# Education Quality and Development Accounting*

Todd Schoellman†

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**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 measure the education quality of their birth country. Immigrants from developed countries earn higher returns than do immigrants from developing countries. 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 output per worker differences, raising the total contribution of education from 10% to 20% of output per worker differences.

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†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 inefficient usage of inputs?

The current literature focuses on years of schooling as a measure of human capital. The literature typically finds that years of schooling account for less than 10% of the cross-country differences in output per worker. The contribution of this paper to the development accounting literature is to measure 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 PPP-adjusted 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 Mexican or Nepalese education raises the wages of Mexican or Nepalese immigrants by less than 2 percent, while an additional year of Swedish or Japanese education raises the wages of Swedish or Japanese immigrants by more than 10 percent.

The second step of the paper is to provide evidence that these differences in returns to schooling are due to differences in education quality, and not alternative interpretations such as selection or skill transferability.[3] I show that the estimated returns to schooling are quantitatively similar for immigrants who enter the United States as refugees and asylees

[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 a development 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).

and are presumably less selected. I also show that the returns to schooling are correlated with another measure of education quality, the scores on internationally standardized achievement tests. In my empirical implementation, I exploit this correlation to use test scores as an instrument for the returns to schooling, adding a further correction for the selection of immigrants.[4]

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 to 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 possible extensions of the accounting framework.

The most closely related paper in the literature is by Hendricks (2002), who also uses the wages of U.S. immigrants to estimate cross-country differences in human capital stocks.

[4] Some previous research has used test scores as a measure of education quality (Caselli 2005, Hanushek and Kimko 2000, Hanushek and Woessmann 2009). I do not use test scores as a direct measure of education quality because their scale is difficult to use in a development accounting exercise. Test scores show that the average student in one country scores one standard deviation higher than the average student in another country, but it is difficult to translate this difference into the relative value of a year of each country's schooling. Returns to schooling show that the wage gain of a year of one country's schooling is twice the wage gain of another country's schooling; under certain conditions explored in the model, this statement implies that each year of the former country's schooling generates twice as much human capital.

[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.

His approach uses the average wage difference between natives and immigrants, which he finds to be small. If immigrants are unselected, this finding implies that human capital differs little between natives and non-migrants. However, recent papers in the literature have noted that Hendricks' results are also consistent with modest positive selection of immigrants and modestly larger differences in human capital between natives and non-migrants (Manuelli and Seshadri 2007). The approach in this paper uses the average wage difference between immigrants from the same country with different levels of education as the main wage statistic. This statistic is a narrower measure of education quality, and is less likely to be affected by the selection of immigrants.

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. Section 3 gives the baseline development accounting results. Section 4 considers extensions to the model and shows that the accounting results are robust. Section 5 concludes.

[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.

## 2 Returns to Schooling of Immigrants

The first step of the paper is to estimate the returns to schooling of 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 potential experience; and an error term $\varepsilon$. A standard Mincerian wage equation might use only Americans, and would have a single intercept $\gamma$ and a common return to schooling $\mu$. 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 $\mu_{US}^{j}$ and ignore the level differences $\gamma_{US}^{j}$.[7] In a cross-section of Mexican or Vietnamese immigrants in the United States, an additional year of schooling is associated with small wage gains; in a cross-section of 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.

I implement this equation using the 5% sample of the 2000 census Public Use Micro

[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.

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), who reported working at least 30 weeks in the previous year and at least 30 hours per week, and who have between 0 and 40 years of potential experience. 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 4.1 million Americans and 210,000 immigrants.

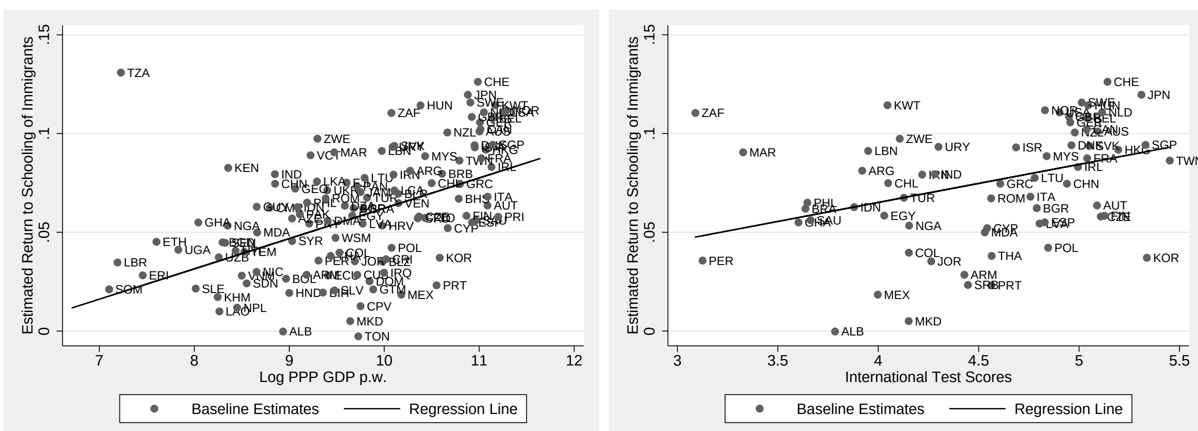
I calculate the wage as the previous year's average hourly wage, computed using annual wage income, weeks worked, and usual hours per week. The census includes a rich set of control variables. I include several standard controls such as a quartic in potential experience and a full set of dummy variables for census region of residence, 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; it also collected information on year of immigration. I enter each as a full set of dummy variables. These last two terms help

[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.

