The Causes and Consequences of Cross-Country Differences in Schooling Attainment

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May 2008

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Abstract

This paper uses labor market evidence to quantify the importance of quality-adjusted schooling differences in accounting for cross-country income differences. I model labor markets that are consistent with cross-country data on schooling attainment, education quality, and the average returns to schooling of a country's emigrants and its non-migrants. The model suggests that the Mincerian returns to schooling of immigrants to the United States measure the education qualities of their source countries. Measured this way, quality differences across countries are large, and the calibrated model shows that schooling accounts for a factor of 5 of the income difference between the U.S. and the poorest countries. The evidence suggests that immigrants to the U.S. are positively selected members of their source country, and that immigrants from developing countries are more selected than those from developed countries. Then the low education quality measured in the sample actually overestimates the education quality of the average non-migrant, particularly for developing countries. Two methods of controlling for selection among immigrants thus predict a moderately larger role for schooling, between a factor of 6.5 and 7.9.

*Thanks to Bob Hall, Mark Bils, Pete Klenow, Lutz Hendricks, Igor Livshits, Soohyung Lee, Romans Pancs, and seminar participants at Stanford University, University of Illinois Urbana-Champaign, University of Missouri - Columbia, Oxford University, University of Western Ontario, Clemson 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 usual disclaimer applies.

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1 Introduction

Recent work by Bils and Klenow (2000) has led to a widely adopted methodology for quantifying the income importance of cross-country schooling differences. The methodology values each year of schooling by the micro-level (Mincerian) returns to schooling for that year, so that education's contribution to income differences between countries i and j with average years of schooling S_i and S_j is given by:

$$\frac{Y_i}{Y_j} = \exp\left(\sum_{k=1}^{S_i} M(k) - \sum_{k=1}^{S_j} M(k)\right)$$

The Mincerian returns schedule $M(k)$ is taken to be the same across countries, so the value of a given (i.e., first) year of schooling is the same across all countries. This assumption is contrary to evidence from internationally standardized achievement tests that there are large education quality differences across countries, but is justified by the fact that Mincerian returns are no higher in developed than developing countries.[1] This paper shows that in an equilibrium model of labor markets, Mincerian returns convey no information about education quality, since returns are an equilibrium price determined by supply and demand. Instead, a country's average schooling attainment and the returns to schooling of that country's emigrants are better sources of information about the size and income importance of education quality differences.

The baseline model features a set of ex-ante identical workers with a single exogenous education quality in each country. Workers choose how long to go to school, which determines the supply of human capital. There is a continuum of heterogeneous industries that vary in the skill-intensity of their production processes. The firms offer different wage schedules and hire workers with different skill levels, determining the demand for schooling. In equilibrium, education quality affects the length of time workers spend in school and their returns to schooling if they emigrate, but not the returns to schooling of non-migrants.

In the standard analysis, higher education quality raises the human capital difference between workers with different years of schooling, implying larger Mincerian returns. In this model, there are two offsetting effects. First, higher returns induce workers to go to school longer. Given diminishing marginal returns to schooling, this supply response acts

[1] Bils and Klenow (2000) use a separate method to account for education quality, as discussed below. Since Hall and Jones (1999), it has been common in the literature to use only the Mincerian term shown here, without the education quality corrections.

to reduce Mincerian returns. Second, countries with higher education quality are more abundant in human capital. The model generates a decrease in the relative prices and wages of skill-intensive industries, so that a demand effect also acts to reduce Mincerian returns. In equilibrium, the total effect of these two changes is that the entire schedule of returns to schooling is constant across countries.

I collect the labor market data necessary to test the model's predictions and show that they are qualitatively consistent with the model. In countries with higher education quality as measured by internationally standardized achivement tests, workers go to school longer and earn higher returns if they emigrate, but they earn no higher returns if they do not migrate. I then construct an education quality measure based on the returns to schooling of workers who completed their education abroad and subsequently immigrated to the United States. This process is an extension of the methodology used in Card and Krueger (1992) to measure cross-state education quality. The resulting series covers a large sample of countries (130), has an economically significant scale (human capital generated per year of schooling), and is highly correlated with other measures of education quality (internationally standardized achievement tests). I use the education quality series as an input to a calibrated model that quantitatively fits labor market data. The model predicts that quality-adjusted schooling accounts for a factor 5 of the income difference between the United States and the poorest country. This number is larger than the usual 2-3 predicted in the literature that uses the Bils and Klenow technique but makes no quality adjustment; see for instance Hall and Jones (1999). It is also larger than the baseline figure from Hendricks (2002), another paper that uses immigrants from many countries in the U.S. to make inferences about cross-country human capital differences. However, one of his extensions is to consider a model with a CES aggregator over skilled and unskilled labor, which produces a relative demand effect similar to that caused by heterogeneity in industry skill intensity in this paper. In his extension he finds that human capital accounts for about a factor of 5 of the income difference across countries, comparable to this paper's results.

