EDUCATION QUALITY AND DEVELOPMENT ACCOUNTING

TODD SCHOELLMAN

BREAD WORKING PAPER No. 277
SEPTEMBER, 2010

BREAD

Working Paper

Bureau for Research and Economic Analysis of Development

© Copyright 2010 Todd Schoellman

Education Quality and Development Accounting*

Todd Schoellman †

September, 2010

Abstract

This paper measures the role of quality-adjusted years of schooling in accounting for cross-country output per worker differences. While data on years of schooling are readily available, data on education quality are not. I use the returns to schooling of foreign-educated immigrants in the United States to infer the education quality of their birth country. Immigrants from developed countries earn higher returns than do immigrants from developing countries; I provide evidence that this pattern is likely explained by education quality differences and not selection. I show how to incorporate this measure of education quality into an otherwise standard development accounting exercise. The main result is that cross-country differences in education quality are roughly as important as cross-country differences in years of schooling in accounting for differences in output per worker, raising the total contribution of education from 10% to 20% of output per worker differences.

*Thanks to Bob Hall, Mark Bils, Pete Klenow, Lutz Hendricks, Scott Baier, Robert Tamura and seminar participants at Stanford University, University of Illinois Urbana-Champaign, University of Missouri - Columbia, Oxford University, University of Western Ontario, Clemson University, Arizona State University the 2007 Midwest Macroeconomics Meeting, the 2007 Society for Economic Dynamics, and the 2007 Conference on Economic Development for helpful comments and discussion. A particular thanks to Michèle Tertilt and Manuel Amador for their gracious guidance throughout this project. The editor and three anonymous referees provided many helpful suggestions that substantially improved the paper. Statistics Canada provided census data used for the international results. The usual disclaimer applies.

†Address: Department of Economics, Arizona State University, Tempe, AZ 85287. E-mail: todd.schoellman@gmail.com

1 Introduction

Cross-country differences in PPP-adjusted output per worker are large: workers in the 90th percentile of countries are more than 20 times as productive as workers in the 10th percentile. The development accounting literature attempts to decompose these large cross-country differences in output per worker into underlying cross-country differences in capital, human capital, and a residual term typically associated with technology and institutions.[1] The goal is to provide quantitative guidance on the proximate sources of output per worker differences: can they be accounted for primarily by a lack of inputs or by poor usage of inputs?

The current literature measures the role of years of schooling in development accounting, and generally finds a small role. Typically, years of schooling account for less than 10% of the cross-country differences in output per worker. This paper contributes to the development accounting literature by measuring the importance of quality-adjusted years of schooling in accounting for cross-country differences in output per worker. Doing so requires solving two challenges. The first challenge is to measure education quality differences across countries. The second challenge is to incorporate measured education quality into development accounting exercises. I make progress in four steps.

The first step of the paper is to estimate the returns to schooling of foreign-educated immigrants in the United States.[2] I estimate returns for 130 countries, including many developing countries; there are nine countries in my sample with output per worker less than $1,000. The estimated returns vary by an order of magnitude between developed and developing countries. For example, an additional year of Somalian or Nepalese education raises the incomes of Somalian or Nepalese immigrants by less than 1%, while an additional year of Swedish or Japanese income raises the incomes of Swedish or Japanese immigrants by more than 10%.

The second step of the paper is to provide evidence that these differences in returns to schooling are due to education quality, and not alternative interpretations such as selection or skill transferability.[3] I show that the returns to schooling are correlated with another measure of education quality, the scores on internationally standardized achievement tests.

[1]See Caselli (2005) for an overview of the accounting literature.

[2]Card and Krueger (1992) first studied returns to schooling of cross-state migrants in the U.S., while Bratsberg and Terrell (2002) used returns to schooling for immigrants. Both papers focus on estimating the education quality production function; this is the first paper to integrate this data into an accounting exercise.

[3]The issue of selection was previously raised with respect to Card and Krueger's work by Heckman, Layne-Farrar, and Todd (1996).

However, returns to schooling measure the rate of human capital formation per year of schooling, while test scores lack an economically significant scale.[4] I conduct a number of robustness exercises and find similar differences in the return to education. For example, I show that the estimated returns to schooling for immigrants are quantitatively similar for immigrants to Canada. I estimate large differences in the return to schooling for refugees and asylees, who are much less selected than other immigrants; this fact suggests that selection is unlikely to drive my results. I also estimate large differences in the return to schooling among immigrants who speak English well, have had time to assimilate, and work in licensed occupations, suggesting that the potential inability of immigrants to transfer their skills to the United States labor market is unlikely to drive my results.

The first two steps provide a measure of education quality, namely the returns to schooling of foreign-educated immigrants. The third step of the paper is measure the role of education quality in producing human capital. I follow in the footsteps of Bils and Klenow (2000) by specifying a human capital production function, now augmented to allow for education quality differences. I use the predictions of a simple school choice model in the spirit of Mincer (1958) and Becker (1964) to estimate the key parameter of the human capital production function, which governs the elasticity of school attainment with respect to education quality.

The fourth step of the paper is to combine the human capital production function and measured education quality to construct estimates of human capital stocks around the world. The baseline finding of this paper is that education quality differences are roughly as important as years of schooling differences. Alternatively, I find that incorporating education quality differences doubles the role of human capital in accounting for cross-country output per worker differences. To put this number into an absolute perspective, Hall and Jones (1999) find that replacing the poorest country's years of schooling with U.S. years of schooling would raise their output per worker from 3% to 7.5% of the U.S. level.[5] This paper's methodology implies that replacing their years of schooling and education quality with U.S. years of schooling and education quality would raise their output per worker from 3% to 20% of the U.S. level. I argue that this finding is robust to several

[4]Test scores show that the average student in one country scores two standard deviations above the average student in another. However, this does not measure the relative rate of human capital formation. Nonetheless, Caselli (2005) uses test scores in a development accounting exercise. Hanushek and Kimko (2000) and Hanushek and Woessmann (2009) use test scores in a regression approach and find that they are robustly associated with higher growth.

[5]Most of the literature values years of schooling differences using the pioneering work of Bils and Klenow (2000). Bils and Klenow also consider a separate methodology to account for education quality, discussed below. Since Hall and Jones it has been common in the literature to ignore education quality.

possible extensions of the accounting framework.

The most closely related paper in the literature is Hendricks (2002), who also uses the wages of U.S. immigrants to estimate cross-country differences in unobserved human capital stock (factors other than experience or years of schooling). His approach uses the average wage difference between observably similar natives and immigrants, which he finds to be small. If immigrants are unselected, this finding implies that unobserved human capital differs little between natives and non-migrants. Hendricks then supplies bounds on the plausible degree of selection. However, recent papers in the literature have noted that these bounds are consistent with a wide variety of hypotheses about the role of unobserved human capital in development; if immigrants are modestly positively selected, this implies larger differences in unobserved human capital between natives and non-migrants (Manuelli and Seshadri 2007). The approach in this paper uses the average wage difference between immigrants with different levels of education. Conceptually, I argue that the return to schooling is a better measure of education quality than is the average wage. Further, I provide evidence that the return to schooling is less likely to be affected by selection.

My paper is also related to a previous literature on cross-country differences in education quality. Since data on education quality is scarce, most research has been driven by models of the education quality production function. Typically student time is augmented by teacher quality or expenditures as in Ben-Porath (1967).[6] This paper provides new estimates of education quality and its importance that are independent of any education quality production function. Independence is a virtue since the education literature is unclear about what attributes produce education quality, and provides a wide range of estimates for education quality production functions; see Hanushek (1995) and Hanushek (2002) for an overview. In particular, while expenditure on education is often thought to be an important way to improve quality, there is little empirical guidance on the size of the channel. Hence, outside evidence can provide a useful check for this literature. On the other hand, the primary deficiency of not specifying a production function is that this paper cannot provide policy prescriptions since it is agnostic about the sources of what are measured to be large quality differences. Their work provides insight on this subject.

The paper proceeds as follows. Section 2 estimates the returns to schooling of immigrants and shows that they cannot be explained easily through selection or skill transferability arguments. Section 3 gives the baseline development accounting results. Section 4 considers extensions to the model and shows that the accounting results are robust. Section

[6] See Bils and Klenow (2000) for teacher quality, Manuelli and Seshadri (2007), Erosa, Koreshkova, and Restuccia (2010), Cordoba and Ripoll (2010), and You (2008) for expenditures, and Tamura (2001) for both.

5 concludes.

2 Returns to Schooling of Immigrants

The first step of the paper is to estimate the returns to foreign-educated immigrants to the United States. The estimation follows in the path of Card and Krueger (1992), who use the returns to schooling of cross-state migrants within the United States to infer the education quality of states. The idea was previously extended to cross-country immigrants by Bratsberg and Terrell (2002); I update their exercise using 2000 U.S. census data. The U.S. census is ideal because it contains a large sample of immigrants from many different countries, includes a large set of controls such as English language ability, and provides the variables necessary to impute which immigrants completed their schooling abroad.

Following Card and Krueger (1992), I estimate the returns to schooling of immigrants using an augmented Mincer wage equation:

$$\log(W_{US}^{j,k}) = \gamma_{US}^{j} + \mu_{US}^{j} S_{US}^{j,k} + \beta X_{US}^{j,k} + \varepsilon_{US}^{j,k}. \tag{1}$$

I adopt the convention that superscripts distinguish workers k and their country of birth j, while subscripts denote the country of observation, typically the United States. The regression equation says that the log of wages W are determined by an intercept term; years of schooling S; a vector of common controls X that includes for example age; and an error term ε. A standard Mincerian wage equation might use only Americans, and would have a single intercept and a common return to schooling μ. The above wage equation is augmented in allowing both the intercept of log-wages and the return to schooling to vary based on the immigrant's country of birth.

In this paper, I focus on the country-specific return to schooling μ_{US}^{j} and ignore the level differences γ_{US}^{j}.[7] Looking only at Mexican or Vietnamese workers, an additional year of schooling is associated with small wage gains; looking only at Swedish workers, an additional year of schooling is associated with large wage gains. I discard the level of the wage profile because it may be influenced by selection of immigrants or other factors unrelated to education quality. I return to this idea below. As is common in studies using immigrants not all parameters of equation (1) are well-identified, but Appendix A shows that the country-specific return to schooling is.

[7] Hanushek and Kimko (2000) previously showed that immigrants from countries with high test scores earn higher average wages in the United States; my findings are consistent with theirs but differ in using the return to schooling rather than the average wage.

I implement this equation using the 5% sample of the 2000 census Public Use Micro Survey, made available through the IPUMS system (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek 2010). Immigrants are identified by country of birth.[8] The census lists separately each of 130 statistical entities with at least 10,000 immigrants counted in the United States. Some of these statistical entities are nonstandard: for instance, there are response categories for Czechoslovakia, the Czech Republic, and Slovakia, since immigrants came both before and after the split. I refer to these statistical entities as countries as a shorthand. I keep as many countries as are separately identified, except that the United Kingdom is merged into a single observation.

The census includes a measure of schooling attainment which I recode as years of schooling in the usual manner. The census does not provide direct information on where the schooling was obtained. Instead, I use information on age, year of immigration, and schooling attainment to impute which immigrants likely completed their schooling abroad. It is important to exclude from the sample immigrants who may have received some or all of their education within the United States to have an unbiased estimate of source-country education quality. My baseline sample includes immigrants who arrived in the United States at least six years after their expected date of graduation to minimize measurement error from immigrants who repeat grades, start school late, or experience interruptions in their education. Thus, high school graduates have to be at least age 24 when they immigrate to be included (expected to complete at age 18, plus six years as a buffer). I also select workers who are strongly attached to the labor market, meaning those aged 18-65 who were employed for wages (not self-employed), and who reported working at least 30 weeks in the previous year and at least 30 hours per week. The first benefit of working with the 2000 U.S. census is that it is a large sample with many immigrants. Even after imposing these sample selection criteria I have a final sample with 4.3 million Americans and 240,000 immigrants.

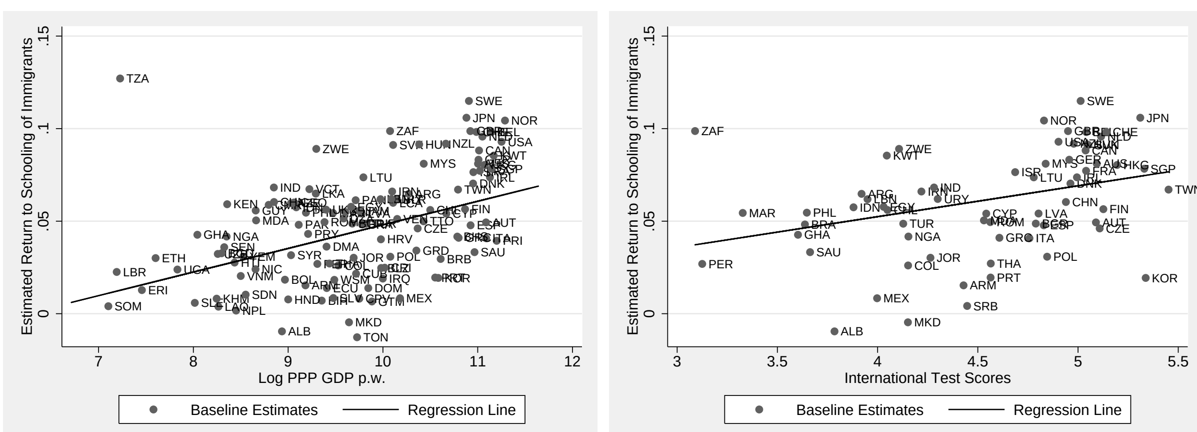
I calculate the wage as the previous year's average hourly wage, computed using annual wage income, weeks worked, and usual hours per week. The census includes a rich set of control variables. I include several standard controls such as a quadratic in age, dummies for census region of residence, and dummy variables for gender, disability status, and living in a metropolitan area. The census also offers two control variables that are particularly useful in the case of immigrants. It asked respondents to self-report English language proficiency on a five option scale, which I enter as dummies. It also collected information on year of

[8] A potential bias could arise if immigrants are born in one country but receive their schooling in another. However, 89% of immigrants who were living abroad five years prior to the census were living in their birth country.

immigration, which I enter as a full set of dummy variables. These last two terms help capture the fact that immigrants' labor market prospects may be limited by language or may be limited upon initial arrival to the United States.