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, $\mu_{US}^{j}$, 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 11.1% per year. Immigrants from several countries earn higher rates of return, including two with statistically significant returns over 12% per year, Japan and Switzerland. At the other end of the spectrum some countries have remarkably low returns, including one 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 1.8% and 2.8% 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 73 immigrants. For this and most subsequent figures, I also include the fitted line from a weighted regression using number of immigrants in the sample as the weights. 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 were constructed by Hanushek and Woessmann (2009) by aggregating the results from a number of tests administered between 1964 and 2003. 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 an education quality adjustment into development accounting exercises. First, I discuss the robustness of the findings in figure 1 and provide evidence against plausible alternative interpretations.

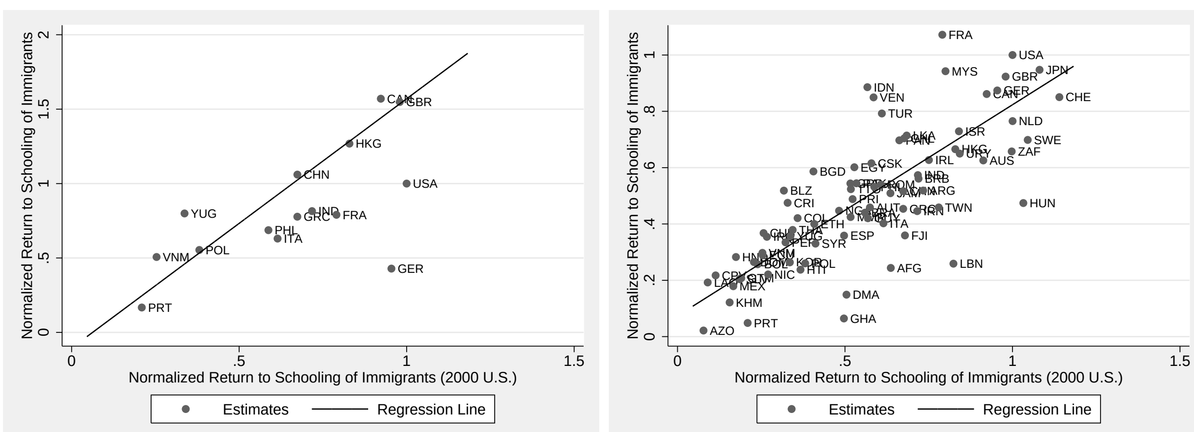
## 2.2 Robustness

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 three or nine 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 potential experience and country of birth. I also experiment with allowing returns to schooling to vary by English-language ability or years since immigration and find little difference in estimated returns to schooling. A supplementary appendix

[9] In practice countries vary in their exclusion and non-response rates so that samples are not perfectly random. Hanushek and Woessmann (2011) document that variation in the sample can account for some of the differences in average test scores by country. They find that even after controlling for this effect, test scores still predict growth rates.

available online provides details of how robustness checks were performed as well as the results.

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.[10] 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. Figure 2 plots the estimated returns to schooling of immigrants from the 2001 Canadian census and the 1990 U.S. census against

[10]The 1990 U.S. census is also available from Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010); the Canadian census is available through Minnesota Population Center (2010).

the baseline estimates from the 2000 U.S. census. In all three samples I have normalized the estimated returns by the returns to schooling for Americans (natives in the U.S. samples, immigrants in the Canadian sample) 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 8-12%, not very different from the return to schooling for Americans of 11.1%. Hence, I focus on the question of whether the low observed returns to schooling for immigrants from developing countries, such as the 1.8% 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.

To motivate the selection discussion it is helpful to repeat the augmented Mincer wage equation:

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

If immigrants are selected on observable characteristics, such as potential experience or schooling, this is directly controlled for in the wage equation. The more important concern is that they may be selected on unobservable characteristics. Some of the effects of selection are captured by country of origin fixed effects $\gamma^j$, 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 solid line is the observed wages of Mexicans who immigrated: the returns to schooling are a modest 1.8% per year. If Mexicans immigrants with different school attainments are all equally selected, then the dashed line is the implied wages that would be observed for an random sample of Mexicans. This selection affects the intercept $\gamma^{Mexico}$, which explains why I do not use the intercepts. However, it does not affect the measured returns to schooling.