The key step in the analysis uses the returns to schooling of immigrants as a measure of their source country education quality. A well-known criticism of the Card and Krueger methodology by Heckman, Layne-Farrar, and Todd (1996) is that selection of immigrants may bias these returns, and hence the overall analysis. Evidence suggests that immigrants are positively selected on their education: for all but one country, immigrants are more educated than non-migrants. The average education gap is 6 years, suggesting a selection problem. Immigrants from lower-income countries are more selected by this measure; the most selected immigrants are from Sierra Leone, with 11.6 more years of schooling than non-migrants. Intuitively, then, accounting for selection should raise the predicted role for schooling. I consider two ways to address the selection problem.

First, I collapse the role of technological heterogeneity in the baseline model. Without heterogeneity, aggregate variables can be approximated with simple closed-form solutions similar to those of Bils and Klenow. The impact of education quality can be accounted for by introducing an additional parameter into the Bils and Klenow methodology, which makes it easy to implement. This parameter is estimated by regressing a country's average schooling attainment on the returns to schooling of its emigrants. If the returns are noisy or biased, an instrumental variable is called for; I instrument using internationally standardized achievement test scores. Implementing this procedure yields the estimate that a year of schooling in the highest education-quality countries is worth 3.4 years of schooling in the lowest education-quality country. Quality-adjusted schooling is predicted to account for a factor 6.5 of the income difference between the richest and poorest country.

Second, I extend the model to incorporate explicit ex-ante heterogeneity in education quality across workers. Calibrating this version of the model includes simulating the education quality type of each country's emigrants. The calibration suggests that immigrants from developing countries are much more selected than immigrants from developed countries. The structural correction for immigrant selection predicts that quality-adjusted schooling accounts for a factor of 7.9 of the income difference between the richest and poorest country, in line with the reduced-form correction.

The approach taken here contrasts with most of the previous work on education quality. Since data on education quality is generally scarce, most research has been model-driven. The key attribute of these models is an education quality production function, which determines what factors combine with student time to produce human capital. Bils and Klenow (2000) use a formulation where human capital of the previous generation augments current schooling, an analogue to allowing for teacher quality. Most research has focused on the role of education expenditures, with the recent work of Manuelli and Seshadri (2005), Erosa, Koreshkova, and Restuccia (2007), Ripoll and Cordoba (2007), and You (2008) adopting the Ben-Porath (1967) human capital production function. Tamura (2001) allows class sizes and the human capital of teachers relative to parents to affect education quality, representing a mixture of teacher quality and expenditure channels.

I view this literature and my paper as strong complements. I produce a measure of education quality and its role in accounting for income differences that is independent of a specified education quality production function. Independence is a virtue since the education literature has produced a broad 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. The calibrated size of this channel is key to the estimates of the importance of quality-adjusted education. Hence, this paper is useful as evidence on education quality that does not rely on this channel. On the other hand, the primary deficiency of not specifying a production function is that this paper can provide no 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 introduces the model without worker heterogeneity and derives the main effects of education quality. Section 3 collects the data and shows that they support the predictions of the model. Section 4 calibrates the model and measures the implied importance of quality-adjusted schooling. Section 5 introduces a reduced-form correction for immigrant selection. Section 6 modifies the model to allow for worker heterogeneity. Section 7 re-calibrates the model to account for worker heterogeneity. Section 8 concludes.

2 A Model with Ex-Ante Identical Workers

The baseline model features a continuum of ex-ante identical workers and heterogeneous intermediate goods firms. The main predictions of the model come from the labor market interactions between these two groups in the face of exogenous cross-country differences in education quality. The labor market features of interest are the schooling choices of workers, the returns to schooling offered in each country, and the returns to schooling of cross-country migrants.

2.1 Population Dynamics

The world consists of J closed economies, with individual economies indexed by subscript j. Each economy has a continuum of measure 1 of ex-ante identical infinitely-lived dynasties, with a representative dynasty denoted by d. A dynasty is a sequence of altruistically linked workers who each live for T_j periods.[2] As soon as a worker dies he is replaced by a young worker who inherits his assets but not his human capital. The date of death across dynasties is staggered so that exactly T_j^{-1} workers die in each year.

2.2 Dynasties

Each dynasty has the same power felicity function with intertemporal elasticity of substitution σ. Preferences over sequences of consumption $c_j(d,t)$ are given by:

$$U = \int_0^\infty e^{-\rho t} \frac{c_j(d,t)^{1-1/\sigma} - 1}{1 - 1/\sigma} dt$$

where ρ is the rate of time discounting.

