THE QUALITY OF IMMIGRANT HUMAN CAPITAL AND IMMIGRANT LABOR MARKET OUTCOMES

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ABSTRACT

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The present study investigates the relationship between quality of education and returns to education, using several measures of quality of education and a sample that consists of immigrants in the United States. Our main findings yield that quality of education has a positive and significant impact on returns to education for our baseline sample (the main immigrant groups). However, when nonlinearity in returns is taken into consideration and thus analyzing the link with returns of two subgroups based on education level (i.e. at most high school graduates and at least some college graduates) separately, we find different impacts of quality on the returns for the subgroups. For the immigrant groups with some college, we conclude that there is a positive and significant effect of quality of education on returns to their education while for the immigrant groups with at most 12 years of education there is no association between the quality of education and returns.

Keywords: quality of education, returns to schooling, immigration, earnings

ÖZET

GÖÇMENLERİN EĞİTİM KALİTESİ VE GÖÇMENLERİN İŞGÜCÜ SONUCU

SİNEM BALKUVAR

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Bu çalışma birkaç eğitim kalitesi ölçüsü verisi ile Amerika Birleşik Devletleri'ndeki göçmenlerden oluşan bir veri setini kullanarak eğitim kalitesi ile eğitimin parasal getirisi arasındaki ilişkiyi incelemekte. Ana sonuçlar, eğitim kalitesinin getiriler üzerinde pozitif ve istatistiksel olarak anlamlı bir etkiye sahip olduğunu göstermekte. Fakat, eğitim yılının maaşlar üzerindeki doğrusalsızlığını dikkate aldığımızda ve buradan hareketle eğitimin parasal getirisini eğitim seviyelerini baz alarak oluşturduğumuz iki farklı gruba göre (12 yıl üstü ve 12 yıl ve altı) hesapladığımızda, eğitim kalitesinin iki farklı grubun getirilere farklı etki gösterdiğini bulduk. 12 yıl üstü eğitime sahip olanların getirisi pozitif ve istatistiksel olarak anlamlı bir etkiye sahipken diğer grup için hiçbir etki saptanamamıştır.

Anahtar Kelimeler: eğitim kalitesi, eğitimin maaşlara geri dönüşü, göç, kazançlar

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1 INTRODUCTION

It has been widely discussed in the literature that quantity of education alone is not a sufficient measure of human capital; quality of education matters in determining income per capita in a country as well. For instance, Schoelmann (2012) finds that after adjusting for quality of education, the contribution of education to cross-country output per worker increases from 10 percent to 20 percent. Reinforcing this, the findings of Kaarsen (2014) highlight the importance of the role of quality-adjusted human capital in development accounting. He suggests that quality-adjusted human capital accounts for income differences across countries to a considerably larger degree than a human capital measure that is derived only from years of education. With a different method, Altinok and Aydemir (2017) provide evidence that the average effect of quality of education on economic growth is strong as opposed to quantity of education (i.e. years of schooling). These results have relevance for policy decisions, underlining the importance of dedicating certain funds to increasing the quality of the educational system in a country.

Quality of education matters not only for countries' economy but also for individuals themselves. The link between quality of education and labor market outcomes have also long been touted in the literature. For example, Card and Krueger (1992) put forth that quality of education[1] has a considerable impact on earnings of white men born in the U.S. They find that decreasing the pupil/teacher ratio by five students leads to a 0.4 percentage point increase in the rate of returns to education, which leads to increase in earnings. With an analogous analysis to Card and Krueger (1992), Heckman, Layne-Ferrar and Todd (1996) find that the estimated effect of schooling quality on earnings weakens when nonlinearity for years of schooling and selection for migration are considered. They provide evidence for the positive and statistically significant association between schooling quality[2] and earnings for skilled white men born in the U.S. while they find no effect on earnings of unskilled counterpart. Moreover, the interaction between region of birth and region of residence downsizes the overall effect of schooling quality on earnings.

The importance of the quality of education on earnings has found a place in immigration-related literature as well. Since the quality of education differs across countries on a large scale, labor market outcomes of immigrants may be affected by it. Bratsberg and Terrel (2002) examine the association between rates of returns to education received by workers and attributes of education. They follow Card and Krueger's (1992) two-stage estimation procedure and apply it to immigrants' returns and cross-country quality of education measures. They use U.S. microdata from the 1980 and 1990 censuses to obtain the rates of returns for immigrants coming from 67 different countries. In the second step, they aim at determining the association of attributes of a source country's educational system such as expenditure per pupil and teacher-pupil ratio, and rates of return. They find a positive association between education expenditures and rates of return to education, and a negative association between pupil-teacher ratios and rates of return,

[1] Quality measures are pupil/teacher ratio, term length and relative teacher salary
[2] Quality measures are pupil/teacher ratio, term length and relative teacher salary

indicating a positive link between attributes of educational quality and the rates of return to education. An important feature of this study is that this is the first paper that applies substantial variation in attributes of the educational systems across countries, as compared to district level variation across the U.S. that Card and Krueger (1992) make use of.

Before incorporating quality adjusted human capital into development accounting, Schoelmann (2012) exploits the differentials in returns to education of immigrants in order to find any correlation between the returns to education of immigrant groups and countries' average quality of education.[3] The immigrants used in his specification were educated in 130 different source countries[4] and appeared to be working in the U.S. 2000 Census. Following Card and Krueger's (1992) methodology, he finds that immigrants from countries that have higher quality of education have higher returns to their education. The two-way scatter plot of returns and quality of education demonstrates this positive association. He highlights two issues that can bias the interpretation of the results: selection and skill transferability. The former includes both the possibility of self-selection by immigrants and selection that imposed by U.S. immigrant policy. Schoelmann demonstrates that selection is not an issue in this context by using a subsample of refugees because refugees are the group that is less likely to be self-selected or selected by the host country.

Li and Sweetman (2014) use micro-level 1986, 1991, 1996 and 2000 Canadian Census to estimate the returns to education of 78 immigrant groups based on country of origin. The quality measure that they use in their study is normalized QL2 measure coming from Hanushek and Kimko (2000). Following Card and Krueger's (1992) methodology,

[3] The quality of education measure comes from Hanushek and Woesmann (2009).

they find a positive and significant association between quality of education and returns to education.

The present study investigates the relationship between quality of education and returns to education, using several measures of quality of education by country and a sample that consists of immigrants in the United States. There is considerable variation in the returns to education among source-country immigrant groups. For example, Canadian immigrants' returns for an additional year in school is 0.091 while Puerto Rican immigrants' comparable returns are 0.047 and Guatemalan immigrants' comparable returns are 0.019 on average. The study makes use of these differentials in order to examine whether differences in returns can be attributable to education quality differences across source countries. We conduct the study with 4 different quality of education measures: mean index based on pupils' achievements (i.e. test score), proportion of the pupils whose score exceeds one standard deviation above the international mean (i.e. advanced level), the proportion of pupils whose score lies above international mean minus one standard deviation (i.e. minimum level), and a mean index that assesses adult skills. The observational units of the quality measures are countries. The first three measures come from Altinok et al. (2014) while the latter comes from the Program for the International Assessment of Adult Competencies (PIAAC). Since quality of education is a latent concept, finding an ideal measure of it has some constraints. Therefore, we conduct our study with as many quality measures as possible. We also introduce a decomposition for returns to education: returns for those with over 12 years of education (at least some college graduates) and at most 12 years of education (at most high school education) for each source-country immigrant groups. Since the immigrant groups' distribution for years of education completed differs, we believe that it will be useful to identify subgroup returns if there is nonlinearity in the years of schooling. Furthermore, the quality of education may matter for these two subgroups to different extents. This reinforces the importance of investigating the link between the quality of education and returns to education separately for these subgroups. Overall, this study aims at improving and extending the current literature by using alternative measures of quality of education and examining returns to education by separate education-level groups by source country groups.

The rest of the paper is organized as follows: section 2 introduces the data; section 3 discusses the empirical specification; section 4 analyses results; section 5 presents robustness check for our empirical specification; and section 6 concludes.

2 DATA

To conduct random coefficient regression analysis as in Card and Krueger (1992), this paper makes use of 5% microdata sample of 1990 and 2000, 1% sample of 2000 U.S. Censuses, all American Community Surveys (ACS) from 2000 to 2016. School quality data comes from Altinok et al. (2014) and PIAAC datasets while GDP per capita is obtained from Penn World Tables 9.0. Censuses and ACSs are available online through IPUMS website (Ruggles et al.,2016). These datasets are pooled in order to get a sufficient number of observations and prevent one year's macroeconomic conditions to drive the results. Besides, to check the sensitivity of results to selected years, the returns to education in the first stage regression are estimated separately: for 1990, for 2000 and for 2001 and onwards.