2.1 Estimates and Baseline Interpretation

Appendix B provides the key estimates of this regression, μ^j_{US}, as well as the standard error of the estimates and the number of observations per country. The results are ordered by rate of return so that the large differences are immediately apparent. The measured U.S. return provides a benchmark of 9.3% per year. Immigrants from several countries earn higher rates of return, including two with statistically significant returns over 10% per year, Japan and Sweden. At the other end of the spectrum some countries have remarkably low returns, including four countries with negative but imprecisely estimated returns to schooling. Two useful benchmarks on the low end are Mexico and Vietnam. Since each country has a large number of immigrants in the United States, they have reasonably precisely estimated returns of 0.8% and 2.0% per year of schooling.



(a) Output per Worker

(b) Test Scores

Figure 1: Patterns for Returns to Schooling of Immigrants

Figure 1a plots the estimated returns to schooling of immigrants against the log of PPP GDP per worker from the Penn World Tables (Heston, Summers, and Aten 2009). It shows already the first punchline of the paper: immigrants from developed countries earn higher returns on their foreign schooling than do immigrants from developing countries. Some of the estimated returns to schooling plotted on the y-axis are based on small samples of immigrants and are somewhat imprecise; for example, the obvious outlier of Tanzania is based on just 76 immigrants. I also include the fitted line from a weighted regression using number of immigrants in the sample as weights, and the basic pattern remains. This regression and all subsequent weighted regressions exclude the U.S. and Mexico. Mexican immigrants are roughly one-third of the total immigrant sample, and there is a concern that their experience may be atypical.

The baseline interpretation of the relationship in figure 1a is that it is the result of differences in education quality between developed and developing countries. Figure 1b offers some evidence for this point of view. It plots again the estimated returns to schooling of immigrants, this time against test scores from internationally standardized achievement tests. These scores come from testing programs that administer comparable exams to randomized samples of students still enrolled in school at a particular age or grade in a variety of countries.[9] The data used here are aggregated results from a number of tests administered between 1964 and 2003, constructed by Hanushek and Woessmann (2009). The figure shows that on average, immigrants from higher test score countries earn higher returns on their schooling in the United States. The intuition is that high-quality education imparts more human capital per year of schooling, which in turn is associated with a larger wage gain per year of schooling.

If the returns to schooling of immigrants measure the education quality of their birth country, then figure 1a has an important message. In addition to the well-known fact that workers in developed countries have higher schooling attainment, each of those years of schooling is also of higher quality. Section 3 shows how to incorporate a quality adjustment into development accounting exercises. First, I discuss the robustness of the findings in figure 1 and provide evidence against plausible alternative interpretations.

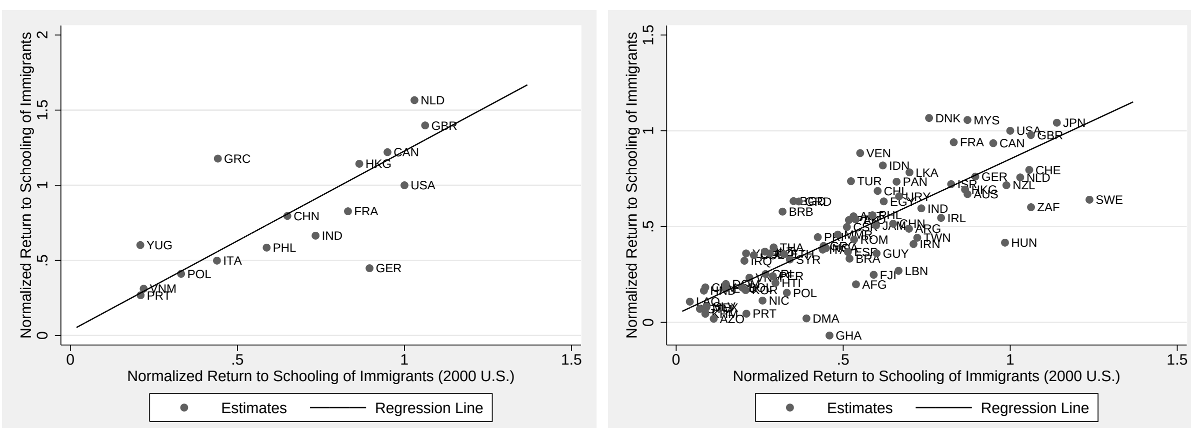
2.2 Robustness

The estimated returns to schooling of immigrants are robust to many of the details of sample selection and to the control variables used. For example, excluding immigrants who entered the United States less than nine or twelve years after their expected date of graduation (instead of six years in the baseline) does not affect the results. Neither does allowing for interactions between age terms and country of birth. There is some evidence that the returns to schooling have a discontinuity around the tenth year of education, for

[9] In practice countries vary in their exclusion and non-response rates so that samples are not perfectly random. Hanushek and Woessmann (2010) document that variation in the sample can account for some of the variation in average test scores by country. They find that even after controlling for this effect, test scores still predict growth rates.

both natives and immigrants. I estimate returns to schooling allowing for nonlinearity and find that the results are driven by the returns to tenth and higher years of schooling, but are only loosely related to returns to lower years of schooling. Details are available in appendix C.1.

If the returns to schooling of immigrants measure their education quality, then returns should be quantitatively similar in other data sets. I focus on two data sets that provide a large number of immigrants from many countries: the 1990 U.S. census, and the 2001 Canadian census. The Canadian census is particularly interesting since it gives results from a different country with different immigration rules and labor market institutions, which could affect the measured returns to schooling. For example, Antecol, Cobb-Clark, and Trejo (2003) document that while around two-thirds of American immigrants enter based on family relationships with current citizens or residents, only one-third of Canadian immigrants do so. Conversely, while less than 10% of American immigrants enter based on labor market skills, around one-third of Canadian immigrants enter through a 'points' system that rewards education, English fluency, and other skills. If returns to schooling measure education quality, then they should be consistent across these two different immigration policies.



(a) 2001 Canadian census

(b) 1990 U.S. census

Figure 2: Returns to Schooling of Immigrants Estimated from Other Samples

These censuses provide very similar information as compared to the 2000 U.S. census, so that estimation of the returns to schooling is quite comparable in terms of sample selection, variable construction, and controls included. Details are available in appendix C.2. Figure 2 plots the estimated returns to schooling of immigrants from the 2001 Canadian census and the 1990 U.S. census against the baseline estimates from the 2000 U.S. census. In all three samples I have normalized the estimated returns by the U.S. return to eliminate variation in the skill premium. Figure 2a shows that the returns to schooling are very similar between the United States and Canada despite differences in immigration policy. Figure 2b shows that the returns within the United States are consistent back to 1990.

Given the results of figure 2 I conclude that the estimated returns to schooling are quantitatively robust. The next question is whether there are plausible alternative interpretations, based on selection or skill transferability. The returns to schooling of immigrants from developed countries are typically 7-10%, not very different from the return to schooling for Americans of 9.3%. Hence, I focus on the question of whether the low observed returns to schooling for immigrants from developing countries, such as the 0.8% return to schooling for Mexican immigrants, can be explained by selection or skill transferability.

2.3 Selection Interpretation

A potential concern with estimating the returns to schooling of immigrants is that they may be affected by selection. Immigrants are potentially selected in two ways: first, they are self-selected, since they have typically decided to come to the United States; and second, they are selected by U.S. immigration policy if they enter the country through formal channels. This section explores what types of selection would explain the relationship between returns to schooling of immigrants and output per worker, and provides some evidence concerning selection.

First note that some of the effects of selection are captured by country of origin fixed effects γ^j, which I discard. For example, suppose that Mexican immigrants with different school attainments are all equally selected: they have unobserved ability that causes them to earn 10% more in labor markets than a randomly chosen Mexican worker with the same school attainment. Figure 3a shows what this selection implies for the relationship between log-wages and schooling. The black line is the observed wages of Mexicans who immigrated: the returns to schooling are a modest 0.8% per year. If Mexicans immigrants with different school attainments are all equally selected, then the red line is the implied wages that would be observed for a random sample of Mexicans. This selection affects the intercept γ^{Mexico}, which explains why I do not use the intercepts. However, it does not affect the measured returns to schooling.

By discarding the fixed effects, this paper is robust to some of the immigrant selection concerns that apply to Hendricks (2002). Hendricks uses a non-parametric estimate of immigrant wages that is close in spirit to regressing

$$\log(W_{US}^{j,k}) = \gamma^j + \mu S_{US}^{j,k} + \beta X_{US}^{j,k} + \varepsilon_{US}^{j,k} \tag{2}$$

although he does not impose linearity restrictions. This regression differs from mine only in the fact that it restricts the return to schooling μ to be the same for all countries, whereas I allow for differences in μ_{US}^j.

Hendricks measures unobserved human capital (human capital not related to years of schooling or potential experience) using the level difference in wages, $\gamma^j - \gamma^{US}$. He compares the wages of natives and immigrants with similar observed characteristics and finds small differences, implying that natives and immigrants differ little in their unobserved human capital. He then draws two inferences. First, if immigrants are unselected, then the small wage differences between natives and immigrants implies small unobserved human capital differences around the world, and a small role for unobserved human capital in accounting for cross-country output per worker differences. Second, he uses a bounding argument to show that immigrants would have be selected to an implausible degree for human capital to account for all of the cross-country differences in output per worker. However, recent papers have noted that his wage results are also consistent with a modest degree of selection and a modestly larger role for human capital than his baseline inference might suggest (Manuelli and Seshadri 2007). This insight is motivated in part by the fact that his estimates suggest that unmeasured human capital is higher than the United States for 28 of the 66 countries in his sample, including Turkey, Syria, and Hungary.

I use different statistics derived from the wages of immigrants to help reduce selection problems and narrow the range of plausible estimates for cross-country differences in human capital per worker. Given that any selection of immigrants will affect the measured γ^j, I discard them. Instead I compare the wages of immigrants from a given country with different years of schooling, as measured by the return to schooling μ_{US}^j. These returns can be explained by selection, but of a very particular form. Immigrants with different education levels need to be *differentially* selected.[10] Specifically, suppose that the returns to schooling for a randomly selected group of Mexican workers would have been 9.3%, the same as Americans. The observed return to schooling for immigrants is 0.8%. Figure 3b shows how these two statements could be consistent: it must be that immigrants with lower education levels are more selected. Further, recall that the returns schooling for immigrants from developed countries are about the same as the returns to schooling for

[10] I am indebted to an anonymous referee for this hypothesis.

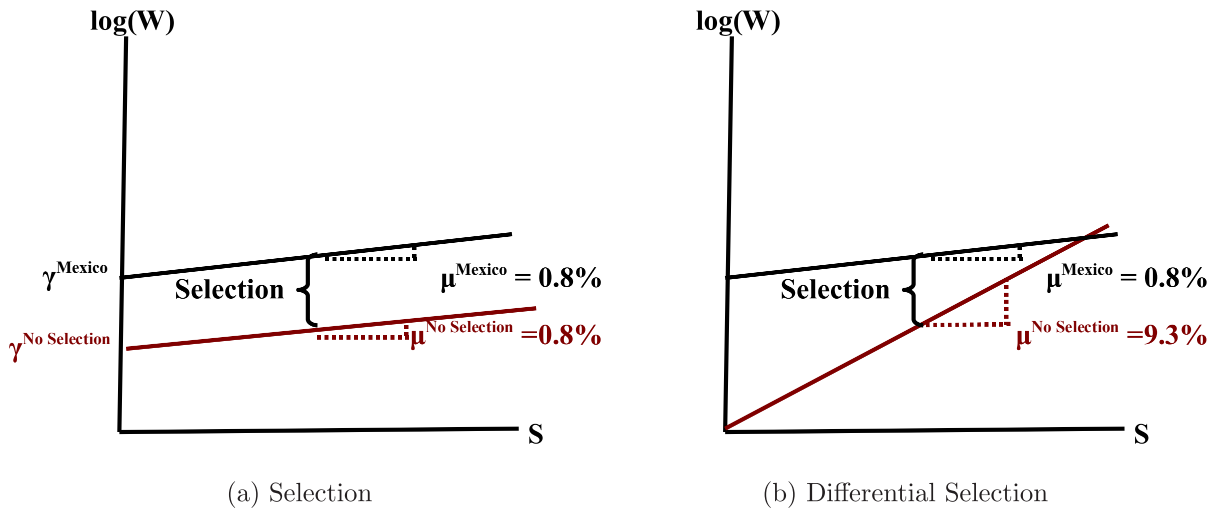


Figure 3: Effect of Two Types of Selection on Estimation Results

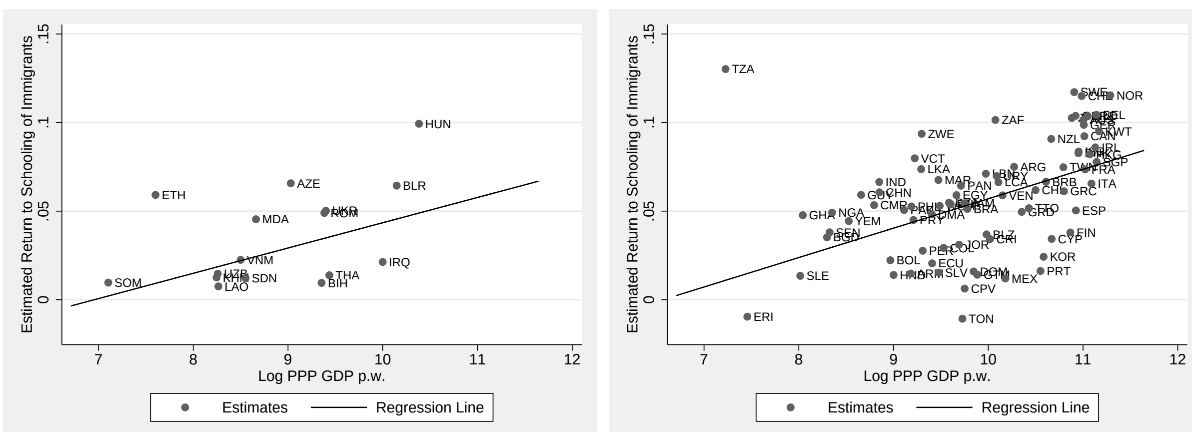
Americans. For selection to explain my results, it must be that less educated immigrants from developing countries are differentially selected, but that less educated immigrants from developed countries are not.