At time t, the dynasty has two sources of income. If the worker has finished school, he earns labor income as a function of his schooling attainment $W_j(S_j(d,t),t)$; the dynasty also earns returns on asset holdings $R_j(t)a_j(d,t)$. The dynasty spends this income on consumption $c_j(d,t)$ and on changes in its net asset holdings $\dot{a}_j(d,t)$. Then its period budget constraint is given by:

$$c_j(d,t) + \dot{a}_j(d,t) = W_j(S_j(d,t),t) + R_j(t)a_j(d,t) \tag{1}$$

The dynasty is subject to a borrowing constraint:

$$\lim_{t\to\infty} a(d,t) \exp\left(-\int_0^t (r(\theta))d\theta\right) \geq 0$$

Its preferences can be summarized by the standard Euler equation:

$$\frac{\dot{c}_j(d,t)}{c_j(d,t)} = \sigma(R_j(t) - \rho) \tag{2}$$

[2] Altruistically linked in the standard sense of Barro (1974). The only demographic factor accounted for here is average life expectancy, but Manuelli and Seshadri (2005) also find large effects when they account for differences in the age distribution of the population. I also ignore issues related to stochastic mortality; see Tamura (2006), Kalemli-Ozcan, Ryder, and Weil (2000), or Soares (2005) for a model where this uncertainty may be important.

2.3 Labor-Schooling Decision

The decision of how to allocate time between work and school is based on the models of Mincer (1958) and Becker (1964). Workers are endowed with one unit of time each period. For simplicity, I abstract from tuition costs of schooling or the possibility that workers may prefer time spent in schooling to time spent in the labor force. Workers take the wage as a function of schooling $W_j(S,t)$ as given. They allocate their time endowment to maximize lifetime income. As is standard, workers separate their lives into two periods: they go to school full-time from the beginning of their life until age S, after which they work full-time. The problem of a worker born at time τ is to choose $S_j(d,t)$ to maximize lifetime income:

$$\max_{S_j(d,t)} \int_{\tau+S_j(d,t)}^{\tau+T_j} e^{-\int_\tau^t R_j(\theta)d\theta} W_j(S_j(d,t),t)dt$$

The worker's income maximization problem has first order condition:

$$\int_{\tau+S_j(d,t)}^{\tau+T_j} e^{-\int_\tau^t R(\theta)d\theta} \frac{\partial W_j(S_j(d,t),t)}{\partial S_j(d,t)} dt = e^{-\int_\tau^{\tau+S_j(d,t)} R(\theta)d\theta} W(S_j(d,t), S_j(d,t)+\tau) \tag{3}$$

Workers go to school until the present discounted value of the future wage gains from an additional unit of schooling equals the wage foregone to obtain that unit of schooling.

2.4 Human Capital Production Function

While workers choose schooling solely to maximize income, firms care about the productive value of schooling. The link between schooling and its productive value is provided by the human capital production function. A worker with $S_j(d,t)$ years of schooling has human capital:

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

Q_j is the exogenous quality of education in country j. The focus here is on measuring education quality, rather than on modeling the allocation of resources or education institutions that imply Q_j. 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.

This function is similar to the one used in Bils and Klenow (2000) and Klenow and

Rodriguez-Clare (1997), particularly in allowing for diminishing returns to schooling. The primary difference is that education quality enters exponentially, rather than multiplicatively as in their formulations. Entering education quality in this way is critical to matching the robust fact that education quality has an effect on workers' decisions about how long to remain in school. Section 3 documents that this holds across countries, but significant microeconomic evidence also exists; see for instance Case and Deaton (1999), Hanushek, Lavy, and Hitomi (2006), or Hanushek and Woessmann (2007). The assumption that $0 < \eta < 1$ is also necessary to obtain this result, so it is maintained throughout.

2.5 Intermediate Goods Producers

Each country has a continuum of industries distributed uniformly on $[\underline{\gamma}, \bar{\gamma}]$. Each industry has its own technology to produce a unique intermediate good. The industries differ in the skill intensity of their technologies. Output in industry γ is given by the production function:

$$Y_j(\gamma, t) = K_j(\gamma, t)^{\alpha} \left(A_j(t) H_j(\gamma, t)^{\gamma} L_j(\gamma, t)\right)^{1-\alpha} \tag{5}$$

where $A_j(t)$ is the labor-augmenting efficiency level general to the entire country, $K_j(\gamma, t)$ and $L_j(\gamma, t)$ are the capital and labor choices specific to the industry, and $H_j(\gamma, t)$ is the human capital per worker in the industry. Efficiency grows exogenously at rate g. Given the human capital accumulation function in equation (4), higher γ industries are more skill-intensive. The standard analysis using human capital assumes $\gamma = 1$ (Bils and Klenow 2000). Considering heterogeneity changes the interpretation of cross-sectional information such as Mincerian returns, but does not affect the interpretation of aggregate outcomes; see Section 5.