Our sample includes male immigrants in the US from 153 identifiable source countries[5], aged from 25 to 65, employed in the reference year[6], with wages above 0.1 percentile in the wage distribution (i.e. above 1$ hourly income at 1999 CPI). We also restrict the sample to those with at least 30 hours in a week and 23 weeks (at least half year) in a year that have been worked. The reason why we exclude the immigrants whose country of origin is not identifiable is to get country-specific returns to schooling. The age,

[5] The data includes some observation who reports their birthplace, namely country of origin, as a region, not a country. For example, Caribbean's North America etc. And some country of origin includes less than 35 observations. We drop these observations.

[6] For the 1990 and 2000 census it is the previous year and for ACSs it is 12 months before the survey date.

employment status, wage, sex, working hours and weeks restrictions are due to mitigate labor supply concerns. We further exclude immigrants who are currently attending school, those who either arrived in the U.S before age 16 or before entering the labor market (i.e. six plus the reported schooling year they have completed). In doing this, along with taking the minimum age for our sample as 25 (not 16), we try to minimize the possibility of holding a degree from the U.S. which fails to reflect the education quality of source country. Note that because the Censuses and ACSs do not provide information where the respondent attained his education, above sample restrictions do not completely guarantee that the immigrants in our sample completed their education in their source countries.

Census and ACSs use some imputation methods for missing values. In our specification, the imputation for wage matters the most because the imputed value is drawn from someone who has same characteristics of sex, occupation, class of worker, weeks worked last year, hours worked per week, and age but not country of origin. Since the wage differentials across immigrants from different countries of origin are important for our specification, to us, a robustness check is needed for the imputed wages.[7]

The dependent variable in the first stage is log hourly wages which only includes the income generated from employment and is adjusted to eliminate inflation. Hourly wage is constructed by inflation-adjusted wage income, weeks worked in the reference year and a usual number of hours worked per week. The weeks worked are reported in intervals in the 2008-2016 ACSs. Therefore, the average number of weeks worked within each interval in previous samples are assigned as weeks worked for the ACS samples. Schooling is reported through educational attainment variable (measured by the highest year of school or degree

[7] This issue will be revisited in the robustness section.

completed in the Censuses and ACSs). This variable is categorized slightly differently through Censuses and ACSs for those whose highest year of school completed is at most 8. The primary school graduates report their level of schooling as 1-4th grade completed or 5-8th grade completed in 1990 Census. The primary school graduate respondents who are sampled from 2000 to 2007 microdata sets report their level of education in three categories: From nursery school to grade 4, 5 or 6 years completed, and 7 or 8 years completed. The microdata from 2008 to 2016 ACSs provides successive integers from 1 to 8 for the variable. The years of schooling of respondents who have more than 8 years of schooling are given as exact years in all microdata sets. To convert the educational attainment to years of schooling, the average of years of schooling for the reference categories are calculated using years from 2008 to 2016 ACSs. For example, the average year of schooling of the male immigrants who are sampled from 2008 to 2016 micro dataset and report their educational attainment as from 1 to 4 years are calculated and used for the years of schooling that is reported as interval (i.e. 1-4th grade completed) in 1990 Census. The control variables are fully comparable through years (a quartic form of potential experience, 4 dummy variables for self-reported English proficiency, marital status, an indicator of source country, dummy for 51 States, dummy for micro datasets) except one control variable that is year of immigration. In 1990 Census, the year in which a foreign-born person entered the United States is reported in 10 categories. To get rid of intervals, the midpoints of the intervals are used instead of reference categories. To eliminate the discrepancy stemming from adjusting the intervals, the year of immigration of the respondents whose birth year is greater than the midpoint of the interval is set to birth year. Then, the age at immigration is calculated by using the adjusted year of immigration (year of immigration-birth year) and categorized into 9 groups. [8] Total experience is calculated as age minus years of schooling minus 6 whereas experience in the US is calculated as age minus age at immigration if immigrants migrated after his potential labor market entrance age. Consequently, the US experience and total experience is same for those who migrated before his potential labor market entrance age. The metropolitan status is not available in 1990 Census and 2001-2004 ACSs, therefore we exclude it from our main specification but we also estimated a model using metropolitan status for robustness check and found similar results. A variable that reports the language spoken at home is also used instead of English proficiency, year of immigration dummies instead of year at immigration, total experience (i.e. the U.S. plus source country experiences) instead of only US experience and additional controls for citizenship status and living in a metropolitan area are also estimated for robustness check.

In the second stage regression, a set of data that measures the quality of education comes from Altinok et al. (2014) that aims at improving Lee and Barro (2001) and Barro (2001) and is an updated version of Altinok and Murseli (2007). This data includes more countries than other quality measure data such as Hanushek and Kimko (2000) and upgraded version of it, Hanushek and Woesmann (2012). Having used Latin American Laboratory for Assessment of the Quality of Education (LLECE), the Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ) and the Program on the Analysis of Education Systems (PASEC) data, along with TIMSS, PIRLS and PISA tests, in their anchoring methodology, they obtain 103 countries/areas' indexes of primary education quality measure and 111 countries/ areas' indexes of secondary education (as

[8] Intervals are 0-5, 6-10, 11-15, 16-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-65.

compared with 77 countries measures given by Hanushek and Woesmann (2012)). These indexes are based on pupils' achievements on the international and regional tests on cognitive skills through years 1965-2010. The dataset not only includes the index of the average of the pupils' achievements, but also the proportion of pupils who obtain higher score than that one standard deviation below the international average (a minimum level) and higher than that one standard deviation above the international average (an advanced level).

Altinok et al. (2014) use a methodology that anchors the different test scores that include a different number of countries, and some of them are surveyed for more than one year. Thus, these tests are not fully comparable both within itself across years and merely across tests, leading to possible biases when anchoring. As the authors highlights, tests measure different skills. For example, some tests measure knowledge others measure cognitive skills. Also, the content of some tests differs in coverage, and the tests are applied to the pupils in different grade, for example, some of the pupils were at 4^{th} grade in some tests and some were at 6^{th} grade. Therefore, in anchoring method, a pupil is supposed to perform in one test the same way as he or she performs on the other test which may be not true. Since the test are adjusted to the grade levels and PISA and TIMSS demonstrate that the ranking of countries is similar according to the grade levels, it partly mitigates the measurement error concerns.

Another set of quality of education data comes from Survey of Adult Skills (PIAAC) conducted under OECD. It provides an index of a measure that assesses the cognitive and workplace skills of adults. [9] In the first round (2008-2013) of the survey, 24 OECD countries participated. In the second round (2012-2016), 9 countries were surveyed, leading the dataset to be available for a total of 33 countries. As Hanushek et al. (2015) discuss, PIAAC enhance our understanding of how economies value skills by providing a measure for accumulated cognitive skills for adults who are in the labor market. Since our data consists of the immigrants who immigrated to the U.S. after they enter the labor market, a measure that gauges adult skills may be a good fit for our aim. However, the drawback of the data is that we have only 33 countries' available measure out of 153 countries of origin groups in our sample.

[9] The survey consists of 3 parts: literacy, numeracy and problem solving in technology-rich environments. The index of measure that assesses numeracy skills are used in this study.

3 EMPIRICAL IDENTIFICATION

The empirical model is the two-step regression analysis of Card and Krueger (1992).[10] They, however, link quality of education to returns to schooling in a different context, i.e. they set up their empirical specification as the differences in returns to schooling and quality of education by states of birth for the white men in the U.S. Their idea is adapted to immigrant context to analyze the relation between returns to schooling and quality of education by country of origin group. Our baseline specification in the first stage regression is an analog of well-known Mincer-type earnings equation in which we obtain average returns to schooling for each country of origin: [11]

$$\text{Log}(w_i) = \beta_0 + \sum \beta_{1j}\, I_{ji}\, S_i + \sum \beta_2\, I_{ji} + \beta' X_i + \beta_4\, C_i + \varepsilon_i \qquad (1)$$

where $\log(w_i)$ denotes the logarithm of inflation adjusted hourly wage income of the immigrant i, I_{ji} is the country of origin dummy which takes the value 1 if the immigrant i is from country j, S_i is the years of schooling. The interaction of the country of origin dummy and years of schooling help identify the average returns to schooling of immigrants according to the country of origin groups. Put differently, in doing this, we obtain 153 different source countries' average returns to schooling. Country of origin dummy is included to control for country of origin fixed effects. Vector X_i includes controls for

[10] Or random coefficient regression analysis.
[11] The unit is immigrants from our baseline sample from Censuses and ACSs.

marital status, quartic function of U.S labor market experience, age at immigration dummies, English language skills dummies, 50 state dummies while C_i is a dummy variable that indicates year fixed effects to capture the level differences in wages through years.

In our context, country of origin fixed effects plays crucial role in capturing the level differences in wages across immigrant groups. For example, Canadian born immigrants may earn higher wages on average than Mexican born immigrants regardless quality of education that they obtain after controlling for years of schooling and other observed characteristics such as potential experience, period of immigration etc.