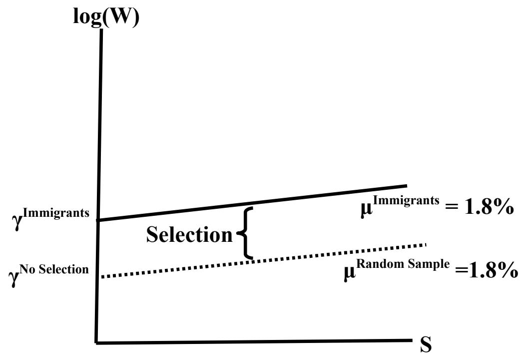
By discarding the fixed effects, this paper is robust to some of the immigrant selection concerns that apply to Hendricks (2002). Hendricks uses a non-parametric estimate of immigrant wages that is close in spirit to regressing

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

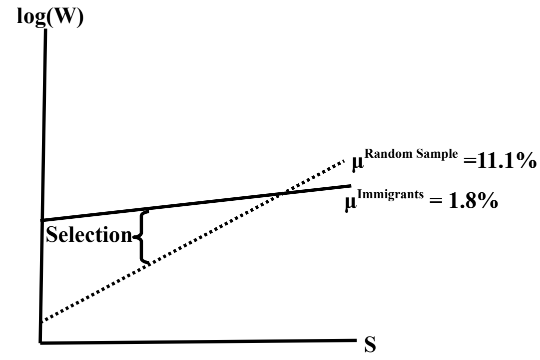
although he does not impose linearity restrictions. This regression differs from mine only in the fact that it restricts the return to schooling $\mu$ to be the same for all countries, whereas I allow for differences in $\mu_{US}^{j}$.

Hendricks measures unobserved human capital (human capital not related to years of schooling or potential experience) using the level difference in wages, similar to $\gamma^j - \gamma^{US}$. The differences in wages between natives and immigrants with similar observed characteristics are small, implying that natives and immigrants differ little in their unobserved human capital. Hendricks 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 results might suggest (Manuelli and Seshadri 2007). This insight is motivated in part by the fact that Hendricks' estimates suggest immigrants from 28 of the 66 countries in his sample have more unmeasured human capital than do Americans, including immigrants from Turkey, Syria, and Hungary.

I use the returns to schooling of immigrants rather than average wage differences to help reduce selection problems and narrow the range of plausible estimates for cross-country differences in human capital per worker. However, returns to schooling can also be affected by selection of two forms. First, if there is within-country heterogeneity in the return to schooling, then immigrants could be selected based on this return. In section 4.2 I incorporate heterogeneity in the return to schooling into my model and show that the model's




(a) Selection




(b) Differential Selection

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

predictions are at odds with the hypothesis that low returns to schooling in developing countries are due to selection on the return to schooling. Since this discussion requires the model, I delay it for now. A second possibility is that immigrants with different education levels are *differentially* selected on $\gamma^j_{US}$, indicating that in fact the intercept is $\gamma^j_{US}(S)$.[11] Specifically, suppose that the returns to schooling for a randomly selected group of Mexican workers would have been 11.1%, the same as Americans. The observed return to schooling for immigrants is 1.8%. 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 to schooling for immigrants from developed countries are about the same as the returns to schooling for 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.

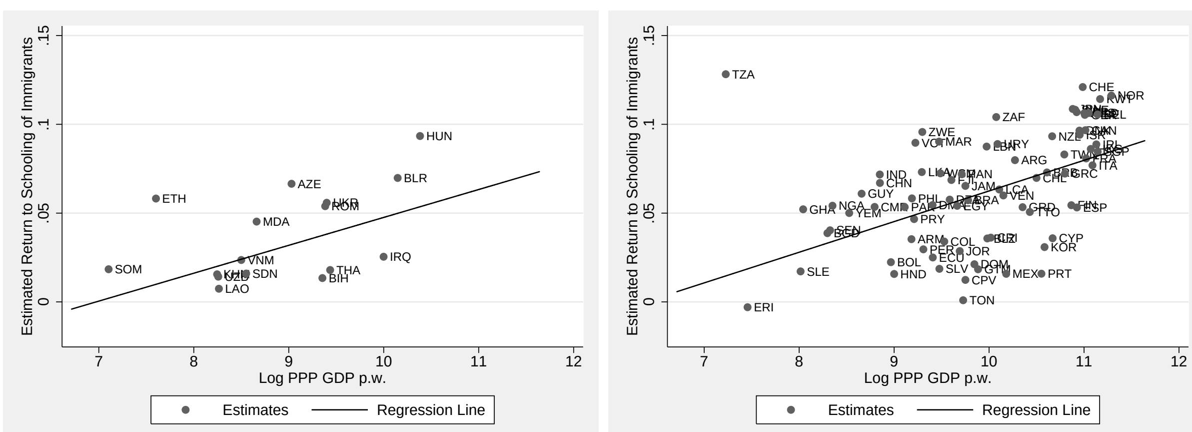
It may be plausible that some form of policy selection or self-selection of immigrants could generate this pattern of differential selection. To investigate whether this is the case, I turn to evidence drawn from a relatively less selected group of immigrants: refugees and asylees. Refugees and asylees 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 includes a commitment to resettle at least 50 percent of all refugees referred for consideration by the United Nations High Commissioner for Refugees, on explicitly humanitarian grounds.[12] Hence, refugees and asylees are less selected by

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

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

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, who 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 Yearbook of the Immigration and Naturalization Service* from 1980-2000 identifies the fraction of each country's immigrants for that 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.