There is a large set of potential entrants, so that no profits are earned and the equilibrium number of firms in each industry is indeterminate. Then industry γ takes the time t real price of its output $P_j(\gamma, t)$, the rental price of capital $R_j(t) + \delta$, and the schedule of wages $W_j(S, t)$ as given. It chooses the capital stock, labor hours, and level of schooling per worker to maximize profits each period. Substituting in for human capital, the industry's problem is:

$$\max_{K_j(\gamma,t),L_j(\gamma,t),S_j(\gamma,t)} P_j(\gamma,t)K_j(\gamma,t)^\alpha \left\{ A_j(t)\exp\left[\frac{\gamma}{\eta}(S_j(\gamma,t)Q_j)^\eta\right] L_j(\gamma,t)\right\}^{1-\alpha}$$
$$-(R_j(t)+\delta)K_j(\gamma,t) - W_j(S_j(\gamma,t),t)L_j(\gamma,t)$$

The first-order conditions for an interior solution are:

$$\alpha P_j(\gamma,t)\frac{Y_j(\gamma,t)}{K_j(\gamma,t)} = R_j(t)+\delta \tag{6}$$
$$(1-\alpha)P_j(\gamma,t)\frac{Y_j(\gamma,t)}{L_j(\gamma,t)} = W_j(S_j(\gamma,t),t) \tag{7}$$
$$(1-\alpha)\gamma P_j(\gamma,t)S_j(\gamma,t)^{\eta-1}Q_j^\eta\frac{Y_j(\gamma,t)}{L_j(\gamma,t)} = \frac{\partial W_j(S_j(\gamma,t),t)}{\partial S_j(\gamma,t)} \tag{8}$$

Combining (7) and (8) yields the equation that relates the optimal schooling level to the log wage returns to schooling:

$$\frac{\partial \log(W(S_j(\gamma,t),t))}{\partial S_j(\gamma,t)} = \gamma S_j(\gamma,t)^{\eta-1}Q_j^\eta \tag{9}$$

2.6 Balanced Growth Path

A final goods producer uses a CES production function with elasticity of substitution ψ to aggregate the intermediate goods into a final good suitable for consumption or investment. Since the focus here is on the interaction between intermediate producers and workers, the firm's problem is described in Appendix A. I also define an equilibrium and the balanced growth path there. For the rest of the paper I confine my attention to the balanced growth path. Most of the equations simplify.

The real interest rate is constant over time and across countries at $R = \frac{g}{\sigma}+\rho$, so the capital-output ratio K/Y will also be constant across countries. This has the effect of isolating the impact of schooling in the usual accounting sense. The optimal schooling decision of workers is:

$$\frac{R-g}{1-\exp[-(R-g)(T_j-S_j(d))]} = \frac{\partial \log(W_j(S_j(d)))}{\partial S_j(d)} = M_j$$

The local change in log wages with respect to schooling in country j is the Mincerian returns to schooling M_j. There exists a large labor literature estimating regressions of log-wages on schooling and other factors that I will be able to exploit for information. For ease of exposition, I adopt the additional assumptions that $\sigma = 1$, i.e. that the felicity function is log, and that the equilibrium $T_j - S_j$ is large. The second assumption is standard in the labor literature, but somewhat unusual here where schooling is endogenous. I use it only to present simplified results familiar from that literature; I drop both assumptions when I calibrate the model. Under these assumptions, the Mincerian returns are given by:

$$M_j = R - g = \rho \tag{10}$$

The model predicts Mincerian returns are constant and unrelated to education quality.[3] Equation (10) is from Becker (1964): workers go to school until the marginal log-wage returns to schooling equal their internal discount rate. As in Mincer (1958), this condition does not define the optimal schooling decision of a worker. Rather, since all workers are ex-ante identical, it defines the indifference curve of the representative worker: a worker is willing to get any number of years of schooling, as long as he receives an appropriately higher wage upon graduation.

The behavior of the intermediate industries also simplifies along the balanced growth path. Rearranging their first-order conditions yields the zero-profit log wage schedule offered in industry γ:

$$\log(W_j(S,t;\gamma)) = A(0) + gt + \log\left[\frac{(1-\alpha)\alpha^{\alpha/(1-\alpha)}P_j(\gamma)^{1/(1-\alpha)}}{(R+\delta)^{\alpha/(1-\alpha)}}\right] + \frac{\gamma}{\eta}(SQ_j)^{\eta} \tag{11}$$

Since industries are competitive, each firm in the industry posts this wage schedule. The intercept of the wage depends on the industry output price $P_j(\gamma)$, and the slope depends on industry skill-intensity γ and education quality Q_j. In equilibrium all varieties are produced, so workers must be willing to work in any industry. Industry prices $P_j(\gamma)$ adjust to satisfy worker indifference. Heterogeneity in skill intensity across industries leads to heterogeneity in schooling outcomes. The equilibrium level of schooling is given by the point of tangency

[3] A more general formulation would allow tuition costs, borrowing constraints, and other factors to affect schooling decisions. These other factors would show up on the right hand side of equation (10). The key point would remain in such a formulation, however: in a model with an endogenous schooling choice, Mincerian returns reflect the opportunity cost of a year of schooling, including time but possibly also tuition, wedges induced by borrowing constraints, and so on.

between workers' indifference curve and the industries' zero-profit wage schedule:

$$S_j(\gamma) = \left[\frac{\gamma Q_j^\eta}{\rho}\right]^{1/(1-\eta)} \tag{12}$$

Given $0 < \eta < 1$, higher education quality leads to higher average schooling attainment. Schooling attainment is a useful source of information about education quality differences.