We also conducted various specifications that include different sets of control variables to check whether results are sensitive to the changes. This will be discussed in robustness section below.

In second stage, the β_{1j} from first stage is set as the dependent variable to investigate link the quality of education and returns to education:[12]

$$\beta_{1j} = \alpha_0 + \alpha_1 Q_j + \alpha' Z_j + u_j \qquad (2)$$

where Q_j is the quality of education measure that comes from Altinok et. al (2014) which provides mean test score index, the proportion of the pupils who obtained test score above the advanced level and the proportion of those who obtain score above the minimum level. Vector Z_j includes average GDP per capita (chained PPP) for the years 1960-1995[13], indicator for English being official language in education and continent dummies for Latin America, Asia, Africa and Arab World. Not only the quality of education that an immigrant obtained in his source country, but also skill transferability may play a crucial role in cross-

[12] Here, the unit is country of origin.

[13] We also use 1960-2010 and 1965-1995 averages in other specifications as well.

country differentials for returns to education. If this is the case, then controlling for some possible observed differences among the immigrant group that leads to different skill transferability is needed. Official language as English in education is used in the second regression as a control for this reason. The GDP per capita is a proxy for countries' development levels. If the development level of a country also affects the returns to education of the immigrant groups, then it may confound the association between the quality of education and returns to schooling. One possible scenario can be the case in which the immigrants of the developed countries tend to transfer their skills to a better extent or have additional skills needed for productivity such as IT skills which our education quality measure does not capture. In order to come up with a relevant measure that captures the conditions for immigrant cohorts that arrived over time, we use the GDP per capita averaged over several years as opposed to using GDP per capita from a single year.

The sample size and standard errors of the returns to education obtained in the first stage differ across country of origin groups. Therefore, a weighting strategy with inverse of variance of the estimate for returns to education is applied as commonly used in the meta-analysis literature. However, in our context, it may lead to problematical results: since the number of immigrants from Latin America and Asia is systematically larger than the number of other immigrants in our sample, inverse of sampling variance of this group is much larger than the others'. Therefore, due to our weighting strategy, the results are likely to be driven by these countries of origin (i.e. Latin American and Asian groups).

Trostel (2005) provides evidence for nonlinearity in the returns to education after conducting a regression analysis with a micro dataset from 12 countries including the U.S.

The findings of the study reveal that linear estimates substantially overstate the marginal rates of return at lower and upper levels of schooling while it understates the marginal rates of returns at middle levels that is around 12 years of education. Figure 2 demonstrates the years of education vs. log hourly wages for all immigrants (Panel a), for Cambodians (Panel b) and for the immigrants from U.K. The figure illustrates nonlinearity in returns to education for two particular countries of origin group (Panel b and c), and for whole countries of origin groups (Panel a). Especially in our context, nonlinearity might be at issue because it is evident that the immigrants' distribution for the years of education completed differs across countries of origin groups (Table 11). In addition to this, if the estimates for returns vary with the level of education, then our linear specification fails to capture it, leading to biased coefficient estimates. To mitigate the concern, we introduce an additional dummy variable to allow for different average returns to education for those who completed at most 12 years in education and for those who completed more than 12 years of education: [14]

$$\mathrm{Log}(w_i) = \beta_0 + \sum \beta_{1jl} I_{ji} S_i E_l + \sum \beta_2 I_{ji} + \beta^{|} X_i + \beta_4 C_i + \varepsilon_i \qquad (3)$$

where E_l is a dummy that takes the value 1 if the immigrant i's completed years of education is greater than 12. In equation 3, we thus obtain two different returns for each country of origin groups. Column 3 and 4 of Table 11 demonstrates the number of observations of the immigrants with at most 12 years of schooling and at least some college by country of origin respectively. For example, Taiwanese immigrants with experience of at least some college constitute 0.82 percent of Taiwanese immigrants while the same ratio is 0.12 for Salvadorian immigrants. If there is nonlinearity in returns to schooling, then the

[14] Card and Krueger (1992) use linear-spline regression model that allows kink at 12 years of education.

estimate for returns to one extra year of schooling would be biased in the equation 1. Furthermore, the quality of education may affect the returns to education differently for these two groups. For example, for those who is at most high school graduates the quality of education may not matter that much for the job he currently works but for those with at least some college may suffer from the relative poor quality of education in his current occupation.

In our two-step regression analysis, we aim at investigating whether the returns to education of the immigrants can be associated with country-specific quality of education measure. An important issue is that the sample whose test score is taken for obtaining quality of education index are not composed only of those who tend to immigrate or already immigrated to the U.S.[15] Thus, the average measure may not reflect the immigrants' quality of education they obtained. If we assume that the immigration decision is totally random, then this would not bias our results. However, if the immigrants are selected and the quality of education measure fails to take this into consideration, then the magnitude of the estimate of the quality of education (α_1) will be biased. In addition to this, the quality of education measure may not reflect the overall education system in a country because the measure is based on pupils' test score in primary and secondary education. Therefore, this measure may fail to proxy the quality of education system in a country. This may be an important issue because for the immigrants with at least some college, the quality of tertiary schools may matter the most. Also, the average measure of quality over 50-years period may also end up being a weak proxy schooling quality of some cohorts in the sample. The pooled sample's birth years range from 1925 to 1991 but consist mostly of

[15] The specification may be more well defined if we had the information of the education institution where immigrants have their education. IPUMS does not provide such information.

the cohorts of 1945-1980[16]. Although some papers in the literature prefer to use teacher pupil ratio, expenditure per pupil or teacher's salaries as a proxy for quality, we believe that achievements of pupils are better measure for a proxy for quality of education. Hanushek and Woesmann (2012) underlines the importance of using a measurement that is based on achievements of pupils instead of other measures of quality, stating that it is output rather than input that the schooling system produces. Also, since Altinok et al. (2014) provides data on wider set of countries and based on more recent tests than other measures of the quality of education that are also based on pupils' achievements (Hanushek and Kimko, 2000 and Hanushek and Woesmann, 2012), we prefer to use this measure for our main results.

[16] Roughly 85% of the observations come from this birth year range. Thus, the average of the specific years is largely relevant for our sample.

4 RESULTS

As previously stated, our baseline sample includes male immigrants employed full-time who are at least 25 years old and at most 65 years old, are currently out of school, earn more than those who lie within the bottom 0.01 percentile in the sample, worked at least half a year during the reference year, and immigrated to the U.S after either at least at the age of 16 or 3 years from their expected graduation. With this specification, we are left with 910,287 immigrants who come from 153 identifiable countries of origin.[17] The estimated returns, along with standardized mean test score index (Altinok et. al, 2014), the number of observations for baseline sample, the number of observations of those with at least some college, and of those with at most 12 years of education, for each country of origin group is shown in Table 11.

In all tables from Table 1 to Table 10, second stage (equation 2) results are presented. As stated, the present study makes use of different quality measures and conducts an additional analysis regarding two subgroups based on education-level. Therefore, each table shows different pairs of returns for the 3 groups (the main group and two subgroups) and different measures of quality of education. All tables are in the same format: column 1 presents simple OLS estimate from equation 2; column 2 adds GDP per

[17] Also, less than 35 number of observations by source country group are dropped, ending up with 153 countries of origin.

capita and official language as English in education as control variables; column 3 adds full sets of controls (GDP per capita, official language in education plus 4 continent dummies); column 4 shows weighted least square estimates without any controls (inverse of the sampling variance of the returns to education estimates obtained in the first stage are used as a weight); column 5 uses the same weight with two control variables, GDP per capita and official language as English in education; and column 6 is weighted version of column 3.

As columns 1, 2 and 3 of Table 1 demonstrate, each OLS estimate is positive and statistically significant, leading us to conclude that the quality of education does matter for immigrants for their returns to education. When the model in column 3 of Table 1 is taken as a reference, a one-standard-deviation increase in mean test score index is associated with around 0.015 increase in returns to education. Since returns range from 0 to 0.14 with a mean of 0.063, a one-standard-deviation increase in test score would lead to a 24 percent increase in returns on average. Due to concerns about reflecting the correct quality of education for the immigrant groups, we prefer to conclude that there is a positive and strong association between quality of education and returns to education instead of causality.