It may be plausible that some form of policy selection or self-selection of immigrants could generate this pattern of differential selection. To investigate whether this is the case, I turn to evidence drawn from a relatively less selected group of immigrants: refugees and asylees. Refugees and asylees are less likely to be affected by both forms of selection. They are fleeing persecution, war, or other violence, and so are less prone to self-selection. Further, U.S. immigration policy commits to resettle at least 50 percent of all refugees referred for consideration by the United Nations High Commissioner for Refugees, on explicitly humanitarian grounds.[11] Hence, refugees and asylees are less selected by immigration policy, as well. Previous work has shown labor market differences between refugees and non-refugees, including a large earnings gap between refugees and non-refugees (Cortes 2004, Jasso, Massey, Rosenzweig, and Smith 2000). Hence, I ask whether the returns to schooling of refugees and asylees look different from the returns to schooling of other migrants, which are collectively called economic migrants.

The census does not identify whether immigrants were refugees/asylees, but it does identify the country of their birth and the year of their immigration. The *Statistical Year-*

[11]United States Department of State and United States Department of Homeland Security and United States Department of Health and Human Services (2009).

book of the Immigration and Naturalization Service from 1980-2000 identifies the fraction of each country's immigrants for the year that were refugees/asylees and the fraction that were economic migrants. I identify 18 countries whose immigrants to the United States were at least 50% refugees/asylees for at least five consecutive years. I estimate the returns to schooling for immigrants in the census who were born in these countries and immigrated in these years. I also identify 82 countries whose immigrants to the United States were never more than 10% refugees/asylees for any year from 1980-2000, and estimate the returns to schooling for immigrants in the census who were born in these countries and immigrated in these years. There is some difficulty with incomplete recording of countries in the Yearbooks, and with imperfect matching between the year of immigration as reported in the Yearbook and the census; see appendix C.3 for details, and for a list of the countries and years that are categorized as refugee/asylee and economic migrant.



(a) Refugees/Asylees

(b) Economic Migrants

Figure 4: Returns to Schooling for Refugees/Asylees and Economic Migrants

Figure 4 plots the returns to schooling for refugees/asylees and economic migrants against the log output per worker of the country. The same positive relationship prevails for both, although the slope of the trend for refugees is significant at the 10% rather than 5% level. Further, refugees from a number of developing countries earn low returns to schooling, including Cambodia, Somalia, Sudan, and Laos.

The low estimated returns to schooling for refugees from these countries are unlikely to be explained by a selection story. To see why, consider the case of Cambodia. Around 600,000-800,000 Cambodians were killed as the country slipped into chaos in the early 1970s, and then another 1 million under the Khmer Rouge regime that ruled from 1975 to

1978. As the Khmer Rouge began to lose control of the country, several hundred thousand Cambodians fled to Thailand and were placed in refugee camps. Around 150,000 of these refugees were resettled in the United States; between 1980 and 1991, 99.5% of immigrants from Cambodia were refugees. The refugees represented a broad swathe of society consisting mostly of those who were able to flee (Mortland 1996). Yet the estimated return to schooling for Cambodians entering the United States in these years is just 1.3% per year of schooling.

2.4 Skill Transferability Interpretation

Immigrants from developing countries earn low returns to their education, even if they enter the countries as refugees and asylees, who are much less selected than the typical immigrant. However, a second potential concern with estimating the returns to schooling of immigrants is that they may reflect the difficulty immigrants face in translating their foreign skills to the U.S. labor market, rather than a lack of skills. This difficulty could arise if different labor markets use different types of skills, or if U.S. labor markets erect barriers that prevent immigrants from exercising their skills.

I present three pieces of evidence against this hypothesis. First, the estimated returns to schooling are similar in Canada, although Canadian immigration policy is more skill-oriented than is U.S. immigration policy. Second, there are large differences in the estimated returns to schooling even among immigrants who have been in the United States for a decade and speak English very well. In appendix C.1 I estimate returns to schooling separately for immigrants who entered the United States before and after 1985, and separately for immigrants with and without strong English skills. For each case the estimated returns are quantitatively similar to the baseline estimates. Hence, differences in returns to schooling persist even for immigrants who have had time to assimilate and who have the language skills to bring their education to bear.

Finally, I explore whether restrictions in the U.S. labor market prevent immigrants from using their skills. In particular, I estimate separately the return to schooling for immigrants who work in licensed and unlicensed occupations. Licensure is the strongest form of occupational restriction: workers are required to obtain a license from the government to practice their profession. To the extent that low returns to schooling are explained by restrictions that prevent immigrants from exercising otherwise valuable skills, then workers who are able to secure a license should presumably earn a rate of return commensurate with their education quality, while workers in unlicensed occupations should presumably earn a lower rate of return. I use licensure data from CareerOneStop (2010), which is sponsored by the U.S. Department of Labor. I define an occupation as licensed if it is federally licensed, or if it is in the top decile in terms of licenses issued at the state level; all other occupations are classified as unlicensed. The list of licensed occupations is heavily weighted towards financial services, engineering, and medical and teaching professionals. It also includes some less-skilled occupations such as hairdresser, which is licensed in many states. Details and a list of occupations classified as licensed are available in Appendix C.4.

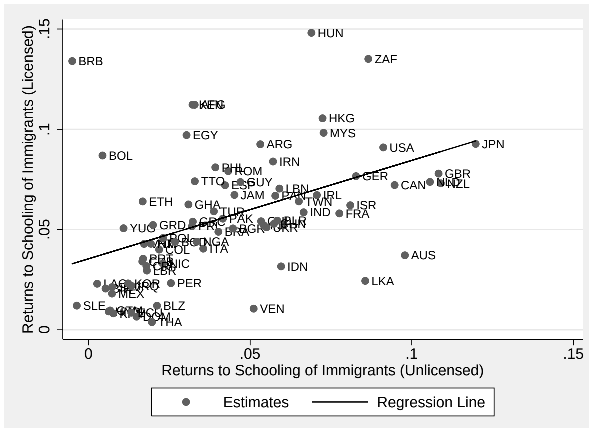


Figure 5: Returns to Schooling of Immigrants in Licensed and Unlicensed Occupations

Figure 5 plots the estimated returns to schooling for immigrants in licensed occupations against the estimated returns to schooling for immigrants in unlicensed occupations. The figure is restricted to countries with at least 50 workers in each category, and shows a strong positive relationship. The trend line from a weighted regression is also included; it is positive and significant. Formal licensure does not explain why returns to schooling for immigrants from developing countries are so low. Since the evidence also points against a selection interpretation, I use the returns to schooling of immigrants as a measure of education quality for the remainder of the paper. I now turn to incorporating these estimates into development accounting exercises.

3 Baseline Accounting Model

The previous section documented large and persistent differences in the returns to schooling of immigrants from developing and developed countries. The baseline interpretation of these returns is that they are measures of the education quality of different countries. This section incorporated these measures of education quality into an otherwise standard development accounting exercise.

The production side of the economy is similar to the development accounting literature such as Hall and Jones (1999) or Caselli (2005). A country's output per worker is related to its efficiency, its capital per worker, and its human capital per worker $h(S_j, Q_j)$, which in turn is a function of the quality and quantity of schooling. Section 2 introduced μ^j_{US} as a measure of Q_j. Then it is possible to perform development accounting exercises if the functional form of h is known, but here it is not. I parameterize h in such a way as to make my results comparable to the previous literature, and use the predictions of a simple school choice model to estimate the key parameter of h. With h in hand, I have all the necessary ingredients to account for quality-adjusted schooling.

3.1 Production

There are J closed economies with country index j. Aggregate output in country j is created using a Cobb-Douglas production function:

$$Y_j = A_j K_j^{\alpha} [h(S_j, Q_j) L_j]^{1-\alpha}. \tag{3}$$

A_j is the exogenous TFP of country j, K_j the labor input and L_j is the number of workers. Human capital h is in turn determined by years of schooling S_j and education quality Q_j. In the previous notation these variables would be labeled for example S^j_j, the years of schooling for country j workers who remain in country j. In the special case of non-migrants I omit the subscript and write only S_j. Education quality Q_j is taken to be exogenous. Education quality is typically determined through a political process involving teachers, parents, voters, and the government, so it is plausible to treat the variable as exogenous to the individual students making decisions on how long to attend school. The focus here is on measuring education quality, rather than on modeling the allocation of resources or educational institutions that imply Q_j.

The choice of the human capital production function is important to the accounting exercise. I generalize the human capital production function of Bils and Klenow (2000) to allow for education quality differences:

$$h(S_j, Q_j) = \exp\left[\frac{(S_j Q_j)^{\eta}}{\eta}\right]. \tag{4}$$

Since most of the development accounting literature follows Bils and Klenow's methodology to account for years of schooling, this functional form will make my results for quality-adjusted years of schooling directly comparable to the literature. By interacting education quality in the exponent, I produce the result (explored below) that education quality and years of schooling are positively correlated as long as $0 < \eta < 1$. I view this result as desirable since there is significant microeconomic evidence supporting such a positive correlation (Case and Deaton 1999, Hanushek, Lavy, and Hitomi 2008, Hanushek and Woessmann 2007).[12]

Given this functional form, I have almost all the ingredients to construct the human capital stocks of countries. S_j is known from Barro and Lee (2001), and I have estimated $Q_j = \mu_{US}^j$. The last component is an estimate of η. To find such an estimate, I write down a simple model of school outcomes. A representative firm hires efficiency units of labor and pays a wage per unit of labor. Workers make a school choice along the lines of Becker (1964) and Mincer (1958). This model makes an equilibrium prediction about the relationship between S_j and Q_j that depends on η; I estimate the values of η so that the model-predicted relationship between S_j and Q_j is consistent with the data. Given this final ingredient, I can conduct development accounting exercises.

3.2 Firm's Problem

The representative firm takes prices, wages, and rental rates as given. It hires labor and rents capital to maximize profits. I assume that the price of the final good is the numeraire, so that the firm's problem is:

$$\max_{K_j, H_j} A_j K_j^\alpha H_j^{1-\alpha} - (r_j + \delta) K_j - w_j H_j$$

where I have omitted time indices since the firm's problem is static. $H_j = h_j L_j$ is the total efficiency units of labor hired by the firm.

3.3 Worker's Problem

Each economy have a continuum of measure 1 of ex-ante identical dynasties. A dynasty is a sequence of workers who are altruistically linked in the sense of Barro (1974). Each worker lives for T years, then dies and is replaced by a young worker who inherits his assets but not his human capital. Hence, it is the death of members of the dynasty that motivates

[12]Bils and Klenow (2000) explored adding education quality of the form $h(S_j, Q_j) = Q_j \exp\left(S_j^\eta/\eta\right)$. This way of modeling education quality has the drawback that it does not affect equilibrium school attainment in simple models of school choice, contrary to the data. Most papers in the development literature have gone a step further and ignored this education quality correction altogether.

further education. The date of death is staggered so that $1/T$ workers die in each year.[13]

Workers are endowed with one unit of time each period to allocate between school and work. They have no direct preferences over work or school, so their school choice is made to maximize lifetime income. While in school workers pay tuition $\lambda_j(S,t)$ and forego labor market opportunities, but acquire human capital. Upon entry into the labor market, workers' earnings are determined by the wage per unit of efficiency labor $w_j(t)$ and the workers' human capital $h(S, Q_j)$. Workers discount future tuition payments and earnings using a constant interest rate r_j. I further assume that wages grow at a constant rate g_j, so that $w_j(t) = w_j(0)e^{g_j t}$, where g_j is determined by the growth rate of A_j on a balanced growth path. I follow Bils and Klenow (2000) in assuming that tuition is a country-specific multiple of the foregone wage, $\lambda_j(S,t) = \lambda_j w_j(t)$. This assumption captures the fact that tuition payments tend to rise with schooling attainment, and gives convenient closed form solutions.

Workers take wages, interest rates, tuition rates, and education quality as given and choose schooling to maximize lifetime income net of tuition costs. The standard result in this model is that workers separate their lives into two periods: they go to school full-time from the beginning of their life until some endogenously chosen age S; then they work full-time until they die. The problem of a worker born at τ is then given by:

$$\max_S \int_{\tau+S}^{\tau+T} e^{-r_j t} w_j(0) e^{g_j t} h(S, Q_j) dt - \int_{\tau}^{\tau+S} e^{-r_j t} \lambda_j w_j(0) e^{g_j t} dt.$$

3.4 Equilibrium School Attainment

Combining the solutions to the problem of the representative firm and the workers yields the equilibrium outcome for schooling:

$$S_j = \left[\frac{Q_j^{\eta}}{M_j}\right]^{1/(1-\eta)}. \tag{5}$$

Schooling is increasing in education quality and decreasing in M_j, where M_j denotes the Mincerian (log-wage) return to schooling for non-migrants, or the return to schooling for a Swede who stays in Sweden. M_j is the standard Mincerian return to schooling discussed in the development accounting literature; Psacharopoulos and Patrinos (2004) and Banerjee

[13] I ignore differences in mortality across countries because incorporating life expectancy differences as T_j was found to be unimportant in earlier versions of the paper. However recent work has suggested that stochastic mortality may play an important role (Tamura 2006, Kalemli-Ozcan, Ryder, and Weil 2000, Soares 2005, Cordoba and Ripoll 2010).

and Duflo (2005) provide data on estimates of M_j for many countries around the world. It differs from my previously estimated μ_{US}^j, which measures the return to schooling for Swedes in the United States.