The Mincerian returns to schooling are the same within and across all countries even if there are large education quality differences. There are two mechanisms that are important for this result. First, there are diminishing marginal returns to schooling. Higher education quality raises the returns on a given year of schooling, but the higher returns induce workers to go to school longer, pushing down marginal returns. This mechanism explains why average returns are similar across countries despite education quality differences. The second mechanism is that the returns to schooling are affected by the demand for schooling. Consider two workers in a given country, of which one has completed primary schooling and one secondary. As education quality (of secondary school) rises, the human capital difference between the workers also rises, suggesting a larger wage differential. However, the heterogeneous technologies allow for an offsetting demand effect. More educated workers are employed in different industries, and the model predicts a decline in the price of the goods they produce, which acts to lower their relative wages. This mechanism explains why the cross-sectional distribution of wages by schooling levels is similar across countries despite education quality differences.

Aggregate Mincerian returns confound information about quality of education and scarcity of human capital. Using immigrants to the United States is a natural way to hold the scarcity of human capital fixed (at the United States level) and measure the quality of education of other countries. Suppose that a worker immigrates from another country i with schooling attainment S_j^i, and that country i has education quality Q_i. As long as $Q_i \neq Q_j$, this worker will earn a different wage than a native worker with the same schooling attainment because they will have different human capital levels. The slope of his log-wage schedule is given by:

$$M_j^i = \frac{Q_i}{Q_j} M_j \tag{13}$$

The returns to foreign schooling are directly proportional to the relative education quality of the foreign schooling. Immigrants from countries with education quality half of the domestic level accumulate half as much human capital per year of schooling and earn half the rate of return per year of schooling.

The model makes three predictions for how education quality interacts with labor market outcomes: it positively affects schooling attainment and the returns to schooling of the country's emigrants, but has no effect on the domestic returns to schooling. It also says that the returns to schooling of immigrants are a measure of their source country's education quality. In the next section I construct the suggested education quality measure and test the three predictions against labor market observations.

3 Cross-Country Data on Schooling

3.1 Four Sources of Data

In this section I show that the predicted relationships hold in the data, using internationally standardized achievement test scores as a measure of education quality. I also use the internationally standardized achievement test scores as a check on the validity of the next step, which is using the returns to schooling of immigrants as a measure of education quality.

Data on schooling attainment is average years of schooling in the over-25 population of different countries in 1999, taken from the Barro-Lee data set (Barro and Lee 1996, Barro and Lee 2001). Scores on internationally standardized achievement tests are taken from Hanushek and Kimko (2000). They construct a test score index for a broad cross-section of countries by aggregating a series of different testing programs running from 1966-1991.[4] Returns to schooling are commonly measured using Mincerian returns gathered from a regression of log-wages on schooling and a series of controls. I use a set of estimates covering many countries gathered by Banerjee and Duflo (2005); their work is an update on Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004).

The fourth source of data is the returns to schooling of immigrants to the United States. Estimation follows Card and Krueger (1992), who use the returns to schooling of cross-state migrants to identify the quality of education of the migrants' source state. Their idea was previously extended to cross-country migrants by Bratsberg and Terrell (2002); I repeat their exercise with a few changes using 2000 U.S. Census data. U.S. Census data is ideal

[4] I also consider test scores from the OECD PISA exam in 2000/2003 and the U.S. Department of Education TIMSS Exam in 1995/1999/2003. Results for both series are qualitatively similar throughout and are available upon request.

because it covers a large sample of immigrants from many different countries and contains information on wages, schooling attainment, and language ability, as well as variables that make it possible to impute which immigrants likely completed their schooling abroad. The regression equation is:

$$\log(W_{US}^{i,k}) = b^i + M_{US}^i S_{US}^{i,k} + \beta X_{US}^{i,k} + \varepsilon_{US}^{i,k} \tag{14}$$

where $W_{US}^{i,k}$ is the wage of immigrant k from country i in the United States. b^i is a country-of-origin fixed effect, M_{US}^i is the returns to country i schooling in the United States, and $X_{US}^{i,k}$ is a vector of control variables. Including country of origin fixed effects gives the estimates a differences-in-differences interpretation: rather than comparing Mexicans with 12 years of education to Americans as in Hendricks (2002), I compare the marginal wage gain associated with an additional year of Mexican schooling with the marginal wage gain associated with an additional year of American schooling. The fixed effect is presumed to help control for at least some forms of immigrant selection.