Columns 4, 5 and 6 of Table 1 shows the coefficients obtained by weighting with inverse of the variance of the estimated returns from the first stage. Note that when we include the full set of controls in the weighted least square regression analysis, the estimate for quality becomes insignificant and negative. As stated in the previous section, our weighting strategy may cause the result to be driven by particular country of origin groups (i.e. Latin America and Asia). To delve into this issue, we re-estimate a model with the same weighting strategy but without including the Latin American and Asian countries.[18] As shown in the appendix, the estimate for this model barely changes from the OLS estimate in magnitude, and it is positive and has marginal significance. Since a remarkable proportion of immigrants from Latin America work illegally in the U.S., under these conditions, they may end up obtaining jobs that do not value their years of education more frequently than they would obtain under normal labor market. The results suggest that the general picture stresses that there is a positive link between the quality of education and returns to education. Therefore, we prefer to interpret the OLS estimates rather than the estimates of weighted models.[19]

As the previous section describes, equation 3 differs from equation 1 (baseline specification) in containing an additional dummy variable, E_i, that takes a value of one if the immigrant has completed more than 12 years of education. Thus, we identify two subgroups' returns to education separately. Table 3 demonstrates the result for the returns obtained from immigrant groups who are at most high school graduates. The OLS estimate with the full set of controls (preferred model) has marginal significance while in the rest of the models it is insignificant. Therefore, we conclude that the estimate for quality of education (mean test score index) does not seem to be well associated with this immigrant subgroup's returns to education. Moreover, the results for this immigrant subgroup align with the results when two alternative measures of quality of education are used: proportion of pupils with advanced scores and proportion of those with at least the minimum score (Table 8 and Table 9). [20] An interpretation for this may be the fact that immigrants with at

[18] 63 countries are left

[19] We show the results in the tables though.

[20] Notice that here the measure is the proportion of the pupils, therefore theoretically it can range from 0 to 1 and thus the magnitudes of the estimates in table 1 and table 4 cannot be directly comparable.

most 12 years of education are employed in occupations which do not require compelling cognitive skills acquired by means of education to a great extent. Thus, differences in returns across these immigrant subgroups cannot be explained by quality of education. On the other hand, for the immigrant subgroup with at least some college, the quality of education that they obtained at home seems to be important in getting additional returns for their marginal increase from a year of schooling. Table 2 shows the results for this group, indicating that quality of education (mean test score) is positively and significantly associated with returns to education. On the one hand Table 6 suggests that there is no statistically significant association between the returns of this group and quality of education measured by the proportion of pupils whose scores exceed the advanced level; on the other hand, there is significant and positive association between the returns and the other alternative measure (i.e. the proportion of pupils whose scores exceed the minimum level), as Table 7 demonstrates. Contrary to the subgroup with at most high school education, the immigrants with at least some college may be placed in jobs that require more enhanced cognitive skills so that they benefit from the higher quality of education that they obtained in their source countries.

Table 4 and Table 5 present the results of the second stage for the baseline specification (for whole immigrant groups) when the alternative measures are used to measure quality of education. Both tables show that the returns are positively and significantly associated with the alternative measures of education quality as well.

The estimates of the second stage's control variables are all reasonable. Column 2 of all tables from Tables 1 to 10 suggest that GDP per capita explains some part of the differences in cross-country returns to education when the continent dummy variables are excluded in the set of controls. However, GDP per capita becomes insignificant when continent dummies are included in the OLS model (column 3) and when the mean text score index is used as the quality measure. As Tables 6, 7, 8 and 9 suggest, GDP per capita is significant and positive when alternative measures are used. The immigrants from more enhanced economies may acquire some other skills needed for productivity that the immigrants from less enhanced economies cannot. Rather than the proportion of pupils whose scores exceed either advanced or minimum level, such skills matter in terms of returns to education. Except for the continent dummy for Latin America, the other continent dummy variables are positive in all specifications and significant in most specifications (column 3). On the other hand, the estimate for Latin America dummy is insignificant in all specifications and negative in most of the specifications. The coefficients for the official language in the education dummy is significant and positive in the baseline specifications regardless of the quality measures but insignificant for both education-level groups.

The correlation between PIAAC and mean test score index (Altinok et. al., 2014) is high (i.e. 0.75) for 31 countries that have both measures. As Table 10 demonstrates, when the mean test score index is replaced by the PIAAC dataset, we obtain insignificant estimates in all models. However, when we use the mean score index for the 31 countries that have both measures, the estimates are also insignificant.[21] Intrinsically, PIAAC data mostly includes the OECD countries, known as developed countries with similar economies. Therefore, the insignificance may stem from the similarity between observations, along with small sample size in observational units (countries). However,

[21] The continent dummies are excluded due to the very few numbers of countries or none from Latin America and Asia and none from Africa and Arab World.

since the survey will include more countries in the future, the dataset is promising for future studies.

First stage results are omitted to save space, but all estimates are as expected. [22]

[22] The results are available upon request.

5 ROBUSTNESS

In the first stage, in order to test the sensitivity for the set of control variables and sample selection, various regression analysis is conducted. As stated in data section, language spoken at home, total experience (host plus source country experience), a set of dummies for year of immigration are used instead of relevant variables in baseline specification. Also, citizenship status and living in metropolitan areas dummy variable are used respectively as additional controls. In all those specifications, the second stage results for quality of education barely change (ranging from 0.0102 to 0.0158 while the baseline estimate is 0.0153) with all remaining within significance level 0.05.[23] Since variable for living in a metropolitan area is not available in the 1990 census and 2001, 2002, 2003, 2004 ACSs, we estimate an additional specification which has the same variables with baseline specification and excludes 2001-2004 ACSs and 1990 Census. We find that the estimate for quality of education is significant and barely changed (0.0158).

An issue may arise due to possible trends in the returns to education through years coupled with the absence of observation of some country of origin groups.[24] For example, all Maltese immigrants in our sample come from 1990 census, therefore, the estimate for returns to education for Maltese group are derived only from this dataset. On the other

[23] GDP per capita, official language and continent levels are included.
[24] The averages of the returns estimated from 1990 census, 2000 census and 2001-206 ACSs are 0.43, 0.053 and 0.060, indicating that there might be a trend through years.

hand, Canadians, for example, appear in all years roughly even. Thus, their estimates for returns come from all datasets. The estimates that come from 1990 census, 2000 census and 2001-2016 ACSs are 0.0114, 0.0218 and 0.0124 respectively. However, the former estimate is statistically insignificant with t-value of 1.13. The reason might be the differences in sample size.

Due to concerns for possible sensitiveness of immigrants' wages to the imputation methods that the Census and ACS adopt, we also estimate a model that excludes the immigrants whose wage is imputed. The results are robust to this restriction as well with coefficient estimates 0.0117 and statistically significance 0.05.

Robustness check for the second stage is conducted by replacing GDP per capita averaged over years 1960-1995 with GDP per capita averaged over the years 1960-2010, 1965-1995, 1960-2012, 19960-2014 and 1960-1995 respectively. The estimate for quality of education is robust to these changes as well and retains its significance in all specifications.[25]

Since the literature widely use Hanushek and Woesmann (2012) quality of education index[26], we also conducted a regression analysis (not shown) that uses this quality of education measure for our baseline sample (equation 1). The result is in line with our baseline results, reinforcing that our findings are robust and follow the literature regarding the positive link between quality of education and returns to education.

As Table 10 presents, there is no association with the quality measure that assesses adult skills (PIAAC), we re-estimate the model with mean test score index and Hanushek

[25] The estimates range from 0.094 to 0.0110.
[26] Schoelmann (2012) uses HW (2012) while Li and Sweetman (2014) use earlier version of measure of it.

and Woesmann (2012) for countries that have both measures.[27] And, these results are in line with the results obtained from PIAAC: all quality estimates are insignificant. As stated in the previous section, the reason might be small sample size and the similarities between observations (i.e. OECD countries).

In our context, the precise estimation for returns to education for immigrant groups is crucial to seize the link between quality and returns correctly. Although we have a sufficient number of observations for the whole immigrants in the U.S., when we classify them according to their source country, the observation number by source country drops. Consequently, some countries of origin have fewer observations and thus the estimate for returns to education for that group becomes less precise. To mitigate the concern, we not only use weighting strategy as previously stated but also drop the countries who have sent less than 70 observations in our baseline sample. [28] This truncation leads estimates of quality of education to become insignificant with p-value 0.117 when the full set of control variables are included (i.e. GDP per capita, official language in education, Africa, Asia and Latin America continents dummies). However, when all control variables are excluded (or at least GDP per capita is excluded) in our specification, the significance level and the magnitude of the estimate for the countries with more than 70 observations barely changes.

[27] 31 countries have both measures.
[28] 5 observations drop: United Arab Emirates, Iceland, Malta, Estonia, Macau.