Since M_j is a property of wages, it is endogenous in the model. The equilibrium expression is

$$M_j = \frac{(r_j - g_j)(1 + \mu_j)}{1 - \exp[-(r_j - g_j)(T - S_j)]}$$

For ease of exposition, I adopt the additional assumption that the equilibrium $T - S_j$ is large, so that the denominator of the first expression is one. This assumption yields the familiar result from the labor literature,

$$M_j = (r_j - g_j)(1 + \mu_j). \tag{6}$$

Workers supply schooling until the Mincerian return to schooling is equal to the opportunity cost, which includes waiting to enter the labor market and paying tuition. The most recent data on M_j for different countries indicates that the returns to schooling are only weakly correlated with schooling and output per worker (Banerjee and Duflo 2005). Motivated by this fact I substitute the average return to schooling $\bar{M}$ of 10% for M_j for the remainder of this section. I return to whether there is any information in country variation of M_j in section 4.1.

I use the equilibrium relationship between years of schooling and education quality to rewrite the human capital production function as:

$$\log(h_j) = \frac{\bar{M} S_j}{\eta}. \tag{7}$$

I use this equation to construct countries' human capital stocks. Since my human capital production function is an augmented version of that in Bils and Klenow (2000), my equation for constructing human capital stocks compares well to theirs, which is given by:

$$\log(h_j) = \bar{M} S_j. \tag{8}$$

The literature values each country's S_j years of schooling using the average log-wage return to schooling $\bar{M}$.[14] This paper's contribution is to account for quality-adjusted years

[14]This approach is taken exactly in Caselli and Coleman (2006). Other papers allow for $M(S)$ to vary with S, which does not affect the insight here (Hall and Jones 1999, Bils and Klenow 2000).

of schooling. The key insight from the microeconomic literature is that the years of schooling differences are themselves optimal responses to differences in education quality, so that countries with higher years of schooling also have higher education quality. In the simplest case there is a one-to-one relationship between years of schooling and education quality, so the additional effect of education quality can be summarized by a single markup parameter η. In essence, η addresses the question: when I see an additional year of schooling, how much extra education quality should I also infer? If η is close to 1, the implied education quality differences are small and the implied human capital stocks are similar to existing measures in the literature. If η is close to 0, the implied education quality differences are large and the implied human capital stocks vary much more than existing measures in the literature.

The quantitative impact of accounting for quality-adjusted schooling, rather than just years of schooling, depends on the parameter η. According to equation (5), $\eta/(1-\eta)$ is the elasticity of years of schooling with respect to education quality. In the next section I estimate this elasticity and η. I can then perform development accounting exercises. Note that estimating η from the elasticity captures the intuition of the previous paragraph, that η allows me to infer the size of education quality differences from observed years of schooling differences.

3.5 Estimating the Elasticity of School Attainment with Respect to Education Quality

I begin by taking equation (5) in logs; I substitute $\mu_{US}^{j} = Q_j$ and $\bar{M} = M_j$. This yields the equation used to estimate η:

$$\log\left(S_j\right) = \frac{\eta}{1-\eta}\log\left(\mu_{US}^{j}\right) - \frac{1}{1-\eta}\log\left(\bar{M}\right). \tag{9}$$

Years of schooling are taken as the average for the over-25 population in 2000, from Barro and Lee (2001). The returns to schooling of immigrants were estimated in section 2. Since $\bar{M}$ is constant across countries it becomes a constant in this formulation.

Figure 6 plots years of schooling from Barro and Lee against the estimated returns to schooling of immigrants. The elasticity of this relationship determines η. This figure raises one potential problem, namely that the returns to schooling of immigrants are measured with some noise. Some of the sample sizes are small and the exact point estimate varies somewhat with the controls and sample used. Further, there may be some residual concern that skill transferability or selection of immigrants explains some of the estimated returns to schooling.

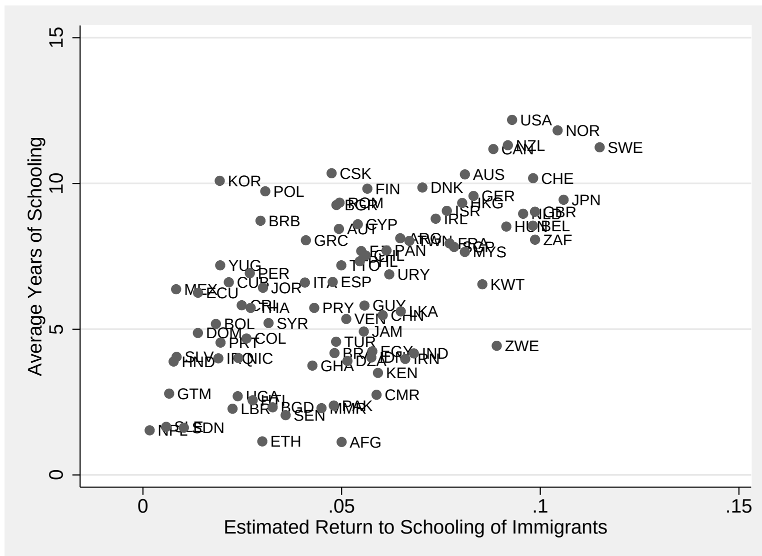


Figure 6: Relationship Between Years of Schooling and Education Quality

To address these issues, I use test scores on internationally standardized achievement tests as instruments for estimated returns to schooling of immigrants. Test scores are a useful instrument because they are also measures of education quality, and so are highly correlated with the returns to schooling of immigrants (figure 1b). They also plausibly satisfy the exclusion restriction. They are immune to the obvious reverse causality (that more years of schooling leads to higher test scores) since they are measured on a sample still enrolled in schooling at a particular grade or age. A second concern is that test scores and education may be spuriously correlated, for example if income per capita explains both. I have several sets of test scores available, so that it is possible to use multiple sets of test scores as instruments and perform a test of overidentifying restrictions; the test fails to reject the null hypothesis that the exclusion restriction is satisfied.[15] For the main analysis I use test score data from Hanushek and Woessmann (2009) and Hanushek and Kimko (2000), both of which aggregate the test scores from a number of testing programs. The former is preferred because every data point comes from an actual test score, but the data

[15] I use the Hanushek and Kimko (2000) and Hanushek and Woessmann (2009) scores discussed below. In this case, the p-value from a Sargan test is 0.29. However, these test score measures use the same underlying data. I also use the test scores from two different programs, Trends in International Mathematics and Science Study and Programme for International Student Assessment, and get a p-value from the Sargan test of 0.25.

Table 1: Estimated Elasticity of Years of Schooling With Respect to Education Quality

	OLS	Baseline Sample, IV				Alternative Samples, IV	
		HW	Weights	Large	HK	1990 U.S.	2001 Canada
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	0.39	1.23	0.70	1.26	0.97	1.25	0.72
	(0.066)	(0.562)	(0.331)	(0.807)	(0.245)	(0.94)	(0.570)
Implied η	0.28	0.55	0.42	0.56	0.49	0.50	0.42
N	88	51	50	37	71	41	13

Table notes: Each column gives one estimate of the elasticity of years of schooling with respect to education quality, and the corresponding implied η. Standard errors are in parentheses.

set is somewhat smaller. The latter includes many countries for which the test score is imputed, which is generally less preferable but allows for a larger sample.

Table 1 gives estimated elasticities of school attainment from different specifications on different samples. The rows contain the estimated elasticity, the standard error, the implied value for η, and the sample size for the regression. Each column gives the results from one particular estimation. Column (1) gives the OLS results, which indicate a low elasticity. If returns to schooling of immigrants are noisy as hypothesized, then this estimate may suffer from attenuation bias.

Columns (2)-(7) give different IV estimates of the elasticity. Columns (2)-(5) use the baseline 2000 U.S. sample. Column (2) is the simplest IV estimation, using only Hanushek-Woessmann test scores. Column (3) uses the same instruments and weights by the number immigrants in the sample; column (4) instead excludes all countries with fewer than 250 immigrants in the sample, but weights all countries equally. Column (5) uses Hanushek-Kimko test scores as instruments. Finally, columns (6) and (7) use estimate the elasticity using alternative samples: the 2001 Canadian sample and the 1990 U.S. sample. Both use the Hanushek-Woessmann test scores as instruments.

The estimated elasticities share two common features. First, all of the IV estimates are much larger than the OLS estimate, which offers support for the concern about measurement error. For the rest of the paper I focus only on IV estimates of the elasticity. The second common feature is that the estimates cluster around an elasticity of 1, with a low estimate of 0.70 and a high estimate of 1.26. In terms of values for η, I take $\eta = 0.5$ as my preferred estimate, and explore sensitivity of η in the range 0.42-0.56.

Table 2: Baseline Accounting Results and Comparison to Literature

	This Paper			Literature	
	$\eta = 0.42$	$\eta = 0.5$	$\eta = 0.55$	Hall and Jones (1999)	Hendricks (2002)
h_{90}/h_{10}	6.3	4.7	4.0	2.0	2.1
$\frac{h_{90}/h_{10}}{y_{90}/y_{10}}$	0.28	0.21	0.18	0.09	0.22
$\frac{\text{var}[\log(h)]}{\text{var}[\log(y)]}$	0.36	0.26	0.21	0.06	0.07

3.6 Accounting Results

Recall that my measure of a country's human capital stock is $\log(h_j) = \bar{M}S_j/\eta$, while the literature's is $\log(h_j) = \bar{M}S_j$. My results differ by a markup factor of $1/\eta$. My preferred estimate of η is 0.5, which would imply that I construct human capital stocks twice those of the literature. The plausible range of η seems to lie between 0.70 and 1.26, which implies that my results would be somewhere between 79% and 143% higher than those that are standard in the literature.

Table 2 gives these results in more detail. I construct human capital stocks using equation (7). I compare the size of cross-country human capital differences in this paper with two standard papers in the literature, Hall and Jones (1999) and Hendricks (2002).[16] The results in the literature can vary somewhat due to the many details in sample selection, choice of the Mincerian return, and so on. Since there is some uncertainty about the true value of η I give results for the baseline $\eta = 0.5$ and for the endpoints of the plausible range. I compute three statistics that measure the importance of human capital. h_{90}/h_{10} is the ratio of human capital in the 90th to 10th percentiles. For both papers in the literature this number is around 2. For my baseline results it is 4.7, with a plausible range of 4.0-6.3.

The last two lines of table 2 give two different estimates of the fraction of output per worker differences that are accounted for by quality-adjusted years of schooling. The second line compares the human capital ratio of the 90th and 10th percentiles to the output per worker ratio of the 90th and 10th percentiles. By this metric quality-adjusted schooling accounts for 18-28% of output per worker differences, larger than the literature. The third line compares the variance of log human capital per worker to the variance of log output per worker. By this metric quality-adjusted schooling accounts for 21-36% of output per

[16] The results that follow are not driven by this functional form. I have also constructed human capital stocks directly using $\log(h_j) = [(S_j Q_j)^\eta/\eta]$, using for Q_j the projection of μ^j_{US} on test scores. The idea is that the any noise in μ^j_{US} will inflate the variation in human capital stocks, but that the projection reduces this noise. The resulting estimates of human capital stock have variability quantitatively similar to that shown here.

worker variation, again larger than the papers in the literature. These results also normalize for the fact that different studies include different sets of countries that may include more or fewer developing countries, and show that differences in the sample do not drive the difference between my results and those in the literature.

Figure 7: Comparison of Accounting Results, Country-by-Country

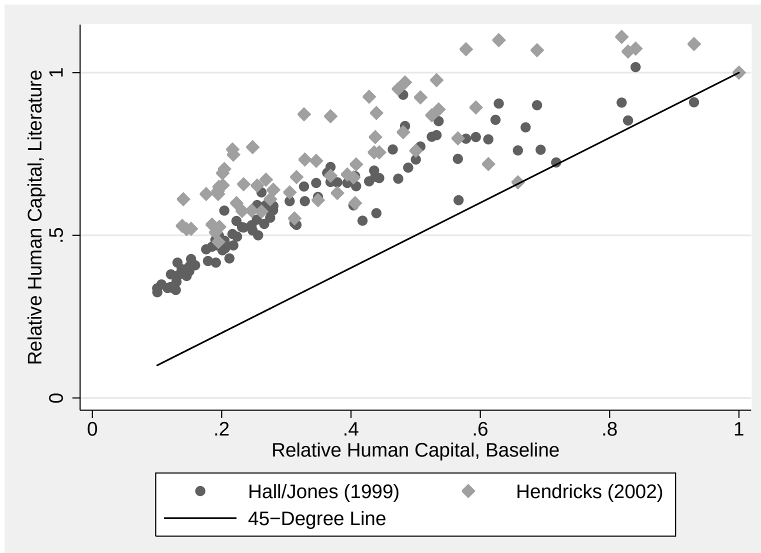


Figure 7 gives a country-by-country comparison of my results for human capital and the literature's. It plots estimated human capital from Hall and Jones (1999) and Hendricks (2002) against my benchmark estimated human capital with $\eta = 0.5$. Human capital is normalized by the level of the U.S. for both axes. The 45-degree line is included for reference. For almost all countries in both papers in the literature the results are above the 45-degree line, indicating that the literature estimates smaller human capital per worker gaps than I do.

