characteristics. Another important feature of this dataset is its ability to compare the results of different countries. There are 11 participating countries. In seven of these countries (Italy, Norway, Switzerland, Bermuda, Canada, Mexico, and United States), data collection took place in 2003, while in four of the countries (Hungary, Netherlands, Australia, and New Zealand) data were collected between 2006 and 2008. Principally, each participating country was required to design and implement the Adult Literacy and Lifeskills Survey according to specified guidelines and standards. Therefore, if we apply the same methodology to all countries’ labor markets, we can compare the importance of non-cognitive skills of the labor markets across the sampling countries.

It is important to remind that our study is not able to consider all dimensions of the non-cognitive skills owing to the reasons that we discussed in the introduction part. Rather, by referring non-cognitive skill, we imply just one dimension of potential non-cognitive skill vector. This dimension can be interpreted as self-confidence or the ability of self-assessment.

We are not able to know sample size of each country seperately without looking at the data.
Sample Definitions. The sample size for each country is at least 34203 individuals. Several sample restriction need to be imposed in order to create a consistent sample across countries. Firstly, we plan to restrict the sample to individuals between aged 18 – 65.

Secondly, students and the self-employed will be excluded as cognitive skills play a weaker role in determining their labor market outcomes 4. Furthermore, when we check the sample questions5 in the tests implemented in the scope of ALL survey, we notice that it is likely to be little variation at the top of skill distribution since the test is designed to capture basic functionalities in pertinent areas.

Hence, we will create two more alternative samples by dividing dataset into two. The first is the sample excluding university graduates. The latter is the sample which consists of only university graduates.

Variable Definitions. We will focus on the wage and employment status as labor market outcome of interest. We operationalize the wage as hourly wage rate on the main job, which is constructed using information on weekly earnings and hours of work per week. Current work situation will be considered as employment status.

In the scope of ALL dataset, we have three potential domains of cognitive skills: numeracy, prose literacy and document literacy. Proficiency in all domains are measured along a scale ranging from 0 to 500. We contemplate to use numeracy domain as a proxy for cognitive skill because of practical reasons. The dataset contains self-reported version of numeracy skills. Participants respond a question which ask about their math or numeracy skills. We will use the answer of this question as a proxy for non-cognitive skills.

Clarke and Skuterud (2016) reports that the scores in all three domains are highly correlated and the effect of cognitive skills on earnings is not sensitive to choice of domain.

People are asked whether they are strongly agree, agree, disagree, or strongly disagree with the following statements: I am good with numbers and calculations. Since the answers constitute a categorical variable, we will transform strongly disagree, disagree, agree and strongly agree into the numbers 125, 250, 375, and 500, respectively.

V. Methodology

To estimate the effect of non – cognitive skills, specifically self – confidence or self – assessment, on people’s labor market outcomes we will apply an OLS estimation, expanding the classical Mincerian earning equation with cognitive and non-cognitive skills components. Below, we will firstly describe our main empirical strategy, before discussing alternative specifications addressing potential threats to identification.

Main Empirical Strategy. Firstly, we will define the wage, w, of person i in country j as the following

\[ w_{ij} = \omega hj(\ell i, si, Xi)\epsilon_{ij} \] (1)

where \( \omega j \) is base wage of the country j, \( hj(\ell i, si, Xi) \) is the human capital function depending on education, \( li \), skill, \( si \), other characteristics vector, \( Xi \), and \( \epsilon_{ij} \) is country and individual specific productivity shock. In addition, definition of the human capital function is the following:

\[ hj(\ell i, si, Xi) = \exp(\alpha lij + \beta sij + \gamma Xij) \] (2)

where \( \alpha j \), \( \beta j \), \( \gamma j \) represent country specific importance of education, numeracy skills, and other characteristics, respectively. We allow different importance parameters for each country since labor market valuation of education, numeracy skills, or other characteristics vector may change according to various characteristics of the countries such as labor market institutions, skill composition of the country, etc.