6 CONCLUSION

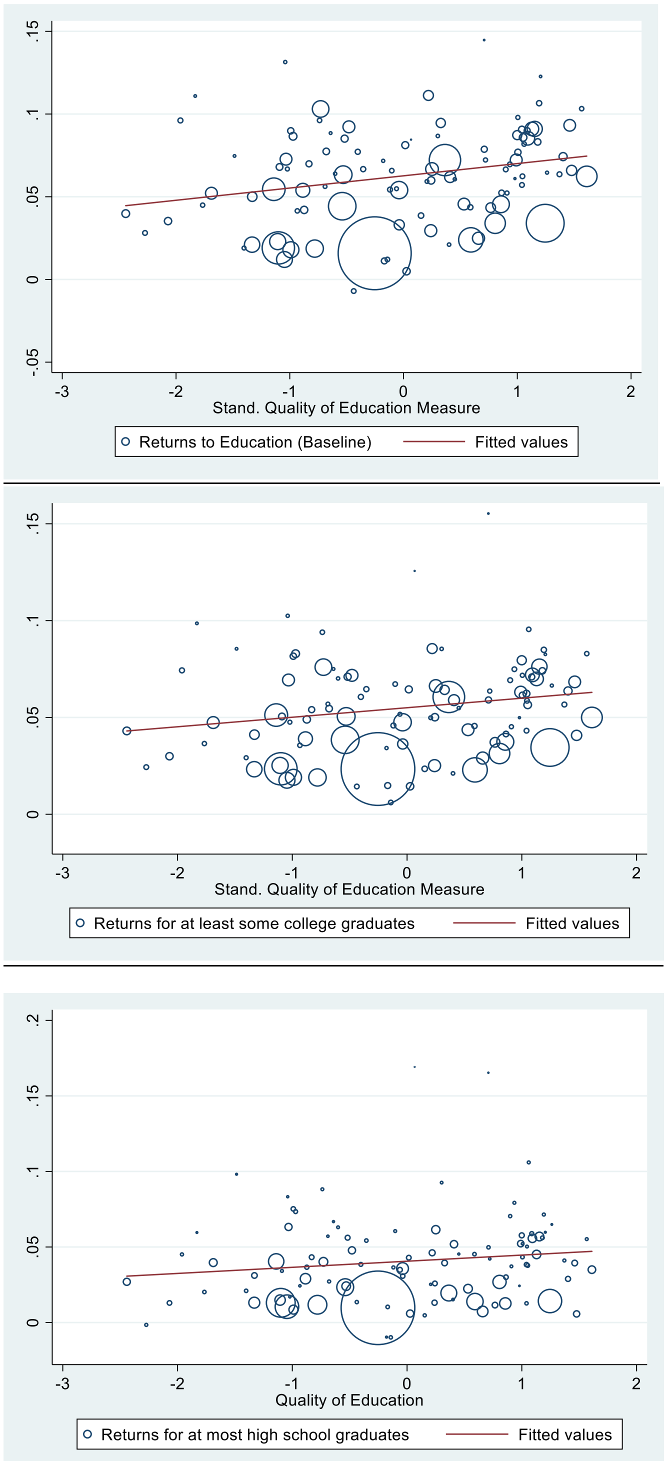
The main objective of the present study is to examine the link between the quality of education and returns to schooling. It is evident that returns to education by source-country immigrant groups differ considerably. Also, obviously, an additional year of education in a country does not provide acquiring some skills at the same rate as compared to another country. These together may suggest that the differences in returns may be attributable to quality of education. Quality measure is latent; therefore, we make use of several quality of education data for a better understanding of the link. Moreover, while analyzing the link, an important issue arises regarding nonlinearity in returns to education: nonlinearity may cause a bias if the immigrant groups have different distribution for years of education.

Our main findings yield that quality of education has a positive and significant impact on returns to education for our baseline sample (the main group). However, when we classify the immigrants according to their education levels, we find different impacts of quality on the returns for each subgroup. For the immigrant groups with some college, we conclude that there is a positive and significant effect of quality of education on returns to their education while for the immigrant groups with at most 12 years of education, there is no association between the quality of education and returns. Different quality measures yield different results for the immigrants with at least some college. An alternative measure (i.e. the proportion of the pupils whose test score exceeds advanced level) have weak impact on returns for this group, while the other alternative measure (i.e. proportion of pupils whose test score exceeds the minimum level) and the mean test score index are positively and significantly associated with the returns.

Additionally, analyzing the link with using PIAAC data results in insignificance for each group. However, this may be due to small sample size and similarity between countries (as most of them are OECD countries). Besides, estimating for the 31 countries that have PIAAC data with Altinok et. al (2014) and Hanushek and Woesmann (2012), we obtain same results that yield insignificance. Since PIAAC data is expanding through years, a close examination of the link between quality and returns to education with using this dataset is promising for the future studies.

Figure 1

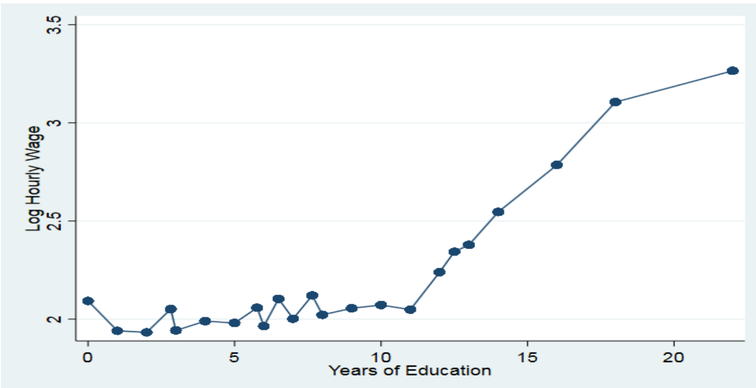
Returns to education and Average Quality of Education by Country of Origin



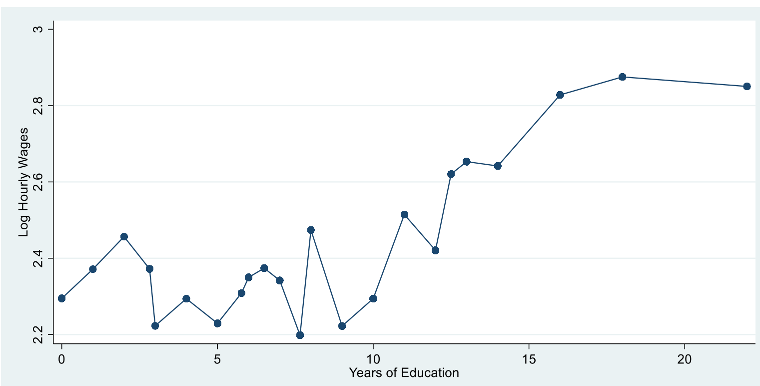
Note: Weighted by inverse of the variance of the returns to education obtained from baseline specification in the first stage (equation1).

Figure 2

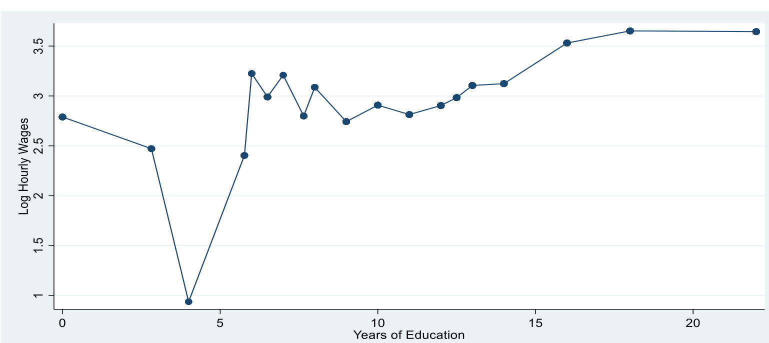
Years of Education and Log Hourly Wages



(a)



(b)



(c)

Notes: Panel (a) demonstrates years of education vs log hourly wages for the whole sample. Panel (b) presents years of education vs log hourly wages for Cambodians while Panel (c) shows years of education vs log hourly wages for immigrants from U.K.

Table 1

Returns to Education and Quality of Education, Baseline sample and mean test score index

	(1)	(2)	(3)	(4)	(5)	(6)
Quality of Education	0.0074***	0.0056*	0.0153***	0.0139***	0.0150**	-0.0117
	(0.0027)	(0.0029)	(0.0051)	(0.0047)	(0.0071)	(0.0080)
GDP per capita		0.0040*	0.0030		-0.0129	0.0149*
		(0.0023)	(0.0025)		(0.0139)	(0.0077)
Education Language=1		0.0085	0.0150**		0.0512***	0.0289***
		(0.0087)	(0.0068)		(0.0165)	(0.0062)
Africa=1			0.0443***			0.0005
			(0.0133)			(0.0148)
Asia=1			0.0157**			0.0181*
			(0.0079)			(0.0102)
Americas=1			0.0041			-0.0429***
			(0.0109)			(0.0093)
Arab World=1			0.0298**			0.0009
			(0.0116)			(0.0130)
Constant	0.0627***	0.0582***	0.0466***	0.0349***	0.0436***	0.0451***
	(0.0028)	(0.0035)	(0.0068)	(0.0076)	(0.0112)	(0.0080)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.055	0.098	0.231	0.139	0.234	0.673

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education that from baseline specification in the first stage (equation 1). Quality of education is standardized mean test score index from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are OLS. Model 4, Model 5 and Model 6 are weighted by inverse of sampling variance of the returns obtained in the first stage.