The main result of this paper comes from equations (7) and (8), along with the baseline value of $\eta = 0.5$. Together they imply cross-country differences in education quality are nearly as important as cross-country differences in years of schooling. Quality-adjusted schooling accounts for 20% of cross-country output per worker differences, as opposed to 10% for years of schooling alone. Table 2 and figure 7 confirm this result by direct comparison with two well-known sets of results int eh existing literature.

4 Extensions

Section 3 established the baseline result of the paper, that quality-adjusted years of schooling account for 20% of cross-country output per worker differences, as opposed to 10% for years of schooling. In this section I consider three extensions to the baseline accounting framework. First, I allow for factors other than education quality to explain cross-country schooling differences, and ask how this changes the baseline result. Second, I allow for heterogeneity within a country in the rate of human capital formation per year of schooling, and study the implications of this model for selection and the baseline results. Finally, I extend the model to allow for imperfect substitutability across skill types, and show that this helps reconcile the patterns of returns to schooling for migrants and non-migrants.

4.1 Alternative Sources of Cross-Country Schooling Differences

In the baseline mode η is estimated using the elasticity of schooling attainment with respect to education quality. To this point the estimation assumes that all of the school attainment differences between developed and developing countries can be explained by education quality differences. In this section I relax that assumption and show that it results in a modest reduction in the development accounting results.

The equilibrium model of schooling suggests some potential alternative factors that affect school choice. As a reminder, the model's predicted equilibrium schooling for country j is given by:

$$S_j = \left[\frac{Q_j^\eta}{M_j}\right]^{1/(1-\eta)} = \left[\frac{Q_j^\eta}{(r_j - g_j)(1+\mu_j)}\right]^{1/(1-\eta)}.$$

While education quality affects school choice, so do tuition costs, expected growth rates, and interest rates.

The next step is to disentangle the relative contribution of education quality from these other factors. The key information for this step comes from the returns to schooling of non-migrants M_j. In equilibrium, workers equate the marginal benefit of schooling (higher human capital) with the marginal cost (foregone wages and tuition); the marginal cost is measured by $M_j = (r_j - g_j)(1 + \mu_j)$. The insight is that education quality affects school choice differently from the other factors. Education quality raises the marginal benefit by making each year more productive. Given that the marginal cost is the same, this induces workers to go to school longer, until marginal benefits and marginal costs are again equated. On the other hand, lower tuition reduces the marginal cost of schooling. Given that the marginal benefit is the same, this induces workers to go to school longer, but it *also* lowers the return to schooling M_j. Thus, the role of non-quality factors can be inferred by asking whether M_j is generally lower for countries with higher school attainment.

The same insight applies to costs more generally defined, and even applies to frictions. For example, suppose that workers' optimal school choice is S_j years of schooling. However, attending school requires paying tuition and foregoing income today in anticipation of higher future earnings. The lack of functioning capital markets in developing countries may make it impractical for families or students to borrow to schooling today. In this case, average school attainment may be limited to $S_j^* < S_j$. Given diminishing returns to schooling, it necessarily follows that returns to schooling in this country are higher than they otherwise would be. Again, the model suggests asking whether M_j is generally lower for countries with higher school attainment.

Since Mincerian returns are noisy, I follow Bils and Klenow (2000) and use the trend relationship between returns to schooling of non-migrants and schooling rather than individual country observations. The estimated relationship is

$$\log(\hat{M}_j(S)) = b_1 + b_2 \log(S_j) = -2.28 - 0.073 \log(S_j),$$

with standard errors 0.200 and 0.108. The fitted relationship has a negative but statistically insignificant slope, indicating only modestly lower returns to schooling for non-migrants and offering only weak support for the hypothesis that much of cross-country schooling differences are explained by costs and frictions. Bils and Klenow estimate a much steeper relationship

$$\log(\hat{M}_j^{BK}(S)) = b_1 + b_2 \log(S_j) = -1.139 - 0.58 \log(S_j).$$

Their data includes several point estimates that have since been identified as potentially noisy, and which were dropped from the Banerjee and Duflo (2005) data used here (see Bennel (1996) for further discussion). Below I show the results that would prevail using their much steeper fitted relationship.

Returns to schooling for non-migrants are generally lower in countries with higher school attainment, which affects the interpretation relationship between years of schooling and education quality. If I re-write equation (9) assuming that $\log(M_j) = \log(\hat{M}_j(S))$ (instead

Table 3: Robustness to Alternative Sources of School Attainment Differences

	Baseline	Allowing for Alternative Sources		
		Banerjee/Duflo	Bils/Klenow	Bils/Klenow Adj.
η	0.50	0.46	0.21	0.21
% S Attributed to Q	100%	86%	26%	26%
h_{90}/h_{10}	4.7	4.1	6.7	3.6
$\frac{h_{90}/h_{10}}{y_{90}/y_{10}}$	0.21	0.18	0.30	0.16
$\frac{\text{var}[\log(h)]}{\text{var}[\log(y)]}$	0.26	0.21	0.40	0.18

Table notes: Baseline results are those from Table 2, attributing all of cross-country schooling differences to education quality. The remaining columns allow for alternative sources of cross-country schooling differences. The quantitative role of alternative sources is estimated from returns to schooling of non-migrants in Banerjee and Duflo (2005) or Bils and Klenow (2000). The adjusted Bils/Klenow column uses the estimated b_2 from Bils and Klenow but lowers the average return to schooling to be consistent with the Banerjee and Duflo's data.

of $M_j = \bar{M}$, as was assumed before) I find:

$$\begin{aligned}\log\left(S_j\right) &= -\frac{b_2}{1-\eta}\log\left(S_j\right) + \frac{\eta}{1-\eta}\log\left(\mu_{US}^j\right)\\ &= \frac{\eta}{1-\eta+b_2}\log\left(\mu_{US}^j\right).\end{aligned}$$

It is still sensible to estimate the elasticity of school attainment with respect to education quality, but accounting for costs and frictions changes the interpretation of the elasticity. Only a portion is causally attributed to education quality, while the rest is attributed to differences in costs and frictions, as revealed through the fitted relationship between returns to schooling of non-migrants and the average school attainment of the country. Finally, human capital can be constructed as:

$$\log(h_j) = \frac{S_j}{\eta}\hat{M}_j(S).$$

Table 3 summarizes the development accounting results for the model with costs and frictions. All of the results are based on the baseline estimated quantity-quality elasticity of 1. The first column repeats the results for the frictionless model given in table 2. In this interpretation $\eta = 0.5$, all of school differences were by assumption due to quality differences, and human capital accounted for 21-26% of output per worker differences.

The remaining three columns interpret the quantity-quality elasticity differently in light of the observation that on average highly educated countries have lower returns to schooling for non-migrants. In the second column I use the $\hat{M}_j(S_j)$ estimated in this paper from Banerjee and Duflo's data. Returns to schooling for non-migrants are only modestly lower in educated countries in their data. Because of this I infer that 86% of average schooling differences across countries are attributable to education quality, and that η is similar to the baseline case. In this case cross-country differences in human capital fall modestly, to a factor of 4.1 between the 90th and 10th percentile, and quality-adjusted schooling accounts for 18-21% of cross-country differences in output per worker.

The third column uses the $\hat{M}_j(S_j)$ estimated by Bils and Klenow, which is much steeper than the one used here. Returns to schooling for non-migrants are much lower in educated countries. In this case the correct inference is that most of school differences are due to factors other than education quality, and the estimated elasticity is quite low at $\eta = 0.21$. Despite this, cross-country differences in human capital are larger, a factor of 6.7 between the 90th and 10th percentiles, and human capital accounts for 30-40% of cross-country output per worker differences. This counterintuitive result obtains because Bils and Klenow estimate an average return to schooling for non-migrants 50% higher than I do, which acts to raise the importance of schooling.

The fourth column contains the results of an exercise that separates the effects of Bils and Klenow's steep decreasing returns to schooling from their high average returns to schooling. I take Bils and Klenow's estimate $M(S)$ and lower the level of returns until it is the same as in Banerjee and Duflo's data (which is also the data I use for M_j). I then construct human capital stocks and compare them to output per worker as above. I find that even this counterfactual exercise with steep decreasing returns to schooling and low average returns to schooling yields only modestly smaller estimates of cross-country differences in human capital stocks. For example, quality-adjusted schooling still accounts for 16-18% of cross-country output per worker differences, much larger than the previous literature. From these results I conclude that the quantitative results are relatively robust to allowing for factors other than education quality to affect cross-country years of schooling choices.

4.2 Cognitive Ability Heterogeneity

The baseline model allows for cross-country variation in the rate of human capital formation per year of schooling, but no variation within countries. In this section I relax that assumption and allow for within-country differences in the rate of human capital formation, which I attribute to cognitive ability heterogeneity in the population, although education quality heterogeneity is also plausible. I revisit the issue of selection and measured returns to schooling in an environment where workers may also be selected on how well they learn.

I augment the human capital production function to allow for two explicit sources of heterogeneity:

$$h(S_j, Q_j, \varepsilon_j^k, C_j^k) = \varepsilon_j^k \exp\left[\frac{(S_j Q_j C_j^k)^\eta}{\eta}\right].$$

ε_j^k is the more standard notion of ability, but could also measure characteristics such as persistence or diligence. C_j^k is cognitive ability, the characteristic that affects how much human capital workers obtain in a given year of schooling.

The two types of ability affect school choices and wages differently. The optimal school choice depends on cognitive ability but not non-cognitive ability,

$$S_j^k = \left[\frac{\left(Q_j C_j^k\right)^\eta}{M_j}\right]^{1/(1-\eta)}. \tag{10}$$

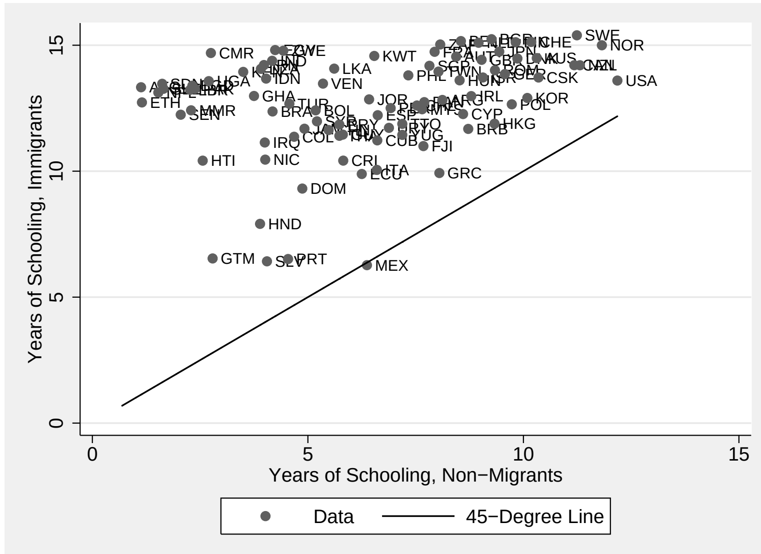
Non-cognitive ability affects the intercept of log-wages, and will be captured by the fixed effect and the error term. Cognitive ability affects the slope of log-wages with respect to schooling and is captured by the return to schooling.

The discussion of selection in section 2.3 implicitly assumed that workers were selected (or differentially selected) on ε_j^k, their non-cognitive ability. A natural extension is to allow for selection on cognitive ability. It follows from equation (10) that since the cognitively able learn more in a year of schooling, then will tend to go to school longer. Then the degree of selection on cognitive ability can be inferred by comparing the school attainment of immigrants relative to non-migrants.

Figure 8 plots the educational attainment of immigrants in my sample against the educational attainment of non-migrants, taken from Barro and Lee (2001). Immigrants from every country except Mexico are positively selected on years of schooling. In some cases, this selection is quite extreme: immigrants from Afghanistan, Nepal, Sierra Leone, and Sudan all have 13-14 years of schooling, while non-migrants in those countries have 1-2 years of schooling.[17] Since immigrants from most countries are positively selected on school attainment, I infer that they are positively selected on cognitive ability. It then follows that the estimated returns to schooling of immigrants generally overstate the education quality

[17]There is a slight discontinuity since the data for immigrants measures schooling for workers, while Barro and Lee's data measures schooling in the population age 25 and over. Hence, the average American in my sample has 13.5 years of schooling, while Barro and Lee's data report an American average of 12.2, indicating that Americans are "selected" by 1.3 years. Still, only Mexican immigrants are less selected.

Figure 8: Schooling of Immigrants and Non-Migrants



of their source country. Further, immigrants from developing countries are more selected on school attainment, so I infer that they are more selected on cognitive ability, and that their estimated returns to schooling overstate the education quality of their source country to a greater extent. In this case, there are actually larger cross-country differences in education quality than what I measured in section 2, and my development accounting results would actually be larger.

An alternative theory is that educational systems in developing countries are less effective at identifying and educating cognitively able students. In developed countries, educational attainment is based in large part on examinations of ability and merit, such as the scholastic aptitude test (SAT) in the United States. But perhaps in developing countries some other factor (such as political connections or family income) determines who is able to attend school. In this case, the low measured returns to schooling for immigrants from developing countries are a function of educating wealthy and politically connected students rather than cognitively able students. My results count this as a form of (low) education quality. This definition is somewhat more expansive than the usual one, which focuses on factors such as training of teachers, availability of books, or class size; it is more in the spirit of an inefficiency or misallocation in the education sector.