(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. A quantitatively similar relationship prevails for both groups, although the slope of the trend line 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 1.6% 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 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 immigrants find it difficult to apply their 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 fifteen years and speak English very well. I have estimated 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.

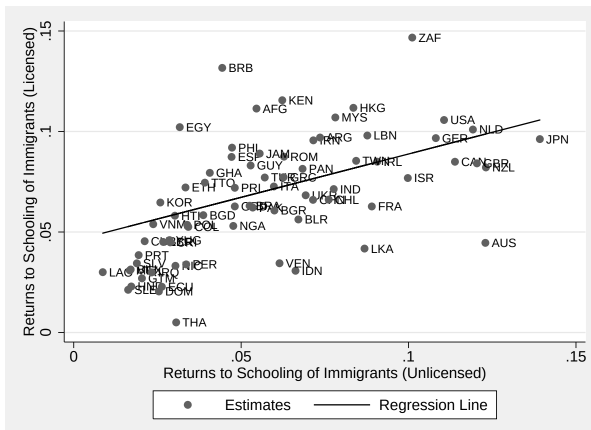



Figure 5: Returns to Schooling of Immigrants in Licensed and Unlicensed Occupations

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 quantitatively similar returns for the two groups. 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 developed and developing countries. The baseline interpretation of these returns is that they are measures of the education quality of different countries. This section incorporates 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 quantity (years) and quality of schooling. Section 2 introduced $\mu_{US}^j$ 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 capital 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 superscript 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 for 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).[13]

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 $\eta$. 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 efficiency unit. 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 $\eta$; I estimate the values of $\eta$ 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. I use $w_j$ to denote the wage rate per unit of human capital and $W_j = w_j h_j$ to denote the hourly wage of an individual with $h_j$ units of human capital.

## 3.3 Worker's Problem

Each economy has 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

[13] 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.

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 further education. The date of death is staggered so that $1/T$ workers die in each year.[14]

Workers are endowed with one unit of time each period to allocate between school and work. They have no direct preferences over school or work, so their school choice is made to maximize lifetime income net of tuition costs. 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 their human capital $h(S,Q_j)$. Workers discount future tuition payments and earnings using a constant interest rate $r_j$. I further assume that the wage rate grows 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, $\lambda_j(S,t) = \lambda_j w_j(t) h(\tau + t, Q_j)$. This assumption captures the fact that tuition payments tend to rise with schooling attainment, and gives convenient closed form solutions.

Workers take wage rates, 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 $\tau$ is then given by:

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

## 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

[14] I ignore differences in mortality across countries because incorporating life expectancy as differences in $T_j$ was found to be unimportant in earlier versions of the paper.

the development accounting literature; Psacharopoulos and Patrinos (2004) and Banerjee and Duflo (2005) provide data on estimates of $M_j$ for many countries around the world. It differs from my previously estimated $\mu^j_{US}$, 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

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

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

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

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.

The relationship between hourly earnings and schooling for natives in the United States is then linear with slope $M_{US}$. The returns to schooling for immigrants will differ. I assume that immigrants are paid the same wages as Americans who share their human capital. Then using the human capital production function twice yields

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

where $c$ is a constant. Thus, the model confirms the intuition that the returns to schooling of immigrants from country $j$ are proportional to their relative education quality $Q_j/Q_{US}$.[15]

[15] The preceding discussion implicitly relies on some force to generate heterogenous school choices among workers. For now I am agnostic about why that might happen; in section 4 I present two different models

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 $\bar{M}$.[16] This paper's contribution is to account for quality-adjusted years 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 a difference in years of schooling also suggests a difference in 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 $\eta$. In essence, $\eta$ addresses the question: when I see an additional year of schooling, how much extra education quality should I also infer? If $\eta$ 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 $\eta$ 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 $\eta$. 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 $\eta$. I can then perform development accounting exercises. Note that estimating $\eta$ from the elasticity captures the intuition of the previous paragraph, that $\eta$ allows me to infer the size of education quality differences from observed years of schooling differences.

that have explicit heterogeneity.

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

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

I begin by taking equation (5) in logs; I substitute $Q_j = \mu^j_{US} Q_{US}/M_{US}$ and $\bar{M} = M_j$. This yields the equation used to estimate $\eta$:

$$\log(S_j) = \frac{\eta}{1-\eta}\log\left(\mu^j_{US}\right) + \frac{\eta}{1-\eta}\log\left(\frac{Q_{US}}{M_{US}}\right) - \frac{1}{1-\eta}\log\left(\bar{M}\right). \tag{9}$$

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. The last two terms condense to a constant in this formulation.

Implementing equation (9) as a regression recovers the elasticity that is key to identifying $\eta$. However, the returns to schooling of foreign-educated immigrants are a right-hand side variable in this regression. At a minimum these returns are measured with some error due to small sample sizes. Further, there may be some residual concern that skill transferability or selection of immigrants biases some of the estimated returns to schooling.