Table 2

Returns to Education and Quality of Education, Immigrants with at least some college and mean test score index

	(1)	(2)	(3)	(4)	(5)	(6)
Quality of Education	0.0051**	0.0026	0.0112***	0.0066**	0.0064*	-0.0055
	(0.0024)	(0.0024)	(0.0042)	(0.0029)	(0.0034)	(0.0039)
GDP per capita		0.0063***	0.0052***		-0.0004	0.0111**
		(0.0015)	(0.0015)		(0.0077)	(0.0047)
Education Language=1		0.0011	0.0051		0.0204*	0.0164***
		(0.0066)	(0.0053)		(0.0108)	(0.0048)
Africa=1			0.0364***			0.0063
			(0.0128)			(0.0107)
Asia=1			0.0071			0.0107
			(0.0068)			(0.0065)
Americas=1			0.0029			-0.0230***
			(0.0092)			(0.0070)
Arab World=1			0.0249**			0.0012
			(0.0098)			(0.0082)
Constant	0.0550***	0.0484***	0.0405***	0.0378***	0.0379***	0.0389***
	(0.0026)	(0.0029)	(0.0060)	(0.0045)	(0.0053)	(0.0062)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.027	0.157	0.246	0.078	0.128	0.483

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education for the education-level group with at least some college obtained in the first stage (equation 3). Quality of education is standardized mean test sore index from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 3

Returns to Education and Quality of Education, Immigrants who are most high school graduates and mean test score index

	(1)	(2)	(3)	(4)	(5)	(6)
Quality of Education	0.0037	-0.0000	0.0075*	0.0031	0.0026	-0.0067***
	(0.0029)	(0.0028)	(0.0044)	(0.0020)	(0.0023)	(0.0020)
GDP per capita		0.0093***	0.0079***		-0.0018	0.0052
		(0.0010)	(0.0011)		(0.0059)	(0.0034)
Education Language=1		-0.0018	-0.0005		0.0263***	0.0196***
		(0.0064)	(0.0065)		(0.0087)	(0.0053)
Africa=1			0.0277*			0.0050
			(0.0164)			(0.0109)
Asia=1			-0.0033			-0.0026
			(0.0077)			(0.0055)
Americas=1			0.0004			-0.0250***
			(0.0097)			(0.0056)
Arab World=1			0.0214*			-0.0008
			(0.0115)			(0.0092)
Constant	0.0410***	0.0313***	0.0278***	0.0176***	0.0182***	0.0296***
	(0.0032)	(0.0031)	(0.0067)	(0.0038)	(0.0031)	(0.0056)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.003	0.195	0.223	0.014	0.084	0.441

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education for the education-level group with at most 12 years of education obtained in the first stage (equation 3). Quality of education is standardized average quality index coming from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of sampling variance of the returns obtained in the first stage.

Table 4

Returns to Education and Quality of Education, Baseline sample and alternative measure of quality (proportion of pupils with advanced score)

	(1)	(2)	(3)	(4)	(5)	(6)
Quality'	0.0469***	0.0375**	0.0550**	0.0822***	0.0815**	-0.0560
	(0.0147)	(0.0158)	(0.0247)	(0.0302)	(0.0393)	(0.0376)
GDP per capita		0.0040*	0.0035		-0.0099	0.0121*
		(0.0022)	(0.0026)		(0.0128)	(0.0065)
Education Language=1		0.0071	0.0141*		0.0446***	0.0324***
		(0.0086)	(0.0076)		(0.0136)	(0.0065)
Africa=1			0.0262**			0.0069
			(0.0118)			(0.0115)
Asia=1			0.0140*			0.0174*
			(0.0078)			(0.0099)
Americas=1			-0.0035			-0.0435***
			(0.0105)			(0.0100)
Arab World=1			0.0203*			0.0023
			(0.0110)			(0.0114)
Constant	0.0528***	0.0505***	0.0394***	0.0202**	0.0269***	0.0579***
	(0.0047)	(0.0047)	(0.0102)	(0.0092)	(0.0090)	(0.0106)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.069	0.110	0.198	0.195	0.267	0.670

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education that comes from baseline specification in the first stage (equation 1). Quality of education is the proportion of pupils whose score exceeds advanced level from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 5

Returns to Education and Quality of Education, Baseline sample and alternative measure of quality (proportion of pupils whose score exceeds minimum level)

	(1)	(2)	(3)	(4)	(5)	(6)
Quality''	0.0255*	0.0175	0.0476**	0.0479**	0.0552**	-0.0379
	(0.0132)	(0.0141)	(0.0229)	(0.0187)	(0.0237)	(0.0276)
GDP per capita		0.0043*	0.0037		-0.0134	0.0140*
		(0.0025)	(0.0028)		(0.0137)	(0.0078)
Education Language=1		0.0099	0.0172**		0.0574***	0.0266***
		(0.0093)	(0.0075)		(0.0194)	(0.0068)
Africa=1			0.0365**			0.0042
			(0.0140)			(0.0131)
Asia=1			0.0149*			0.0179*
			(0.0080)			(0.0103)
Americas=1			-0.0014			-0.0391***
			(0.0115)			(0.0076)
Arab World=1			0.0210*			0.0063
			(0.0110)			(0.0107)
Constant	0.0437***	0.0448***	0.0132	-0.0018	0.0016	0.0725***
	(0.0107)	(0.0106)	(0.0222)	(0.0143)	(0.0141)	(0.0189)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.029	0.080	0.186	0.091	0.201	0.662

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education that comes from baseline specification in the first stage (equation 1). Quality of education is proportion of pupils whose score is above the minimum level from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 6

Returns to Education and Quality of Education, Immigrants with at least some college and alternative measure of quality (proportion of pupils with advanced score)

	(1)	(2)	(3)	(4)	(5)	(6)
Quality'	0.0305**	0.0174	0.0336	0.0378**	0.0361*	-0.0289
	(0.0129)	(0.0126)	(0.0202)	(0.0181)	(0.0194)	(0.0181)
GDP per capita		0.0063***	0.0058***		0.0007	0.0105**
		(0.0014)	(0.0016)		(0.0072)	(0.0046)
Education Language=1		0.0005	0.0049		0.0186**	0.0175***
		(0.0066)	(0.0059)		(0.0091)	(0.0051)
Africa=1			0.0214*			0.0096
			(0.0114)			(0.0088)
Asia=1			0.0057			0.0114*
			(0.0067)			(0.0066)
Americas=1			-0.0043			-0.0234***
			(0.0091)			(0.0070)
Arab World=1			0.0160*			0.0029
			(0.0093)			(0.0067)
Constant	0.0486***	0.0448***	0.0372***	0.0305***	0.0302***	0.0447***
	(0.0042)	(0.0040)	(0.0091)	(0.0062)	(0.0055)	(0.0074)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.029	0.160	0.216	0.105	0.154	0.488

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education for the education-level group with at least some college obtained in the first stage (equation 3). Quality of education is proportion of the pupils whose score exceeds advanced level from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 7

Returns to Education and Quality of Education, Immigrants with at least some college and alternative measure of quality (proportion of pupils whose score exceeds the minimum level)

	(1)	(2)	(3)	(4)	(5)	(6)
Quality''	0.0176	0.0066	0.0367**	0.0253**	0.0245*	-0.0192
	(0.0118)	(0.0118)	(0.0182)	(0.0108)	(0.0128)	(0.0152)
GDP per capita		0.0065***	0.0057***		-0.0005	0.0106**
		(0.0016)	(0.0017)		(0.0076)	(0.0047)
Education Language=1		0.0019	0.0067		0.0219*	0.0155***
		(0.0069)	(0.0058)		(0.0122)	(0.0046)
Africa=1			0.0316**			0.0075
			(0.0127)			(0.0105)
Asia=1			0.0067			0.0100
			(0.0067)			(0.0064)
Americas=1			-0.0005			-0.0217***
			(0.0092)			(0.0066)
Arab World=1			0.0191**			0.0035
			(0.0091)			(0.0073)
Constant	0.0418***	0.0433***	0.0144	0.0189**	0.0195**	0.0530***
	(0.0094)	(0.0091)	(0.0179)	(0.0093)	(0.0087)	(0.0126)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.012	0.151	0.220	0.057	0.110	0.477

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education for the education-level group with at least some college obtained in the first stage (equation 3). Quality of education is the proportion of pupils whose score is above the minimum level from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 8

Returns to Education and Quality of Education, Immigrants who are most high school graduates and alternative measure of quality (proportion of pupils with advanced score)