I implement this equation using the 5% sample of the 2000 Census Public Use Micro Survey, made available through the IPUMS system (Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander 2004). Immigrants are identified by country of birth.[5] 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 preserve every statistical entity which is separately identified, and refer to them as countries as a shorthand.[6]

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 before immigrating. It is important to exclude from the sample immigrants who may have received

[5] A potential bias could arise if immigrants are born in one country but receive their schooling in another. Fortunately, the Census asks all persons where they lived 5 years ago. For the subset of workers who immigrated within the last 5 years, 89% report living in their country of birth 5 years ago. Examining the data country-by-country, there is little evidence that the probability varies by income or other variables of interest.

[6] There are two exceptions to this rule: I exclude the USSR, Russia, and North Korea because the data do not allow me to differentiate these groups to the extent necessary. I also merge the United Kingdom into a single observation.

some or all of their education within the United States to have an unbiased estimate of source-country education quality. The sample used includes all workers who immigrated to the United States at least six years after their expected date of completing their reported education. For instance, a high school graduate (12 years of schooling) would need to be at least 24 (start school at 6, go to school 12 years, add 6) to be included in the sample. The extra six years are allowed to help minimize the noise coming from workers who repeat grades or delay school, for instance to fulfill mandatory armed forces obligations.

The sample includes respondents aged 19-64 who were employed but not self-employed in the previous year. The wage is calculated as previous year's average weekly wage. The vector of controls includes age and its square, gender, a dummy for residence in metropolitan area, a set of dummies for self-assessed English language proficiency on a five-option scale, dummies for Census region of residence, a disability dummy, and a full set of year of immigration dummies.

The final sample includes 4.1 million Americans and 220,000 immigrants from 130 different source countries. Appendix B provides regression results, including number of observations and standard errors. The measured U.S. returns are 10.2%. Results from other countries vary widely. The highest returns are observed for immigrants from Tanzania, Sweden, and Belgium, at 14-15%. A few countries have negative returns, although none of these coefficients is statistically significant. Two useful benchmarks on the low end of the scale are Laos and Mexico, with 0.8% and 0.9% returns estimated with a large sample of immigrants.

3.2 Testing the Model

I can now test the model's three predictions, using internationally standardized achievement test scores as a measure of education quality. The first prediction is that average schooling attainment and education quality are positively correlated across countries. Figure 1 plots average years schooling against test scores. The relationship is positive and economically significant.

The second and third predictions are that the returns to schooling are uncorrelated with school quality at home, but are positively correlated with school quality for emigrants. Figure 2 plots both types of returns. Returns observed in the same country are actually slightly negatively correlated with education quality.

The data support both of the model's predictions about returns to schooling. It is worth

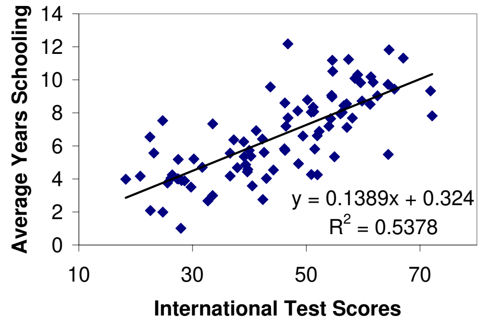
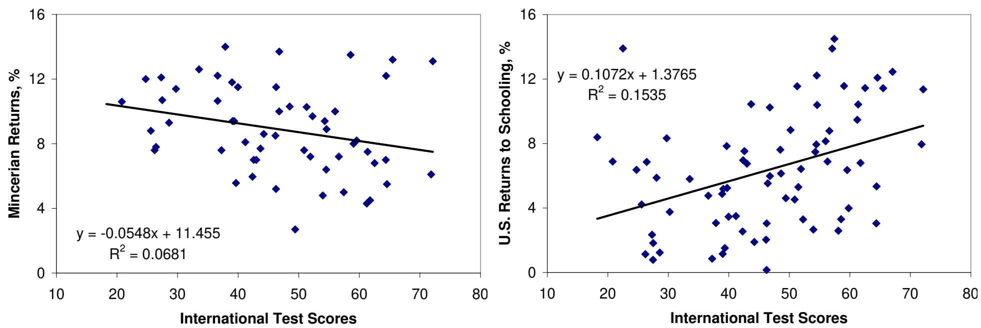


Figure 1: Relationship Between School Quality and School Quantity



(a) Own-Country Returns

(b) U.S. Immigrant Returns

Figure 2: Hanushek-Kimko Quality and Returns to Schooling

illustrating the facts about returns with a specific country-pair example. Data from test scores indicate that Swedish students have access to much higher education quality than do Mexican students. On the 2003 PISA exam mathematics section, a Swedish student would have had to score 1.18 standard deviations below average to have the average score of a Mexican student. Despite this, the Mincerian returns to schooling are actually higher in Mexico. The model explains this fact by (more than) offsetting supply and demand effects. High returns have induced Swedish workers to go to school longer (the average Swede has 11.2 years of schooling, against 6.4 for the average Mexican). Additionally, the abundance of human capital in Sweden has driven down the returns to human capital accumulation. Among immigrants to the United States, Swedish immigrants earn much higher returns on their schooling than do Mexican immigrants: since the aggregate scarcity of human capital in the United States is fixed, there can be no offsetting demand effect, and the lower education quality of Mexican schooling is observed. A standard single-technology model cannot replicate both of these effects, since it requires that Mincerian returns be the same regardless of where they are observed.