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.[17] 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 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.

[17] 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 0.21. 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 0.50.

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 | 0.56 | 1.36 | 0.72 | 1.28 | 1.26 | 1.15 | 0.95 |
| | (0.096) | (0.556) | (0.300) | (0.647) | (0.316) | (0.689) | (1.118) |
| Implied $\eta$ | 0.36 | 0.58 | 0.42 | 0.56 | 0.56 | 0.53 | 0.49 |
| $N$ | 88 | 51 | 50 | 37 | 71 | 40 | 12 |

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

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 $\eta$, 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 instrument 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) 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 0.72 and a high estimate of 1.36. In terms of values for $\eta$, I take $\eta = 0.5$ as my preferred estimate, and explore sensitivity of $\eta$ in the range 0.42–0.58.

Table 2: Baseline Accounting Results and Comparison to Literature

| | This Paper | | | Literature | |
|---|---|---|---|---|---|
| | $\eta = 0.42$ | $\eta = 0.5$ | $\eta = 0.58$ | Hall and Jones (1999) | Hendricks (2002) |
| $h_{90}/h_{10}$ | 6.3 | 4.7 | 3.8 | 2.0 | 2.1 |
| $\frac{h_{90}/h_{10}}{y_{90}/y_{10}}$ | 0.28 | 0.21 | 0.17 | 0.09 | 0.22 |
| $\frac{\text{var}[\log(h)]}{\text{var}[\log(y)]}$ | 0.36 | 0.26 | 0.19 | 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 quality markup factor of $1/\eta$. My preferred estimate of $\eta$ is 0.5, which would imply that I construct log human capital stocks twice those of the literature. The plausible range of $\eta$ seems to lie between 0.42 and 0.58, which implies that my results would be somewhere between 72% and 138% 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). 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 $\eta$ 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 3.8–6.3.

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 17–28% 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 19–36% of output per 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 6: Comparison of Accounting Results, Country-by-Country

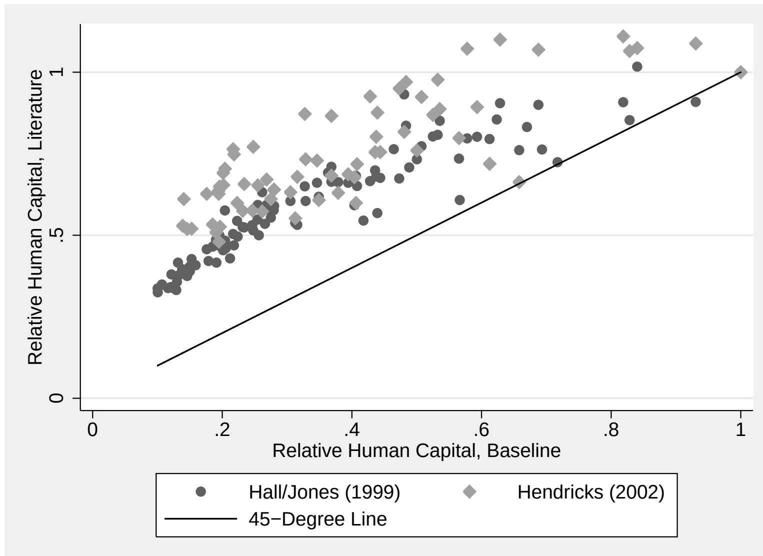



Figure 6 gives a country-by-country comparison of my results for human capital and the literature's. It plots estimated human capital from Hall and Jones (1999) and Hendricks (2002) against my benchmark estimated human capital with $\eta = 0.5$. Human capital is normalized by the level of the U.S. for 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.

My figures lie within the large bounds in the endogenous education quality literature. For example Erosa, Koreshkova, and Restuccia (2010) compute that human capital variation accounts for 13% of output per worker variation for two hypothetical economies differing by a factor of 20 in income. On the other hand, Manuelli and Seshadri (2007) compute that human capital variation accounts for 67% of output per worker variation between the top and bottom deciles, although their model includes a broader notion of human capital than I do here, with a large role for investments before schooling as well as on-the-job training. My results are in the middle, and are quantitatively closer to those of Erosa, Koreshkova, and Restuccia.

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 6 confirm this result by direct comparison with two well-known sets of results in the 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 alone. 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 immigrants and non-migrants.

## 4.1 Alternative Sources of Cross-Country Schooling Differences

In the baseline model $\eta$ 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:

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

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 well-functioning capital markets in developing countries may make it impractical for families or students to borrow to finance 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 of the relationship between years of schooling and education quality. If I re-write equation (9) assuming that $M_j = \hat{M}_j(S)$ (instead of $M_j = \bar{M}$, as was assumed before) I find:

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

where $c$ again gathers together a number of terms that are constant. 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 are by assumption due to quality differences, and human capital accounts for 21-26% of output per worker differences.