	(1)	(2)	(3)	(4)	(5)	(6)
Quality''	0.0135	-0.0024	0.0277	0.0060	0.0038	-0.0284***
	(0.0139)	(0.0134)	(0.0192)	(0.0086)	(0.0076)	(0.0079)
GDP per capita		0.0094***	0.0082***		-0.0009	0.0064*
		(0.0010)	(0.0011)		(0.0055)	(0.0037)
Education Language=1		-0.0016	0.0006		0.0270***	0.0177***
		(0.0064)	(0.0066)		(0.0093)	(0.0055)
Africa=1			0.0260			0.0051
			(0.0162)			(0.0107)
Asia=1			-0.0034			-0.0026
			(0.0075)			(0.0056)
Americas=1			-0.0010			-0.0240***
			(0.0093)			(0.0051)
Arab World=1			0.0185*			0.0013
			(0.0109)			(0.0085)
Constant	0.0310***	0.0331***	0.0076	0.0126**	0.0142**	0.0496***
	(0.0108)	(0.0105)	(0.0186)	(0.0059)	(0.0058)	(0.0073)
Observations	103	102	102	103	102	102
Adjusted R-squared	-0.001	0.195	0.217	-0.005	0.072	0.451

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education for the education-level group with at most 12 years of education obtained in the first stage (equation 3). Quality of education is proportion of the pupils whose score exceeds advanced level from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 9

Returns to Education and Quality of Education, Immigrants who are most high school graduates and alternative measure of quality (proportion of pupils whose score exceeds the minimum level)

	(1)	(2)	(3)	(4)	(5)	(6)
Quality''	0.0142	-0.0021	0.0222	0.0069	0.0030	-0.0296***
	(0.0118)	(0.0114)	(0.0162)	(0.0089)	(0.0077)	(0.0081)
GDP per capita		0.0096***	0.0084***		0.0003	0.0077**
		(0.0009)	(0.0010)		(0.0053)	(0.0036)
Education Language=1		-0.0016	-0.0001		0.0264***	0.0171***
		(0.0053)	(0.0054)		(0.0093)	(0.0050)
Africa=1			0.0205			0.0042
			(0.0125)			(0.0102)
Asia=1			-0.0059			-0.0023
			(0.0070)			(0.0059)
Americas=1			-0.0035			-0.0237***
			(0.0080)			(0.0051)
Arab World=1			0.0158*			-0.0010
			(0.0093)			(0.0078)
Constant	0.0300***	0.0322***	0.0131	0.0122**	0.0140**	0.0494***
	(0.0090)	(0.0086)	(0.0158)	(0.0061)	(0.0059)	(0.0074)
Observations	103	102	102	103	102	102
Adjusted R-squared	0.002	0.262	0.293	-0.003	0.083	0.474

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable is returns to education for the education-level group with at most 12 years of education obtained in the first stage (equation 3). Quality of education is proportion of pupils whose score is above the minimum level from Altinok et. al. (2014). Model 1, Model 2 and Model 3 are unweighted OLS. Model 4, Model 5 and Model 6 are weighted by inverse of sampling variance of the returns obtained in the first stage.

Table 10

	(1)	(2)	(3)	(4)
PIAAC	0.0005	-0.0047	0.0077	0.0016
	(0.0026)	(0.0038)	(0.0046)	(0.0066)
GDP per capita		0.0134*		0.0158
		(0.0077)		(0.0116)
Education Language=1		0.0174***		0.0190**
		(0.0055)		(0.0087)
Constant	0.0733***	0.0502***	0.0685***	0.0403**
	(0.0034)	(0.0114)	(0.0061)	(0.0173)
Observations	31	31	31	31
Adjusted R-squared	-0.034	0.194	0.034	0.439

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Returns to Education and Quality of Education, Baseline sample and PIAAC

Notes: The dependent variable is returns to education that comes from baseline specification in the first stage (equation 1). Model 1 and Model 2 are unweighted OLS. Quality of education is standardized measure of adult skills from PIAAC. Model 3 and Model 4 are weighted by inverse of the sampling variance of the returns obtained in the first stage.

Table 11

Country	Obs	HighSch	College	Quality	Returns	ReturnsC	ReturnsH
Afghanistan	1098	447	651	.	.04599518	.03588099	.02521305
Albania	1609	907	702	-.4378394	-.00700007	.0143522	.01354242
Algeria	607	166	441	-.8736088	.04204922	.0489895	.03662425
American Samoa	527	356	171	.	.01744863	.01681197	.01517159
Antigua	332	227	105	.	.0542113	.04244692	.03154258
Argentina	4102	1829	2273	-.4801326	.0922675	.07173224	.04778164
Armenia	915	331	584	.1537382	.03862854	.02346948	.004768
Australia	2425	478	1947	1.040531	.09061213	.06229265	.03836014
Austria	715	169	546	1.045137	.06236766	.05861095	.05029127
Azerbaijan	334	77	257	-.1189398	.05432915	.04585393	.03647172
Azores	620	579	41	.	-.00133081	.02721016	.00098805
Bahamas	386	200	186	.	.03971127	.05266384	.0518289
Bangladesh	3790	1260	2530	.	.05621388	.04794564	.03392226
Barbados	1188	815	373	.	.04609955	.03723297	.01549541
Belgium	680	108	572	1.179351	.08314928	.07407078	.05610241
Belize	741	494	247	-1.402096	.01899595	.0292193	.02098894
Bermuda	149	80	69	.	.12316259	.06723265	.0424891
Bhutan	368	275	93	.	.00354462	.00874766	-.00834865
Bolivia	1580	671	909	.	.03745328	.02159078	.00465008
Bosnia	3370	2229	1141	.026547	.00496481	.01444248	.00595282
Brazil	6874	3318	3556	-.5304431	.06337017	.05054173	.02406942
Bulgaria	1440	370	1070	.7095992	.07873155	.05903861	.04978301
Byelorussia	944	204	740	.	.07654027	.08120936	.08395948
Cambodia	3058	2136	922	.	.02917918	.02580862	.01456475
Cameroon	563	103	460	-1.090261	.06800037	.05051045	.03416282
Canada	16682	3727	12955	1.128524	.09102413	.0698993	.04507384
Cape Verde	767	632	135	.	.0211982	.02062938	.01163058
Chile	2289	947	1342	.0151551	.08120713	.06449773	.04292954
China	29972	14195	15777	.3639113	.07218859	.06056484	.01952223
Colombia	12970	6669	6301	-.539017	.04428404	.03843295	.02340044
Congo	79	37	42	-2.272461	.028133	.02434981	-.00156301
Costa Rica	1750	1120	630	-.0377592	.03302517	.03629871	.03075075
Croatia	852	508	344	.861955	.05236086	.04145674	.03003349
Cuba	21585	14022	7563	.5918112	.02394115	.022922	.01390961
Cyprus	142	69	73	.2058483	.05926	.04983819	.02528936
Czech republic	475	168	307	1.060304	.08185387	.09550579	.10599985
Czekchoslavakia	665	208	457	.	.07041156	.04891149	.04065106
Denmark	810	157	653	1.00537	.07689214	.06147934	.04333316
Dominica	533	368	165	.	.02423685	.03805773	.03720969
Dominican Rep.	13894	10171	3723	-1.331353	.02104521	.02327554	.01315621
Ecuador	9033	6399	2634	-1.106361	.02289554	.02524242	.01487017
Egypt	4147	702	3445	-.601191	.06392912	.07014169	.06305734
El Salvador	31014	27396	3618	-1.04661	.01208236	.01756314	.01049116
Eritrea	599	290	309	.	.05020814	.04571424	.03380856
Estonia	55	21	34	1.26149	.06456788	.06646272	.06492666
Ethiopia	3053	1130	1923	.	.03840812	.02751959	.01078037
Fiji	1082	670	412	.	.03539376	.02869741	.01436878
Finland	447	65	382	1.370764	.06360287	.05667016	.04106946
France	3688	654	3034	.9994179	.08725957	.07953252	.05771964
Gambia	106	54	52	.	.06745657	.06796652	.0617196
Georgia	235	48	187	-.1790809	.07170365	.03419847	-.00963214
Germany	9112	2445	6667	1.092098	.08537433	.07198995	.05575126
Ghana	3142	1122	2020	-1.688722	.05213251	.04737785	.03968125
Greece	2759	1890	869	.5313135	.0455899	.04365593	.02239095
Grenada	611	414	197	.	.08008022	.0525403	.03432995
Guam	867	454	413	.	.06892481	.06574323	.05827529
Guatemala	20902	18365	2537	-1.100359	.01907622	.02348459	.01306724
Guinea	177	86	91	.	.03736036	.03258841	.01989677
Guyana	6030	3958	2072	.	.04420169	.04170431	.02053038
Haiti	11405	7628	3777	.	.02817563	.02728335	.01515207