The fact that the more able go to school longer raises a second and distinct concern. This framework captures the common concern of ability bias in measured returns to schooling: some of the measured return to schooling is actually attributable to the fact that the more (cognitively) able go to school longer. A lengthy empirical literature has examined this issue. Instrumental variables approaches typically finds that IV and OLS estimates of the return to schooling are similar, suggesting that ability bias may not be quantitatively important; see Card (2001) for an overview. If this conclusion is wrong and the private return to schooling is lower than the observed return, then both my results *and* those of the literature will tend to be reduced, since both approaches treat $\bar{M}$ as the private return to schooling. In this case, my results will continue to be a factor of $1/\eta$ larger than those of the literature, but the role of schooling in accounting for output per worker differences will decline. For example, if 50% of the observed return is bias, I will predict that human capital per worker varies by only a factor of 2.2 between the 90th and 10th percentiles, but the predictions of the literature will decline by a similar proportion.

4.3 Reconciling the Returns to Schooling of Immigrants and Non-Migrants

This paper uses two different sets of estimated returns to schooling: those of immigrants (μ_{US}^{j}), and those of non-migrants M_j. These two sets of returns have very different relationships with the average schooling attainment or output per worker in country j. One of the key facts of this paper is that immigrants from highly-educated, high output per worker countries earn higher returns per year of schooling. On the other hand, Banerjee and Duflo (2005) document that there is a weak and negative correlation between returns to schooling for non-migrants and average schooling attainment or output per worker in country j. It follows that returns to schooling for migrants and non-migrants differ greatly, and are even negatively correlated (-0.17). This subsection considers a simple extension to the baseline model to explain why this might be the case.

To see that this is a puzzle, consider the implications of the baseline accounting model, common in the literature. Workers are paid in efficiency units whether not the immigrate, but the level of the wage varies. Their total wage is $w_j(t)\exp\left[(SQ)^{\eta}/\eta\right]$ if they remain in country j and $w_{US}(t)\exp\left[(SQ)^{\eta}/\eta\right]$ if the immigrate to the United States. It follows immediately from this fact that the model predicts that the returns to schooling for migrants and non-migrants should be the same:

$$M_j = \mu_{US}^{j} = S^{\eta-1}Q_j^{\eta}.$$

Hence, an extension of the standard accounting model is needed to explain why returns to schooling for migrants and non-migrants differ.

The simplest way to resolve this puzzle is to allow workers of different skill types in imperfect substitutes. With imperfect substitutes, low education quality in developing countries is offset by the general scarcity of human capital, and the high education quality in developed countries is offset by the general abundance of human capital, so that the return to schooling in the two countries is roughly the same. However, immigrants from developing countries have low-quality education and move to a country where human capital is abundant, so that their return to schooling is low.

To formalize this intuition, I augment the aggregate production function to allow different skill types to be imperfect substitutes. It is important to be careful in defining skill types. In standard models, workers are differentiated by their educational attainment: high school versus college (Katz and Murphy 1992), or uneducated versus educated (Caselli and Coleman 2006). In this model, workers can have the same educational attainment but very different human capital levels if they have different education quality. I modify the standard approach so that workers of different human capital levels are imperfect substitutes. Then if $l_j(h)$ is the density of workers with human capital h, output is given by

$$Y_j = A_j K_j^{\alpha} \left[\int_1^{\bar{h}} (h l_j(h))^{1-1/\sigma} \, dh \right]^{\sigma(1-\alpha)/(\sigma-1)}$$

where a lower bound of 1 is suggested by the human capital production function and the upper bound is set to $\bar{h}$. This equation yields the familiar relationship between the wage premium for workers of two different human capital endowments,

$$\frac{w_j(h)}{w_j(h')} = \left[\frac{l_j(h)}{l_j(h')} \right]^{-1/\sigma} \left(\frac{h}{h'} \right)^{1-1/\sigma} .$$

The relative wage paid to workers with different human capital (and schooling) levels depends on the relative supply of labor with those two types, unlike in the standard development accounting framework.

The problem of the workers remains the same. At an interior solution workers must be indifferent between obtaining different levels of schooling. In equilibrium, this indifference condition implies that the Mincer returns to schooling are given by $M_j = (r_j - g_j)(1 + \lambda_j)$. To find the returns to schooling of immigrants, use the human capital production function twice along with the return to schooling for natives given by equation (6) to find:

$$\begin{aligned}
\log(W(S_{US})) &= c + M_{US}S_{US} \\
&= c + M_{US}\frac{[\eta\log(h)]^{1/\eta}}{Q_{US}} \\
\log(W(S^j_{US})) &= c + M_{US}\frac{Q_j}{Q_{US}}S^j_{US}
\end{aligned}$$

Hence the returns to schooling of immigrants (relative to natives) measures relative education quality,

$$\mu^j_{US} = \frac{Q_j}{Q_{US}}M_{US}.$$

The standard development accounting framework has to be extended to allow imperfect substitutability of different skill types to explain the patterns of return to schooling for migrants and non-migrants. However, this extension reconciles the two in a simple way. Further, it clarifies why returns to schooling of immigrants are the right wage statistic to learn about education quality. Using the returns to schooling of non-migrants risks confounding the quality of education with the supply of human capital, whereas using the returns to schooling of immigrants holds the supply of human capital fixed (at the U.S. level) and allows for measurement of the quality of education.

5 Conclusion

This paper measures the role of quality-adjusted schooling in accounting for cross-country differences in output per worker. Doing so required finding a measure of education quality across countries and incorporating it into an otherwise standard development accounting exercise. This paper showed how to do so in four steps. First, it measured the returns to schooling of immigrants, and documented large differences in returns between immigrants from developing and developed countries. Second, it provided evidence that these should be interpreted as the result of education quality differences and not selection or skill transferability. Third, it suggested and estimated a particular human capital production function that allows for education quality differences. Fourth, it conducted development accounting exercises. The model suggests that differences in education quality account for about as much of cross-country output per worker differences as years of schooling. The total contribution of quality-adjusted years of schooling is 20% of cross-country output per worker differences, against 10% for years of schooling alone. Several extensions to the model yield similar results.

Policy advocates often suggest an expansion of education in developing countries as one way to increase income per capita. This paper offers mixed conclusions on the efficacy of such a policy. On the one hand, quality-adjusted schooling does account for a large fraction of cross-country income differences. On the other hand, education quality plays a large role in this conclusion. Most proposed experiments expand quantity through compulsory school laws, building additional schools, and so on. The estimates of η here (approximately 0.5) imply steep diminishing returns to schooling conditional on quality, rendering an expansion of years of schooling of questionable value. For example, while the observed return to schooling in the world averages 10%, doubling a country's schooling without raising quality increases human capital by just 8.2% per year of schooling; tripling it raises it by 7.3% per year. Given limited budgets, an increase in quantity may be implemented through a decline in quality, further complicating the tradeoff.

By design, this paper has nothing to say about the sources of education quality differences. Hence, it is not appropriate to offer policy advice about improving education quality. Rather, it is hoped that these estimates will provide useful evidence for future work.

References

Antecol, H., D. A. Cobb-Clark, and S. J. Trejo (2003): "Immigration Policy and the Skills of Immigrants to Australia, Canada, and the United States," *Journal of Human Resources*, 38(1), 192–218.

Banerjee, A. V., and E. Duflo (2005): "Growth Theory Through the Lens of Development Economics," in *Handbook of Economic Growth*, ed. by P. Aghion, and S. N. Durlauf, vol. 1A, chap. 7, pp. 473–554. Elsevier Science, North-Holland Publishers.

Barro, R. J. (1974): "Are Government Bonds Net Wealth?," *Journal of Political Economy*, 82(6), 1095–1117.

Barro, R. J., and J.-W. Lee (2001): "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers*, 53(3), 541–563.

Becker, G. S. (1964): *Human Capital*. University of Chicago Press, Chicago.

Ben-Porath, Y. (1967): "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, 75(4), 352–265.

Bennel, P. (1996): "Rates of Return to Education: Does the Conventional Pattern Prevail in Sub-Saharan Africa?," *World Development*, 24(1), 183–199.

Bils, M., and P. J. Klenow (2000): "Does Schooling Cause Growth?," *American Economic Review*, 90(5), 1160–1183.

Borjas, G. J. (1999): "The Economic Analysis of Immigration," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 3A, pp. 1697–1760. Elsevier Science, North-Holland Publishers.

Bratsberg, B., and D. Terrell (2002): "School Quality and Returns to Education of U.S. Immigrants," *Economic Inquiry*, 40(2), 177–198.

Card, D. (2001): "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," *Econometrica*, 69(5), 1127–1159.

Card, D., and A. B. Krueger (1992): "Does School Quality Matter? Returns to Education and the Characteristics of Public Schools in the United States," *Journal of Political Economy*, 100(1), 1–40.

CareerOneStop (2010): "Licensed Occupations," Available online at http://www.acinet.org/ACINET/LICENSEDOCCUPATIONS/lois_keyword.asp?nodeid=16&by=keyword.

Case, A., and A. Deaton (1999): "School Inputs and Educational Outcomes in South Africa," *Quarterly Journal of Economics*, 114(3), 1047–1084.

Caselli, F. (2005): "Accounting for Cross-Country Income Differences," in *Handbook of Economic Growth*, ed. by P. Aghion, and S. N. Durlauf, vol. 1A, chap. 9, pp. 679–741. Elsevier.

Caselli, F., and W. J. Coleman, II (2006): "The World Technology Frontier," *American Economic Review*, 96(3), 499–522.

Cordoba, J. C., and M. Ripoll (2010): "What Explains Schooling Differences Across Countries?," mimeo, University of Pittsburgh.

Cortes, K. E. (2004): "Are Refugees Different From Economic Immigrants? Some Empirical Evidence on the Heterogeneity of Immigrant Groups in the United States," *The Review of Economics and Statistics*, 86(2), 465–480.

Erosa, A., T. Koreshkova, and D. Restuccia (2010): "How Important is Human Capital? A Quantitative Theory Assessment of World Income Inequality," *Review of Economic Studies*, forthcoming.

Friedberg, R. M. (1992): "The Labor Market Assimilation of Immigrants in the United States: The Role of Age at Arrival," mimeo, Brown University.

Hall, R. E., and C. I. Jones (1999): "Why Do Some Countries Produce So Much More Output Per Worker Than Others?," *Quarterly Journal of Economics*, 114(1), 83–116.

Hanushek, E., and L. Woessmann (2007): "The Role of School Improvement in Economic Development," PEPG 07-01.

——— (2010): "Sample Selectivity and the Validity of International Student Achievement Tests in Economic Research," NBER WP 15867.

Hanushek, E. A. (1995): "Interpreting Recent Research on Schooling in Developing Countries," *World Bank Research Observer*, 10(2), 227–246.

——— (2002): "Publicly Provided Education," in *Handbook of Public Economics*, ed. by A. J. Auerbach, and M. Feldstein, vol. 4, chap. 30, pp. 2045–2141. Elsevier Science, North-Holland Publishers.

Hanushek, E. A., and D. D. Kimko (2000): "Schooling, Labor-Force Quality, and the Growth of Nations," *American Economic Review*, 90(5), 1184–1208.

Hanushek, E. A., V. Lavy, and K. Hitomi (2008): "Do Students Care About School Quality? Determinants of Dropout Behavior in Developing Countries," *Journal of Human Capital*, 2(1), 69–105.

Hanushek, E. A., and L. Woessmann (2009): "Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation," NBER Working Paper 14633.

Heckman, J., A. Layne-Farrar, and P. Todd (1996): "Human Capital Pricing Equations with an Application to Estimating the Effect of Schooling Quality on Earnings," *The Review of Economics and Statistics*, 78(4), 562–610.

Hendricks, L. (2002): "How Important Is Human Capital for Development? Evidence from Immigrant Earnings," *American Economic Review*, 92(1), 198–219.

Heston, A., R. Summers, and B. Aten (2009): *Penn World Table Version 6.3*. Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Jasso, G., D. S. Massey, M. R. Rosenzweig, and J. P. Smith (2000): "The New Immigrant Survey Pilot (NIS-P): Overview and New Findings About U.S. Legal Immigrants at Admission," *Demography*, 37(1), 127–138.

Jones, B. F. (2008): "The Knowledge Trap: Human Capital and Development Reconsidered," NBER Working Paper 14138.

Kalemli-Ozcan, S., H. E. Ryder, and D. N. Weil (2000): "Mortality Decline, Human Capital Investment, and Economic Growth," *Journal of Development Economics*, 62, 1–23.

Katz, L. F., and K. M. Murphy (1992): "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 107(1), 35–78.

Manuelli, R. E., and A. Seshadri (2007): "Human Capital and the Wealth of Nations," Mimeo, University of Wisconsin - Madison.

Mincer, J. (1958): "Investment in Human Capital and Personal Income Distribution," *Journal of Political Economy*, 66(4), 281–302.

Mortland, C. A. (1996): "Khmer," in *Refugees in American in the 1990s: A Reference Handbook*, ed. by D. W. Haines, chap. 11, pp. 232–258. Greenwood Press.

Psacharopoulos, G., and H. A. Patrinos (2004): "Returns to Investment in Education: A Further Update," *Education Economics*, 12(2), 111–134.

Ruggles, S., J. T. Alexander, K. Genadek, R. Goeken, M. B. Schroeder, and M. Sobek (2010): "Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]," Minneapolis: University of Minnesota.

Soares, R. R. (2005): "Mortality Reductions, Educational Attainment, and Fertility Choice," *American Economic Review*, 95(3), 580–601.

Tamura, R. (2001): "Teachers, Growth, and Convergence," *Journal of Political Economy*, 109, 1021–1059.

——— (2006): "Human Capital and Economic Development," *Journal of Development Economics*, 79, 26–72.

United States Department of State and United States Department of Homeland Security and United States Department of Health and Human Services (2009): *Proposed Refugee Admissions for Fiscal Year 2009: Report to the Congress.*

U.S. Immigration and Naturalization Service (1980-2000): *Statistical Yearbook of the Immigration and Naturalization Service*. U.S. Government Printing Office, Washington, D.C.