Even we have numeracy skill data of each individual, it is not perfectly observable in the labor market.

Thus, \( si \) will not represents the numeracy skill which is observed in the labor market. Rather, we will define the \( si \) in the following form:
where \( Cij \) is numeracy test score and \( Nij \) is the self-reported numeracy skill. Hence, \( Nij − Cij \) is the variable that we denote as non-cognitive skill above. Here, we assume that numeracy test score is not fully observable in the labor market, thus, employer is able to observe just a fraction, \( \delta 1j \), of test score. He/she also uses the self-assessment or self-confidence of employee to make inference about his/her actual numeracy skill. Thus, a part of the perceived skill by employers is related to non-cognitive skills.

The \( \delta 2j(Nij − Cij) \) in equation 3 explains this part. The relative importance of cognitive skill and noncognitive skill in the labor market is allowed to be different across each country. After taking logarithm and plug in human capital (2) and skill (3) in to equation 1, we will reach the following equation:

\[
\ln(wij) = \ln \sigma_j + a\tilde{j}ij + \beta_j\delta 1jCij + \beta_j\delta 2j(Nij − Cij) + \gamma_jXij + \ln \epsilon ij(4)
\]

and the empirical counterpart of the equation (4) is the following:

\[
\ln(wij) = \theta_j + a\tilde{j}ij + \eta_jCij + \phi_j(Nij − Cij) + \gamma_jXij + \epsilon ij(5)
\]

where \( \theta_j \) is country fixed effect, \( lij \) years of schooling, \( Cij \) cognitive skill (numeracy test score), \( Nij − Cij \) is non-cognitive skill (self-assessment or self-confidence), \( Xij \) is set of control variables, including age, experience, migration status, etc., and \( \epsilon ij \) is error term. We will estimate the same equation by using employment status as dependent variable, as well.

**Alternative Strategies.**

The first problem that our main identification encounters is the reverse causality. The wage rate that people gain may determine their self-confidence level. Since income is an important status symbol in the society, people with higher income may be more optimistic about their skills because of their self-confidence endorsed by society. If this mechanism works, our estimates of equation 5 will be biased. However, Dunning et al. (2004) propose that employees tend to overestimate their skills as they take less feedback from colleges in the workplace. To solve this problem, we plan to use the supervisory responsibility and number of worker employed at the workplace as instruments which may create an exogenous variation in the level of self-assessment because of the feedback opportunities.

Another problem is related to the assumption that non-cognitive skills affect labor market outcomes linearly. Bonebau and Tirole (2002) assert while self-confidence can improve welfare in the labor market, it can also be self-defeating. In other words, self-confidence can increase the wage of a person via motivation or positive signals to the employers. However, over-confidence may lead wrong decisions and mismatched occupation or task choices and, consequently, decrease labor market productivity. To control such mechanism, we will specify equation 5 by adding the quadratic non-cognitive skill term, \((Nij − Cij)^2\).

In addition, as aforementioned, it is likely to be almost no variation in test scores at the top of skill distribution since the test is designed to capture only basic functionalities. In other words, above a specific education level, people will acquire almost full test scores.

Hence, the coefficient of cognitive skill will be downward biased due to lack of variation in test scores. Besides, the coefficient of noncognitive skill may also be problematic. To see whether our results will be sensitive to the numeracy test’s weak prediction power for high educated workers, we will estimate the equation 5 for the alternative samples that we defined in the previous section, sample without university graduates, and sample which consist of only university graduates.
However, this research plan has some weaknesses. Most importantly, there may be a substantial measurement error. The reference point of people’s self-reported skills is ambiguous. If their reference point when they assess themselves systematically differ, which is most likely to be the case, our estimation result probably will be problematic. Nevertheless, since it will be the first study which investigates the comparative effects of non-cognitive skills on labor market outcomes, it will be lucrative for further research even if it is descriptive but not causal.

References