Honduras	10483	9068	1415	-.7805516	.01867364	.01901963	.0117701
Hong Kong	3541	1652	1889	1.402544	.07427236	.06370253	.02889946
Hungary	1374	593	781	1.051025	.08584779	.05651134	.03780121
Iceland	56	11	45	.7085732	.14473624	.15529762	.1653427
India	45441	6261	39180	-.7287499	.1030662	.07598573	.04018838
Indonesia	1587	404	1183	-.5179802	.08514169	.07101609	.05614397
Iran	5566	1385	4181	-.3546368	.06669631	.06461565	.05425452
Iraq	2574	1259	1315	.	.04468852	.0364137	.02442857
Ireland	3801	1619	2182	1.086676	.08998248	.07092155	.05886699
Israel	3032	1033	1999	.3272459	.09461053	.06424402	.03942489
Italy	7206	4795	2411	.8562599	.04545525	.03741993	.01263758
Jamaica	12233	8325	3908	.	.04215392	.03824185	.0243264
Japan	8734	1392	7342	1.477398	.0659298	.04075658	.00571409
Jordan	1088	417	671	-.1035806	.06578145	.0672298	.0605352
Kazakhstan	216	59	157	.4508418	.06060388	.0548472	.04535926
Kenya	1367	256	1111	-.9912702	.08987283	.08162521	.075215
Korea	13612	3610	10002	1.610613	.06233061	.05000858	.03500772
Kosovo	38	26	12	.	-.00452588	-.00358131	-.00532572
Kuwait	297	77	220	-1.039972	.13143867	.10248768	.08326138
Laos	4371	3413	958	.	.01276479	.0152679	.00821185
Latvia	244	54	190	.9351649	.06962142	.07490147	.0792577
Lebanon	2206	921	1285	-.4024498	.07718589	.06061675	.03847105
Liberia	1060	329	731	.	.05507185	.05483249	.04979865
Libya	65	11	54	.	.09526965	.09258931	.08940854
Lithuania	458	129	329	.8984611	.06653484	.06923967	.07044733
Macau	39	19	20	1.204749	.12271699	.08258185	.05974193
Macedonia	551	352	199	-.1689654	.01121884	.01483785	.01033247
Malaysia	1160	412	748	.2188913	.11124235	.08556231	.04616247
Malta	50	36	14	.4003774	.02108046	.02111437	.01523148
Marshall Islands	76	58	18	.	-.01133483	-.0048907	.00671167
Mexico	308848	280966	27882	-.2535408	.01584	.02336512	.00974608
Micronesia	326	196	130	.	.02298546	.02098979	.01724389
Moldavia	558	168	390	.3014502	.08675239	.08540463	.09261633
Montenegro	128	86	42	-.1417652	.0120984	.00610838	-.00981904
Morocco	1703	659	1044	-1.32988	.05003719	.04112262	.03116057
Myanmar	2053	1128	925	.	.02485836	.02603431	.00126578
Nepal	1113	308	805	.	.05259778	.03918327	.0165754
Netherlands	2060	295	1765	1.19184	.10655907	.08492435	.07147861
New Zealand	1040	286	754	1.004946	.09794066	.07176867	.05213191
Nicaragua	5412	3458	1954	-.9901149	.01796727	.01909163	.00854718
Nigeria	4589	695	3894	-1.033023	.07271764	.06934746	.06326561
Northern Mariana I.	49	31	18	.	.06335243	.0603363	.03323898
Norway	596	103	493	.720457	.07224594	.06361884	.04216093
Pakistan	6986	2264	4722	.	.07224627	.06214574	.04453181
Palestine	119	52	67	-.6897173	.05615706	.05694168	.05711579
Panama	1593	678	915	-.8313562	.06990955	.05402658	.04324915
Paraguay	293	162	131	-.933808	.04146663	.03560545	.02430449
Peru	9324	4217	5107	-.8852576	.05391628	.03899356	.02901402
Philippines	40533	8773	31760	-1.140337	.05454649	.0512336	.04046664
Poland	11570	6080	5490	.8056722	.03397787	.03138217	.02688158
Portugal	5435	4832	603	.6589058	.02491076	.02903431	.00734789
Puerto Rico	19644	12601	7043	.	.04717542	.03994073	.02080019
Romania	4072	1367	2705	.4089973	.06191174	.05893087	.05185789
Russia	7987	1571	6416	.9905498	.07225153	.06306596	.05224541
Saudi Arabia	251	63	188	-.7380716	.09615888	.09400039	.08821085
Senegal	475	189	286	-2.070109	.0352981	.02997179	.01297916
Serbia	307	130	177	.587496	.04366381	.0455807	.04526116
Sierra Leone	682	224	458	.	.02429023	.02886318	.01566105
Singapore	477	89	388	1.565785	.10325854	.08295581	.05522846
Slovakia	373	156	217	.9091846	.05227632	.04521557	.03717973

Somalia	810	509	301	.	.01410806	.01645947	.00521945
South Africa	2488	366	2122	-1.961353	.0961348	.07431109	.0451018
Spain	2243	950	1293	.7660792	.04343231	.03717664	.01155199
Sri Lanka	1252	345	907	.	.09164942	.07185557	.04579707
St. Kitts-Nevis	178	118	60	.	.0854932	.06489394	.04263403
St. Lucia	295	221	74	.	.05618417	.05505468	.04403115
St. Vincent	438	297	141	.	.04371049	.04667241	.03141053
Sudan	807	312	495	.	.0287324	.02418223	.01166042
Sweden	1141	130	1011	1.040763	.05712497	.04317455	.01271536
Switzerland	1135	182	953	.9792576	.06099276	.04989913	.02429009
Syria	1271	557	714	-.6791537	.07740507	.05456645	.02718163
Taiwan	5994	1026	4968	1.460825	.09318343	.06836949	.03939089
Tanzania	399	105	294	-1.021097	.06678625	.04755308	.01699315
Thailand	2035	797	1238	.2396163	.02949938	.02513801	.01313822
Togo	150	60	90	-1.766077	.04493119	.03652049	.02022328
Tonga	368	260	108	.	-.01577299	-.01518556	-.02089198
Trinidad and Tobago	4281	2599	1682	-.0391813	.05403977	.04753602	.03575481
Turkey	2165	860	1305	.242631	.05988405	.05013443	.02588855
U.S. Virgin I.	638	385	253	.	.06132113	.04641878	.02769444
UK	20465	3868	16597	1.153136	.09101831	.07626011	.05693423
Uganda	423	71	352	-1.485717	.07466439	.085444	.09815883
Ukraine	5495	1399	4096	.2503065	.06675421	.0662485	.06146224
United Arab E.	38	5	33	.0659619	.08453684	.12565487	.16919383
Uruguay	1177	742	435	-.0617586	.0548533	.0516458	.03492352
Uzbekistan	700	243	457	.	.04040214	.02889778	.01334808
Venezuela	3214	711	2503	-.9710793	.08654479	.08293573	.07342207
Vietnam	25309	16143	9166	1.245484	.03400221	.03448974	.01423384
Western Samoa	149	100	49	.	.03101038	.02960269	.01346926
Yemen	655	497	158	-2.44202	.03981983	.04305131	.02696886
Yugoslavia	2520	1533	987	.	.03886924	.03438991	.0236212
Zaire	150	41	109	.	.05309421	.05389684	.05418729
Zambia	80	8	72	-1.831239	.11089908	.09858943	.05958555
Zimbabwe	420	45	375	-.6409829	.0884918	.07502832	.06682341

Notes: Column 2 presents the number of observation for baseline sample (main immigrant group), Column 3 shows number of observation for at most high school graduates in the baseline sample, Column 4 demonstrates number of observation for those with at least some college in the baseline sample, Column 5 gives standardized mean test score index (Altinok, 2014), Column 6 shows estimated returns for the baseline specification (equation 1), Column 7 presents returns to education for those with at least some college, Column 8 demonstrates returns to education for at most high school graduates.

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APPENDIX

Table A.1

Returns to Education and Quality of Education, without Latin American and Asian countries

	(1)	(2)	(3)
Quality of Education	0.0166*	0.0150*	0.0151*
	(0.0097)	(0.0081)	(0.0086)
GDP per capita	0.0166**	0.0100*	0.0012
	(0.0065)	(0.0055)	(0.0061)
Education Language=1	0.0175**	0.0093	0.0078
	(0.0070)	(0.0070)	(0.0095)
Africa=1	0.0637***	0.0530***	0.0481**
	(0.0213)	(0.0186)	(0.0221)
Arab World=1	0.0480***	0.0398***	0.0345*
	(0.0171)	(0.0142)	(0.0173)
Constant	0.0216*	0.0253**	0.0222**
	(0.0115)	(0.0098)	(0.0110)
Observations	63	63	63
Adjusted R-squared	0.493	0.348	0.072

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: The dependent variable of Model 1 is returns to education for baseline specification. The dependent variable of Model 2 is returns to education for the immigrants with at least some college. The dependent variable of Model 3 is returns to education for the immigrants who is at most high school graduates. Each model is weighted by inverse of the sampling variance. Meant test score index is used for the measure of education quality.