You, H. M. (2008): "The Contribution of Rising School Quality to U.S. Economic Growth," mimeo, University at Buffalo, SUNY.

A Identification of Parameters for Immigrants' Wages

The baseline regression of equation (1) omits a number of additional factors that are often considered of interest in the broader immigration literature. In particular previous work has argued for a role for assimilation and the age at arrival of immigrants (Friedberg 1992). A more general model that allows for these factors will make several parameters of the wage equation unidentified, but the country-specific return to schooling remains identified. To see this, consider an extension of the baseline model along lines suggested in the immigration literature:

$$\log(W_{US}^{j,k}) = b^j + M_{US}^j S_{US}^{j,k} + \beta X_{US}^{j,k} + \xi Age^{j,k} + \gamma C_l^{j,k} + \delta Yrs^{j,k} + \phi ArrAge^{j,k} + \varepsilon_{US}^{j,k} \quad (11)$$

where $C_l^{j,k}$ is the cohort (year) of immigration for immigrant k from country j, $Yrs^{j,k}$ is the years that immigrant has spent in the United States, and $ArrAge^{j,k}$ is their age at arrival. While the baseline model allows for cohort fixed effects, log-linearity in cohort simplifies the exposition; $Age^{j,k}$ is separated out from $X^{j,k}$ for reasons that will become clear.

The standard problem with this specification is that there are linear dependencies among the right-hand side variables (Friedberg 1992, Borjas 1999). In particular, $ArrAge^{j,k} + Yrs^{j,k} = Age^{j,k}$, and $C^{j,k} + Yrs^{j,k} = 2000$ since all immigrants are observed in 2000. Substituting out for these dependencies yields

$$\log(W_{US}^{j,k}) = b^j + 2000(\delta - \phi) + M_{US}^j S_{US}^{j,k} + \beta X_{US}^{j,k} + (\xi + \phi) Age^{j,k} + (\gamma + \phi - \delta) C_l^{j,k} + \varepsilon_{US}^{j,k}. \quad (12)$$

Note that the interpretation of the coefficients on the country fixed effect, age, and cohort change from the baseline model. Each now captures multiple effects and is no longer well-identified; for example, the coefficient on age captures the true age effect ξ and the effect of age at arrival ϕ. However, the coefficient on country j schooling remains well-identified.

B Estimated Returns to Schooling of Immigrants

Table 4: Estimated Returns to Schooling of Immigrants

Country	Obs	Returns	S.E.
Tonga	111	-0.013	0.061
Albania	349	-0.010	0.033

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

Country	Obs	Returns	S.E.
Macedonia, FYR	147	-0.005	0.049
Kosovo	43	-0.004	0.071
Nepal	89	0.002	0.058
Lao PDR	1633	0.004	0.010
Somalia	178	0.004	0.031
Serbia	86	0.004	0.054
Sierra Leone	220	0.006	0.055
Guatemala	5146	0.007	0.007
Bosnia and Herzegovina	1163	0.007	0.021
Honduras	2829	0.008	0.010
Cambodia	1071	0.008	0.013
Cape Verde	292	0.008	0.031
Mexico	78575	0.008	0.002
El Salvador	8519	0.008	0.006
Sudan	118	0.010	0.052
Azores	195	0.010	0.044
Eritrea	152	0.013	0.046
Dominican Republic	5075	0.014	0.008
Ecuador	2461	0.014	0.011
Armenia	321	0.015	0.034
Samoa	90	0.018	0.055
Bolivia	432	0.018	0.034
Iraq	600	0.019	0.019
Korea, Rep.	653	0.019	0.026
Yugoslavia	559	0.019	0.024
Portugal	1666	0.020	0.013
Vietnam	8922	0.020	0.005
Cuba	6091	0.022	0.008
Liberia	351	0.023	0.041
Uganda	108	0.024	0.068
Nicaragua	1905	0.024	0.012
Belize	253	0.025	0.041
Costa Rica	520	0.025	0.024
Colombia	4116	0.026	0.009
Peru	2679	0.027	0.013
Thailand	877	0.027	0.017
Haiti	4329	0.028	0.009
Antigua and Barbuda	138	0.029	0.071

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

Country	Obs	Returns	S.E.
Barbados	470	0.030	0.036
Ethiopia	581	0.030	0.030
Jordan	191	0.030	0.047
Poland	3929	0.031	0.011
Yemen, Rep.	102	0.031	0.041
Syrian Arab Republic	308	0.032	0.029
Uzbekistan	162	0.032	0.065
Bangladesh	632	0.033	0.021
Saudi Arabia	64	0.033	0.091
Grenada	226	0.034	0.047
Senegal	90	0.036	0.052
Dominica	142	0.036	0.060
Puerto Rico	5530	0.039	0.007
Croatia	277	0.040	0.037
Italy	1720	0.041	0.012
Greece	728	0.041	0.021
Bahamas, The	128	0.042	0.069
Nigeria	1080	0.042	0.022
Ghana	748	0.043	0.027
Paraguay	66	0.043	0.080
Myanmar	352	0.045	0.026
Czech Republic	114	0.046	0.079
Czechoslovakia	160	0.047	0.057
Spain	516	0.048	0.023
Pakistan	1390	0.048	0.015
Brazil	1716	0.048	0.014
Turkey	459	0.049	0.026
Bulgaria	313	0.049	0.041
Austria	159	0.049	0.050
Romania	1158	0.049	0.019
Trinidad and Tobago	1617	0.050	0.019
Afghanistan	226	0.050	0.039
Moldova	175	0.050	0.058
Venezuela, RB	633	0.051	0.023
Algeria	89	0.051	0.058
Cyprus	43	0.054	0.081
Latvia	97	0.054	0.085
Morocco	267	0.054	0.039

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

Country	Obs	Returns	S.E.
Philippines	13581	0.055	0.006
Fiji	321	0.055	0.036
Jamaica	5192	0.056	0.011
Guyana	2074	0.056	0.014
Chile	611	0.056	0.025
Ukraine	2065	0.056	0.016
Finland	131	0.056	0.067
Indonesia	402	0.057	0.036
Egypt, Arab Rep.	781	0.058	0.027
Cameroon	77	0.059	0.089
Kenya	264	0.059	0.048
Azerbaijan	134	0.060	0.059
St. Lucia	117	0.060	0.079
Georgia	71	0.060	0.080
China	8726	0.060	0.005
Panama	632	0.061	0.030
Belarus	327	0.062	0.046
Lebanon	481	0.062	0.026
Uruguay	213	0.062	0.048
Argentina	884	0.065	0.021
Sri Lanka	262	0.065	0.042
Iran, Islamic Rep.	1468	0.066	0.019
Taiwan	1670	0.067	0.018
St. Vincent and the Grenadines	168	0.067	0.047
India	6669	0.068	0.008
Denmark	159	0.070	0.057
St. Kitts and Nevis	100	0.073	0.103
Lithuania	115	0.074	0.079
Ireland	772	0.074	0.030
Israel	585	0.076	0.027
France	719	0.077	0.024
Singapore	116	0.078	0.064
Hong Kong, China	1198	0.080	0.017
Malaysia	325	0.081	0.029
Australia	477	0.081	0.040
Germany	2773	0.083	0.014
Bermuda	62	0.085	0.090
Kuwait	43	0.085	0.096

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

Country	Obs	Returns	S.E.
Canada	4183	0.088	0.012
Zimbabwe	95	0.089	0.089
Slovak Republic	105	0.091	0.091
Hungary	316	0.091	0.039
New Zealand	203	0.092	0.059
United States	4.30E+006	0.093	0.000
Netherlands	364	0.096	0.039
Belgium	134	0.098	0.054
Switzerland	210	0.098	0.057
United Kingdom	4485	0.099	0.013
South Africa	525	0.099	0.036
Norway	127	0.104	0.071
Japan	2345	0.106	0.017
Sweden	237	0.115	0.054
Tanzania	76	0.127	0.095

Note: Country is the country name as it is recorded in the census files. Obs is the number of observations in the 2000 5% PUMS meeting the sample restrictions. Returns are the log-wage returns to schooling. The returns are measured in percentage points. S.E. is the standard error of the returns.

C Robustness Details

C.1 Basic Robustness

The baseline estimates of the returns to schooling of immigrants suggest large differences in rates of return across countries and in particular between immigrants from developed and developing countries. This section shows that the quantitative results are robust to many of the details of the measurement process. I re-estimate the returns to schooling of immigrants using a number of different samples, using different sets of control variables, and using subsets of the data. From each exercise I collect an alternative estimate $\tilde{M}^j_{US}$ of the returns to schooling of immigrants from the U.S. To show that this return is comparable to the baseline, I then regress the baseline estimate M^j_{US} on the alternative estimate $\tilde{M}^j_{US}$ using as a weight the minimum of the number of observations in the baseline and the alternative samples. I report the coefficient, standard error, and R^2 of the regression. A close match corresponds to a coefficient close to 1, indicating similar variability in returns, and a higher R^2, indicating a similar ranking of countries' education quality. Results are reported in table 5.

I begin by considering a number of alternative sample selection rules. I use only men (in case women bias the results) and exclude Americans (who currently affect the estimated coefficients on certain common effects such as region dummies). The first two rows of table 5 show that the estimated returns to schooling are nearly identical for these alternatives. I try including the self-employed, although at the margin only 4% of the immigrant sample is self-employed. I also experiment with excluding immigrants who migrated less than three or nine years after their expected date of graduation, rather than the six-year window used in the paper. Again, the results are robust.

I try several different controls. First, I re-create the results of Bratsberg and Terrell (2002) by using a common intercept rather than country-specific fixed effects. The reported coefficient of 1.66 means that the baseline results vary much more than this alternative. However, recall that the country fixed effect is used to control for some of immigrant selection. Unless this is known to be unimportant, it seems inappropriate to exclude country-specific intercepts. I also allow for all countries to share a trend break in the return to schooling at high school graduation, allow for country-specific age effects, and for country-specific age and age-squared effects. The results are similar.

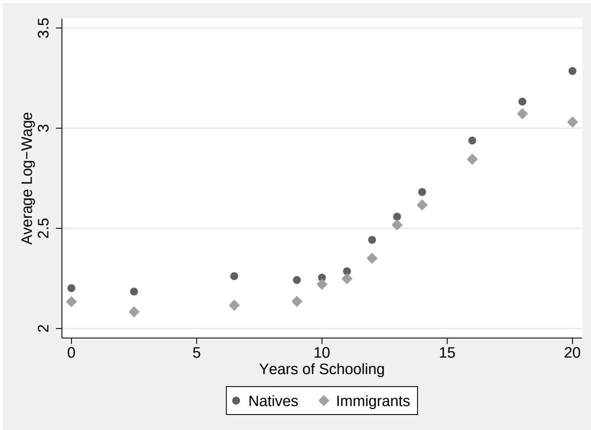
I also split the sample into subsamples. A potential concern is that immigrants need time to assimilate, and so using immigrants from relatively recent cohorts might bias the results. I split the sample into those immigrants who immigrated before or during 1985, and those who immigrated after. The results from each subsample are similar to the baseline. A second potential concern is that English skills and education may interact in determining wages. I split the sample into immigrants who speak only English or speak it very well versus the other categories. Again, the results are similar for the subsamples.

Finally, I estimate the returns to schooling accounting for the nonlinearity in wages in the United States. Figure 9 shows the profile of average wages by schooling attainment for natives and for all immigrants pooled together. Figure 9a plots the simple average wage, while figure 9b plots adjusted wages that first net out the effect of the control variables such as age, sex, and year of immigration (for immigrants). The figures both show a nonlinearity. The return to schooling is nearly zero for the first ten years of schooling and high for years exceeding the tenth. Figure 10 shows the distribution of the level of log-wages for all natives and immigrants with ten or fewer years of schooling. The wages are low; the federal

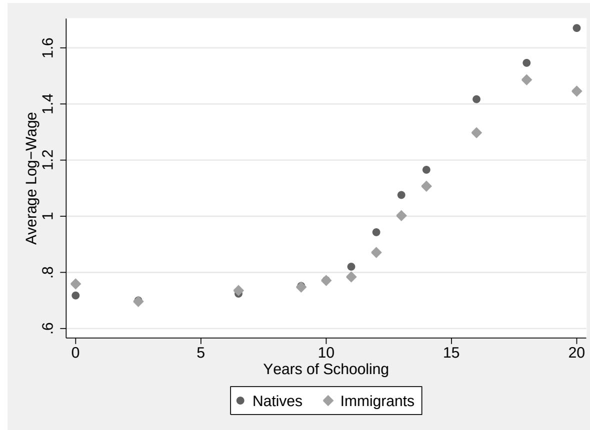
Table 5: Robustness Results

Alternative Estimate	Coefficient	S.E.	R^2
Alternative sample selection			
Only men	0.968	0.022	0.94
No Americans	1.002	0.010	0.99
Include self-employed	1.015	0.007	0.99
3-year buffer	1.006	0.015	0.97
9-year buffer	0.975	0.014	0.97
Alternative controls			
No fixed effects	1.655	0.096	0.70
Common trend break	1.018	0.002	1.00
Country-specific age effect	1.010	0.007	0.99
Country-specific age & age-squared	1.034	0.009	0.99
Subsamples of immigrants			
Immigrate before 1985	0.954	0.043	0.80
Immigrate during or after 1985	0.977	0.019	0.95
Speaks English well	1.022	0.041	0.83
Does not speak English well	1.052	0.049	0.80
Nonlinear returns			
Returns past high school	0.682	0.056	0.54
Returns past 10th year	0.761	0.050	0.64
Returns up to high school	0.486	0.174	0.06
Returns up to 10th year	0.128	0.116	0.01

Note: Dependent variable is the baseline estimate of the return to schooling of immigrants, and the independent variable is an alternative estimate of the return to schooling of immigrants, using alternative sample selection rules, using alternative control variables, using a subsample of immigrants, or allowing for nonlinear returns.