The remaining two 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 $\hat{M}_j(S)$ 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 cross-country differences in years of schooling are attributable to education quality, and that $\eta$ is similar to the baseline case. Then cross-country differences in human capital account for 18-21% of cross-country differences in output per worker, slightly lower than in the baseline. The $\hat{M}_j^{BK}(S)$ estimated by Bils and Klenow is much steeper. Returns to schooling for non-migrants are much lower in educated countries. The third column shows that in this case the correct inference is that most cross-country 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

Table 3: Robustness to Alternative Sources of School Attainment Differences

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

*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).

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 evidence from cross-country differences in returns to schooling for non-migrants suggest a small role for costs and frictions in explaining cross-country schooling differences. Alternatively, exogenous differences in the skill bias of technology provide a potential competing explanation for cross-country schooling differences without implying counterfactually large differences in Mincer rates of return across countries. However, papers in the literature typically assume the opposite causality, that exogenously higher schooling leads to endogenous skill bias in innovation (Acemoglu 2002) or to the choice of more skill-biased technologies among the set of existing technologies (Caselli and Coleman 2006). This paper explains why such schooling differences may exist (as a result of education quality differences). Endogenous technology choice would provide an amplification mechanism that interacts with the schooling differences caused by education quality.

## 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:

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

$\varepsilon_j^k$ 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,

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

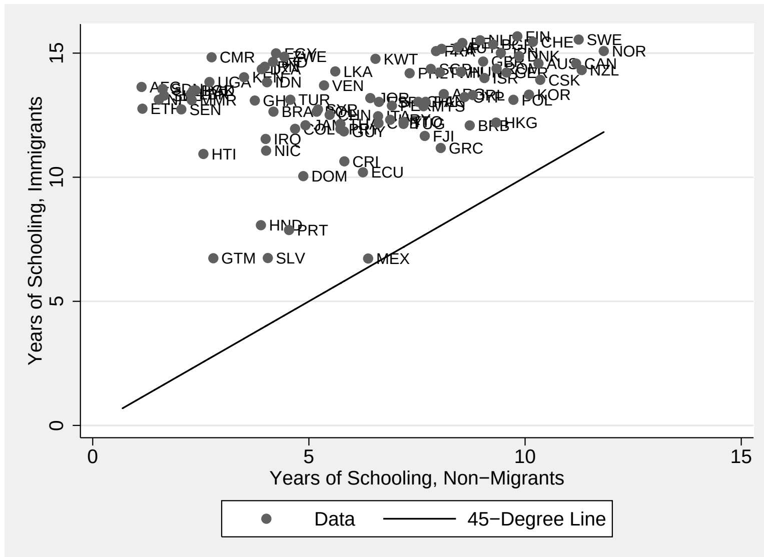
Non-cognitive ability affects the intercept of log-wages, and will be captured by the fixed effect $\gamma_{US}^j$. Cognitive ability affects the slope of log-wages with respect to schooling and is captured by the return to schooling $\mu_{US}^j$.

The discussion of selection in section 2.3 focused on the case where workers were selected or differentially selected on $\varepsilon_j^k$, 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 they 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 to non-migrants.

Figure 7 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 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.[18] 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

[18]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 7: Schooling of Immigrants and Non-Migrants




to schooling of immigrants generally overstate the education quality of their source country, since immigrants are a selected sample of those who gain most from a year of schooling. 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 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 large; 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 attributable to ability 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

The key fact of this paper is that immigrants from highly-educated, high output per worker countries earn higher returns to their schooling. On the other hand, Banerjee and Duflo (2005) document that there is only a weak relationship between returns to schooling for non-migrants and average schooling attainment or output per worker. It follows that the returns to schooling of immigrants and non-migrants are very different; in fact, the correlation between the two is negative (-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 or not they 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 they immigrate to the United States. It follows that the model predicts that the returns to schooling for migrants and non-migrants should be the same:

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

The standard accounting model counterfactually predicts that the returns to schooling will be the same for immigrants and non-migrants; given this, it is not clear why the returns to schooling of immigrants are the appropriate measure of education quality.

A simple extension to account for the negative correlation is to allow workers of different skill types to be imperfect substitutes. With imperfect substitutes, low education quality in developing countries is offset by the lack of skilled labor, and the high education quality in developed countries is offset by the abundance of skilled labor, so that the return to schooling in the two countries is roughly the same. However, a worker who emigrates from a developing country to the United States has low education quality and enters a labor market where human capital is abundant, yielding a low return to schooling. Intuitively, the reason to measure returns to schooling using immigrants is that the aggregate labor market conditions for workers are held constant.

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; this allows me to preserve the assumption that all workers who can read earn the same wage, regardless of how many years of schooling were needed to acquire literacy. 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 returns to schooling of non-migrants are given by $M_j = (r_j - g_j)(1+\lambda_j)$. However, the returns to schooling of immigrants are given by $\mu_{US}^j = M_{US} \frac{Q_j}{Q_{US}} \neq$

$M_j$. Hence, this simple extension can explain why returns to schooling differ for immigrants and non-migrants. Further, it explains why returns to schooling of immigrants are preferable for the purpose of measuring education quality.