Since the model makes qualitative predictions supported by the data, I now match the data quantitatively. In particular, I use the immigrant test scores as a measure of education quality Q_j for the large number of countries available. Another way to view Figure 2b is as an outside check on the validity of this step: education quality measured through returns to schooling of immigrants is highly correlated with quality measured through internationally standardized achievement test scores. I then calibrate the model to fit facts about schooling levels and Mincerian returns, and back out the implied importance of quality-adjusted schooling in accounting for cross-country income differences.

4 Calibration of the Model

4.1 Fixing Model Parameters

Calibrating the model requires a set of J countries with the necessary inputs to the model: $(\{Q_j, T_j, A_j\}_{j=1}^{J})$. Values of Q_j are taken from returns to immigrant schooling; see Table 8. T_j, the potential working life span in country j, is taken to start at age 5 and continue until the average worker dies or retires. Hence, I set T_j equal to the country's age 5 life expectancy (worker expects to die before retirement at 65) or 60 (retirement at 65), whichever is smaller.[7] A_j is set equal to one, which is innocuous in this model since efficiency does not affect schooling decisions or returns to schooling. Then the income differences predicted by the model come solely from differences in education and life expectancy. I compare the performance of the calibrated model against the actual data values S_j and M_j, which are taken from the data sources listed in Section 3. Finally, I compare the model's income predictions to the data values for Y_j, measured as PPP income per capita from the World Development Indicators (World Bank 2006).

Relatively few countries have all 6 data points. Rather than discard a large fraction of the sample, I aggregate over countries. I take the 117 countries that have data for both Y_j and Q_j and form them into five quintiles by income per capita. For each quintile, the values

[7] Age 5 life expectancy is estimated using data on life expectancy at birth, infant mortality rate, and under 5 mortality rate, taken from the 2005 Human Development Report (United Nations Development Programme 2005). I assume that infants who die before age 1 live 0.25 years on average, and that those who die between ages 1 and 5 live 3 years on average.

Table 1: Representative Quintiles

	Quintile					
Observation	1	2	3	4	5	U.S.
M^j_{US}	4.14%	4.02%	4.39%	5.73%	9.70%	10.2%
M_j	8.72%	10.0%	11.8%	8.76%	8.06%	10.0%
Life Exp.	61.4	72.5	72.8	74.4	79.5	77.9
PPP GDP p.c.	1,545	4,004	6,510	13,356	28,060	36,465
Schooling	2.80	5.09	5.89	7.58	9.46	12.2

M^j_{US} and M_j are the log-wage returns to schooling of emigrants to the U.S. and non-migrants. Life expectancy is age 5 life expectancy calculated as explained in the text; the value used for T_j is different, as reported. Schooling is average years schooling from Barro-Lee.

$(Q_j, T_j, S_j, M_j, Y_j)$ are the average values for the quintile, ignoring missing observations. Table 1 gives the resulting values for the five quintiles, as well as the United States for reference.

The model also requires ten parameters to be fully specified. Using immigrant returns identifies education quality relative to the U.S. level, so I need to calibrate one normalization $\bar{Q}$; then each country's education quality is $Q_j = M^j_{US}\bar{Q}$. The other nine parameters are $\eta, \underline{\gamma}, \bar{\gamma}, \alpha, \rho, g, \delta, \sigma$, and ψ. Values for some of these parameters are based on outside evidence or convenient benchmarks. $\alpha = 0.33$, $\sigma = 0.5$, and $\delta = 0.06$ are standard values (Cooley and Prescott 1995). I set $g = 1.75\%$ to match the average long-term growth rate of real GDP/capita for a large sample of countries.[8] The distribution $[\underline{\gamma}, \bar{\gamma}]$ is centered on $\gamma = 1$ to make my work more comparable with the existing literature.

Then five parameters need to be calibrated in the model: ρ, η, $\bar{\gamma}$, $\bar{Q}$, and ψ. I calibrate the model using a set of moments related to each parameter's role in the model. ρ determines the Mincerian returns, so the first moment is the world average Mincerian returns of 9.1%. The model predicts little variation across countries, so trying to match each country's returns individually yields no additional benefit.