(a) Unadjusted



(b) Adjusted

Figure 9: Log-Wages and Schooling

minimum wage at the time was 5.15, but median wages of 8.00 and 9.57 for immigrants and natives are not much higher. One interpretation is that workers with ten or fewer years of schooling generally work in unskilled occupations and do not use their education, so that their wages are roughly unrelated to their schooling.

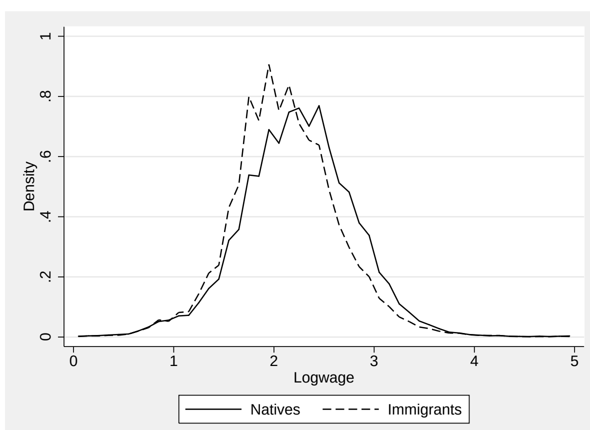


Figure 10: Distribution of Wages for Workers with Fewer than 11 Years of Schooling

Figure 9 suggests estimating log-wages in a way that captures the nonlinearity in returns. I estimate two different augmented Mincer wage equations that allow for breaks in the return to schooling. In the first, I allow for the return of the first ten years of schooling to differ from the returns to subsequent years; I also allow both returns to vary by country. In the second I do the same, but assuming that the returns to the first twelve years of schooling differ from the returns to subsequent years. The results are estimates of $\mu^j_{US}(<= 10)$, $\mu^j_{US}(> 10)$, and so on. Table 5 gives the results from the comparison of these returns to the baseline returns. The returns to high levels of schooling (after the tenth or twelfth year) are similar to the baseline results, with somewhat lower coefficients (0.68 and 0.76) but fairly high R^2 (0.54 and 0.64). The returns to lower levels of schooling are less related; the returns to schooling before the tenth year are essentially unrelated. These results are related to the finding of Jones (2008) that wage gaps are concentrated among college graduates who enter the U.S. after age 30. However, I find that differences in returns to schooling begin around the tenth year.

C.2 Estimation for Alternative Censuses

The key ingredients for estimating equation (1) are a large sample with many immigrants from many countries; information on wages and schooling, to calculate the rate of return; and information on country of birth, year of immigration, and age, to impute where an immigrant was educated. Both earlier U.S. censuses and Canadian censuses have the required characteristics. I focus in the 1990 U.S. census and the 2001 Canadian census as the most recent.

Canadian censuses include nearly the same information as U.S. censuses, making estimation very comparable. I use the same sample restrictions as in the United States: expected to complete schooling at least six years prior to immigration, 18-65 years old, employed for wages, and work at least 30 hours a week for at least 30 weeks. Wage is also constructed as average hourly wage and I use nearly identical controls: age and its square, gender, self-assessed English language proficiency, dummies for province of residence (instead of state), and a full set of year of immigration dummies. The Canadian census lacks the metropolitan area dummy and the disability dummy used in the U.S. census. The primary difference is that the sample is much smaller: 175,000 Canadians plus slightly fewer than 10,000 immigrants from 15 different source countries.

The 1990 U.S. census is also comparable. The sample restrictions and control variables are the same, except that it also lacks the dummy for living in a metropolitan area. The sample size is also smaller than the baseline: 3.9 million Americans plus 122,000 immigrants from 115 different source countries.

C.3 Identifying Refugees

Each issue of the *Statistical Yearbook of the Immigration and Naturalization Service* between 1980 and 2000 gives data on the number of immigrants by country of birth and class of entry for the year. Class of entry includes refugees/asylees as well as a number of different categories of economic migrants, including primarily those who enter for family reunification, those who are sponsored by employers, and those who enter under rules designed to promote diversity in the country of origin of immigrants. I aggregate all these other categories and study only the differences between refugees/asylees and economic migrants.

I measure the fraction of immigrants from each country and each year that are refugees/asylees. For countries where this fraction exceeds 50%, I categorize them as refugee/asylee countries. For countries where it is less than 10%, I categorize them as economic migrant countries. I exclude the countries with intermediate values. I also exclude Cuban refugees. Cuba is the only country that meets the test above and is from the Western Hemisphere. Given their close geographic proximity and the ongoing nature of the refugee flows, I am concerned that Cuban refugees may in fact be making an economic decision rather than fleeing their country.

There are two difficulties with the data available. First, it does not cover every country of birth in every year. From 1986-1997, countries with small flows of immigrants were not presented separately. I always exclude country-years with missing data from the refugee country designation. In part this is a conservative choice, but it is also the case that most refugee/asylee flows of interest are large enough that they should exceed the threshold for a country to be included in the data. I do include some countries with missing data in the economic migrant group. These countries satisfy two properties: for years where data are available, the flows are mostly economic migrants; and the country is not known to be a significant source of refugees or asylees. Countries with missing data that do not satisfy these criteria are dropped.

The second difficulty with the data is that the census asks immigrants what calendar year they enter the country, while the Yearbook records how many refugees/asylees were adjusted to legal permanent resident status in the fiscal year. Adjustment lags entry by at least a year, and is not required for refugees/asylees to remain in the United States. To help minimize the noise stemming from the imperfect match between data sources, I look for extended periods of large refugee flows, defined as 50% or more refugees for five or more years. The idea is to focus on large and continual flows so that timing issues are minimized to the extent possible. Countries that have brief periods of refugee/asylee flows are excluded from the exercise entirely. I also allow for a one-year lag between Yearbook and census data to help account for the delay in adjustment of status. For example the Yearbook records that many Hungarian refugees adjusted status between 1984 and 1991; I classify Hungarians who report entering the U.S. between 1983 and 1990 in the census as refugees/asylees. Table 6 gives the country-years used as high refugee/asylee periods, as well as the countries with mostly economic migrants for the whole period. The names of countries that that are included in the latter category despite some missing data are italicized.

C.4 Identifying Licensed Occupations

Licensure data comes from CareerOneStop (2010), sponsored by the U.S. Department of Labor. Although some occupations are federally licensed, most licensure is at the state level. The database includes a list of 9,308 data points, each consisting of a license-occupation pair. Licenses may cover a portion of an occupation or multiple occupations. The data are reported by states, but they are not comprehensive. Not all states participate, and participating states may not report all licenses. I treat the data as proxies, and consider several different thresholds to separate heavily licensed from less licensed occupations.

The baseline definition of heavily licensed occupations includes all federally licensed occupations, plus those occupations in the top decile in terms of number of licenses issued, which requires being covered by at least 59 licenses across all states. Table 7 gives the census names of the occupations that are classified as licensed. For comparison I also consider two other definitions. The first alternative definition includes all federally licensed occupations plus the top 10% of occupations in terms of number of states covered by at least one license. To be included in this group an occupation has to be licensed in at least 34 states. The relationship between returns to schooling for immigrants in licensed and unlicensed occupations by this definition is given in figure 11a. The second definition also includes all federally licensed occupations plus the top 25% of occupations in terms of the total number of licenses issued across all states, which requires being covered by at least 18 licenses across all states. The relationship between returns to schooling for immigrants in licensed and unlicensed occupations by this definition is given in figure 11b. There is a strong relationship between the returns to schooling of immigrants in licensed and unlicensed occupations for both of these alternative definitions of licensure.

Table 6: Countries and Years Included in Refugee/Asylee and Economic Migrant Samples

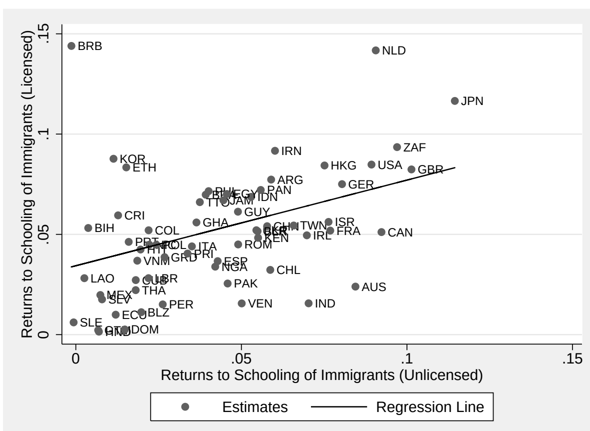
Refugee/Asylee Countries (18) (Years as Listed.)			
Country	Years	Country	Years
Czechoslovakia	1980-1990	Hungary	1983-1990
Romania	1980-1992	Bosnia-Herzegovina	1995-1999
Belarus	1991-1999	Moldova	1991-1999
Ukraine	1991-1999	Azerbaijan	1991-1996
Uzbekistan	1999-1999	Cambodia	1979-1991
Laos	1979-1991	Thailand	1981-1994
Vietnam	1979-1996	Afghanistan	1980-1993
Iraq	1992-1999	Sudan	1991-1996
Ethiopia	1980-1993	Somalia	1993-1999
Economic Migrant Countries (82) (All Years 1979-1999.)			
Canada	*Bermuda*	Cape Verde	Mexico
Belize	Costa Rica	El Salvador	Guatemala
Honduras	Panama	Dominican Republic	Jamaica
Antigua-Barbuda	Barbados	Dominica	Grenada
St. Kitts-Nevis	*St. Lucia*	*St. Vincent & Grenadines*	Trinidad & Tobago
Argentina	Bolivia	Brazil	Chile
Colombia	Ecuador	Guyana	*Paraguay*
Peru	*Uruguay*	Venezuela	*Denmark*
Finland	*Norway*	Sweden	Ireland
United Kingdom	*Belgium*	France	Netherlands
Switzerland	Greece	Italy	Portugal
Spain	Germany	Armenia[a]	China
Hong Kong	Taiwan	Japan	Korea
Philippines	*Singapore*	India	Bangladesh
Myanmar	Pakistan	Sri Lanka	*Cyprus*
Israel	Jordan	Kuwait	Lebanon
Yemen	*Algeria*	Egypt	Morocco
Ghana	Nigeria	*Senegal*	Sierra Leone
Tanzania	*Zimbabwe*	Eritrea[a]	*Cameroon*
South Africa	Australia	*New Zealand*	Fiji
Tonga	*Samoa*		

Note: Countries in italics were included despite missing data for some years.
[a] From date of independence.

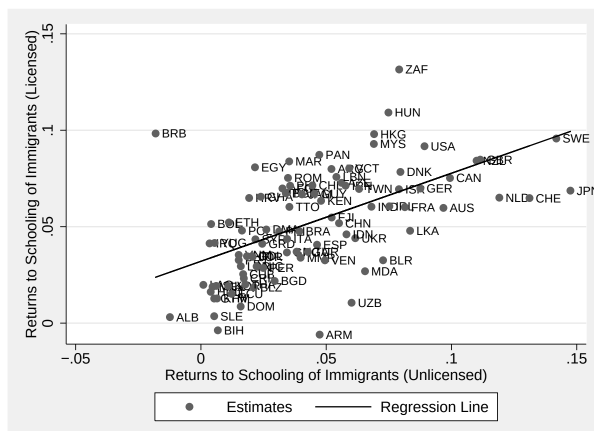
Table 7: Licensed Occupations Under Baseline Definition

Construction Managers	Education Administrator
Funeral Director	Agents and Business Managers
Accountants and Auditors	Appraisers and Assessors of Real Estate
Tax Examiners, Collectors, and Revenue Agents	Architects, Except Naval
Surveyors, Cartographers, and Photogrammetrists	Electrical and Electronics Engineers
Industrial Engineers, Including Health and Safety	Petroleum, Mining, and Geological Engineers
Psychologists	Counselors
Social Workers	Postsecondary Teachers
Preschool and Kindergarten Teachers	Elementary and Middle School Teachers
Secondary School Teachers	Special Education Teachers
Athletes, Coaches, Umpires, and Related Workers	Broadcast and Sound Engineering Technicians
Chiropractors	Dentists
Pharmacists	Physicians and Surgeons
Physician Assistants	Registered Nurses
Speech-Language Pathologists	Diagnostic Technologists and Technicians
Emergency Medical Technicians and Paramedics	Health Diagnosing and Treating Technicians
Other Healthcare Practitioners	Nursing, Psychiatric and Home Health Aides
Security Guards and Gaming Surveillance Officers	Grounds Maintenance Workers
Barbers	Hairdressers, Hairstylists, and Cosmetologists
Miscellaneous Personal Appearance Workers	Retail Salespersons
Insurance Sales Agents	Securities and Financial Services Sales Agents
Real Estate Brokers and Sales Agents	Electricians
Pipelayers, Plumbers, Pipefitters, and Steamfitters	Construction and Building Inspectors
Hazardous Materials	Radio and Telecommunications Installers and Repairers
Avionics Technicians	Electrical and Electronics Repairers
Aircraft Mechanics and Service Technicians	Power Plant Operators, Distributors, and Dispatchers
Water Treatment Plant and System Operators	Aircraft Pilots and Flight Engineers
Air Traffic Controllers and Airfield Operations	Sailors and Marine Oilers
Ship and Boat Captains and Operators	Ship Engineers
Transportation Inspectors	

Note: Names as given in the census documentation; some were abbreviated.



(a) Top Decile, Number of States Licensed



(b) Top Quartile, Number of Licenses Issued

Figure 11: Returns to Schooling of Immigrants in Licensed and Unlicensed Occupations, Alternative Definitions of Licensure