# 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 are roughly as important as differences in years of schooling in accounting for differences in output per worker across countries. 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 $\eta$ 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.

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# 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:

$$\log(W_{US}^{j,k}) = b^j + \mu_{US}^j S_{US}^{j,k} + \beta X_{US}^{j,k} + \gamma C_{US}^{j,k} + \delta Yrs_{US}^{j,k} + \phi ArrAge_{US}^{j,k} + \varepsilon_{US}^{j,k} \qquad (11)$$

where $C_{US}^{j,k}$ is the cohort (year) of immigration for immigrant $k$ from country $j$, $Yrs_{US}^{j,k}$ is the years that immigrant has spent in the United States, and $ArrAge_{US}^{j,k}$ is their age at arrival. While the baseline model allows for cohort fixed effects, log-linearity in cohort simplifies the exposition.

The standard problem with this specification is that there are linear dependencies among the right-hand side variables (Borjas 1999). In particular, $C_{US}^{j,k} + Yrs_{US}^{j,k} = 2000$ since all immigrants are observed in 2000. Substitution yields

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

The true cohort and assimilation effects cannot be identified without pooling census years, but this fact does not affect the measured returns to schooling. Among immigrants, there is also a linear dependency between arrival age, cohort, and age or potential experience. However, as noted in Friedberg (1992), it is possible to estimate age at arrival effects by pooling immigrants with natives and assuming that the return to age or experience is the same for both. Results for such a regression (available upon request) are similar to the baseline.

# B Estimated Returns to Schooling of Immigrants

Table 4: Estimated Returns to Schooling of Immigrants

| Country | Returns | S.E. | Obs |
|---|---|---|---|
| Tonga | -0.003 | 0.068 | 100 |

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

| Country | Returns | S.E. | Obs |
|---|---|---|---|
| Albania | 0.000 | 0.038 | 324 |
| Macedonia, FYR | 0.005 | 0.058 | 121 |
| Azores | 0.009 | 0.061 | 89 |
| Lao PDR | 0.010 | 0.011 | 1344 |
| Nepal | 0.012 | 0.058 | 89 |
| Cape Verde | 0.013 | 0.040 | 222 |
| Cambodia | 0.017 | 0.015 | 898 |
| Kosovo | 0.018 | 0.075 | 41 |
| Mexico | 0.018 | 0.002 | 67026 |
| Honduras | 0.019 | 0.011 | 2604 |
| Bosnia and Herzegovina | 0.019 | 0.022 | 1130 |
| Antigua and Barbuda | 0.020 | 0.082 | 118 |
| El Salvador | 0.021 | 0.006 | 7557 |
| Guatemala | 0.021 | 0.008 | 4701 |
| Somalia | 0.021 | 0.033 | 170 |
| Sierra Leone | 0.022 | 0.055 | 217 |
| Portugal | 0.023 | 0.017 | 1017 |
| Serbia | 0.023 | 0.064 | 76 |
| Sudan | 0.024 | 0.053 | 115 |
| Dominican Republic | 0.025 | 0.009 | 4210 |
| Bolivia | 0.026 | 0.037 | 394 |
| Vietnam | 0.028 | 0.006 | 7720 |
| Ecuador | 0.028 | 0.012 | 2165 |
| Eritrea | 0.028 | 0.052 | 143 |
| Cuba | 0.028 | 0.010 | 4551 |
| Armenia | 0.028 | 0.038 | 308 |
| Iraq | 0.030 | 0.021 | 545 |
| Nicaragua | 0.030 | 0.014 | 1672 |
| Liberia | 0.035 | 0.044 | 333 |
| Belize | 0.035 | 0.048 | 211 |
| Jordan | 0.035 | 0.054 | 174 |
| Peru | 0.036 | 0.015 | 2393 |
| Costa Rica | 0.036 | 0.025 | 471 |
| Korea, Rep. | 0.037 | 0.034 | 583 |
| Yugoslavia | 0.037 | 0.029 | 448 |
| Uzbekistan | 0.037 | 0.070 | 157 |
| Thailand | 0.038 | 0.021 | 757 |
| Colombia | 0.040 | 0.010 | 3520 |

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

| Country | Returns | S.E. | Obs |
|---|---|---|---|
| Yemen, Rep. | 0.040 | 0.044 | 89 |
| Haiti | 0.041 | 0.011 | 3717 |
| Uganda | 0.041 | 0.079 | 102 |
| Poland | 0.042 | 0.013 | 3398 |
| Senegal | 0.045 | 0.057 | 87 |
| Bangladesh | 0.045 | 0.022 | 615 |
| Ethiopia | 0.045 | 0.031 | 564 |
| Syrian Arab Republic | 0.046 | 0.033 | 264 |
| Samoa | 0.047 | 0.066 | 81 |
| Moldova | 0.050 | 0.059 | 171 |
| Cyprus | 0.052 | 0.094 | 36 |
| Nigeria | 0.053 | 0.022 | 1062 |
| Croatia | 0.053 | 0.046 | 208 |
| Paraguay | 0.054 | 0.081 | 60 |
| Latvia | 0.054 | 0.087 | 93 |
| Ghana | 0.055 | 0.028 | 720 |
| Spain | 0.055 | 0.026 | 423 |
| Dominica | 0.056 | 0.065 | 129 |
| Saudi Arabia | 0.056 | 0.090 | 64 |
| Azerbaijan | 0.057 | 0.069 | 123 |
| Grenada | 0.057 | 0.058 | 191 |
| Myanmar | 0.057 | 0.031 | 305 |
| Trinidad and Tobago | 0.057 | 0.023 | 1353 |
| Puerto Rico | 0.058 | 0.009 | 4671 |
| Czech Republic | 0.058 | 0.083 | 103 |
| Finland | 0.058 | 0.090 | 119 |
| Egypt, Arab Rep. | 0.058 | 0.029 | 742 |
| Pakistan | 0.059 | 0.016 | 1312 |
| Brazil | 0.062 | 0.015 | 1597 |
| Bulgaria | 0.062 | 0.042 | 305 |
| Cameroon | 0.062 | 0.092 | 74 |
| Indonesia | 0.063 | 0.038 | 368 |
| Guyana | 0.063 | 0.017 | 1799 |
| Algeria | 0.063 | 0.064 | 85 |
| Austria | 0.064 | 0.060 | 132 |
| Czechoslovakia | 0.064 | 0.065 | 148 |
| Venezuela, RB | 0.065 | 0.025 | 608 |
| Philippines | 0.065 | 0.008 | 12066 |

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

| Country | Returns | S.E. | Obs |
|---|---|---|---|
| Bahamas, The | 0.067 | 0.077 | 114 |
| Romania | 0.067 | 0.022 | 1067 |
| Turkey | 0.068 | 0.029 | 415 |
| Italy | 0.068 | 0.018 | 998 |
| Belarus | 0.070 | 0.048 | 315 |
| Jamaica | 0.070 | 0.013 | 4348 |
| Afghanistan | 0.070 | 0.043 | 218 |
| St. Lucia | 0.071 | 0.100 | 104 |
| Ukraine | 0.071 | 0.019 | 1922 |
| Georgia | 0.072 | 0.088 | 67 |
| Panama | 0.073 | 0.034 | 561 |
| Greece | 0.075 | 0.030 | 460 |
| China | 0.075 | 0.005 | 7445 |
| Chile | 0.075 | 0.030 | 530 |
| Fiji | 0.075 | 0.048 | 280 |
| Sri Lanka | 0.076 | 0.045 | 249 |
| Lithuania | 0.078 | 0.083 | 109 |
| Iran, Islamic Rep. | 0.079 | 0.021 | 1344 |
| India | 0.079 | 0.008 | 6255 |
| Barbados | 0.080 | 0.046 | 388 |
| Argentina | 0.081 | 0.024 | 725 |
| Kenya | 0.083 | 0.049 | 254 |
| Ireland | 0.083 | 0.034 | 690 |
| Taiwan | 0.086 | 0.020 | 1559 |
| France | 0.088 | 0.026 | 664 |
| Malaysia | 0.089 | 0.032 | 306 |
| St. Vincent and the Grenadines | 0.089 | 0.059 | 138 |
| Morocco | 0.090 | 0.044 | 254 |
| Lebanon | 0.091 | 0.033 | 414 |
| St. Kitts and Nevis | 0.092 | 0.114 | 89 |
| Hong Kong, China | 0.092 | 0.019 | 1102 |
| Israel | 0.093 | 0.029 | 543 |
| Uruguay | 0.093 | 0.056 | 168 |
| Slovak Republic | 0.094 | 0.097 | 95 |
| Denmark | 0.094 | 0.064 | 147 |
| Singapore | 0.094 | 0.072 | 110 |
| Bermuda | 0.096 | 0.101 | 55 |
| Zimbabwe | 0.097 | 0.089 | 89 |

Continued on Next Page

Table 4: Estimated Returns to Schooling of Immigrants

| Country | Returns | S.E. | Obs |
|---|---|---|---|
| New Zealand | 0.101 | 0.061 | 195 |
| Australia | 0.101 | 0.041 | 460 |
| Canada | 0.102 | 0.014 | 3783 |
| Germany | 0.106 | 0.016 | 2452 |
| Belgium | 0.108 | 0.058 | 125 |
| United Kingdom | 0.108 | 0.014 | 4042 |
| South Africa | 0.110 | 0.037 | 495 |
| United States | 0.111 | 0.001 | 4.1e+06 |
| Netherlands | 0.111 | 0.044 | 329 |
| Norway | 0.112 | 0.073 | 123 |
| Hungary | 0.114 | 0.046 | 271 |
| Kuwait | 0.114 | 0.107 | 42 |
| Sweden | 0.116 | 0.055 | 226 |
| Japan | 0.120 | 0.018 | 2188 |
| Switzerland | 0.126 | 0.063 | 188 |
| Tanzania | 0.131 | 0.097 | 73 |

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