From equation (12), $[\underline{\gamma}, \bar{\gamma}]$ determines within-country schooling variation between the most and least skill-intensive industries. The 2000 U.S. Census organizes workers into 475 occupation codes. The average years of schooling by occupation for employed natives aged

[8]Barro and Sala-i-Martin (1999), p.3.

19 to 64 ranges from 10.93 years of schooling for dishwashers to 19.87 years for optometrists. I compare the model and the data on the basis of the ratio of these values, so the second moment is $\frac{S_{US}(\bar{\gamma})}{S_{US}(\underline{\gamma})} = \frac{19.87}{10.93} = 1.82$.

$\bar{Q}$ determines the average world schooling level and η determines the cross-country variation in schooling that arises from observed education quality differences. I use the schooling levels of the five quintiles as the corresponding moments for these parameters.

The elasticity of substitution across varieties ψ is difficult to pin down directly because varieties are defined differently here than is standard in the trade literature. However, elasticity across varieties also implicitly determines the elasticity of substitution across workers with different education levels. Katz and Murphy (1992) estimate that the elasticity of substitution between high school and college educated workers in the United States is 1.4. I use this moment to calibrate ψ.

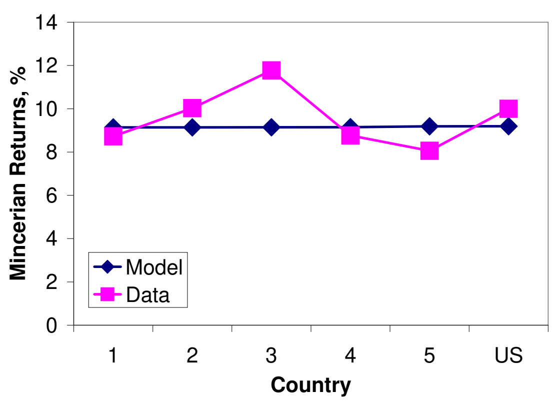
Table 2: Baseline Model Calibrated Parameters

Parameter	Role	Value
	Calibrated to Outside Evidence	
α	Capital Share	0.33
δ	Capital Depreciation Rate	0.06
σ	Intertemporal Elasticity of Substitution	0.5
g	GDP p.c. Growth Rate	1.75%
	Calibrated to Fit Data	
ρ	Time Discount Rate	0.073
η	$\varepsilon_{H,S}$	0.54
$\bar{Q}$	Quality Level	0.92
$\underline{\gamma}$	Least Skill-Intensive Technology	0.86
$\bar{\gamma}$	Most Skill-Intensive Technology	1.14
ψ	Substitution Across Varieties	0.18

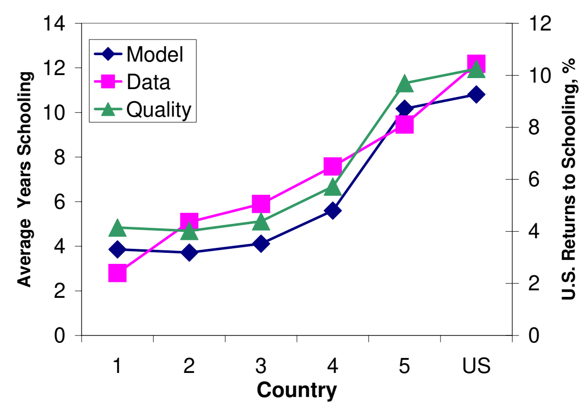
The model has five free parameters (ρ, η,$\bar{\gamma}$, $\bar{Q}$, and ψ) to match eight moments (average Mincerian returns, within-U.S. schooling variation, schooling levels for five quintiles, and elasticity of substitution between U.S. high school and college graduates). Since the model is overidentified, I minimize a loss function over the sum of squared percentage deviations. Table 2 presents the full set of baseline calibrated parameters. The rate of time preference here is higher than the typical $\rho = 0.05$. The elasticity of schooling across countries is slightly larger than the $\eta = 0.4$ used in Bils and Klenow (2000), but the identification is very different. The variation in skill intensity across industries is modest. Goods of different skill intensities are very poor substitutes; a value of 2-5 is common for varieties as they are measured in the trade literature. The model's income predictions are very insensitive to the value of ψ; setting $\psi = 5$ produces virtually identical income differences across countries.

4.2 Model Fit and Income Differences

The model fits the world average Mincerian returns and the within-U.S. variation in schooling closely. The model predicts within-U.S. variation in education levels of 1.82, almost exactly equal to the data; it predicts world average Mincerian returns to education of 9.13%, in line with the data moment of 9.1%. Figure 3a shows that the predicted Mincerian returns are nearly constant across countries. The lack of trend in the model fits well with the data, although the model is unable to explain any of the observed variation. The elasticity of substitution between high school and college graduates in the U.S. is 1.41, nearly identical to the Katz and Murphy value.



(a) Predicted vs. Actual M_j



(b) Predicted vs. Actual S_j

Figure 3: Calibrated Model vs. Data

Figure 3b plots the model's predicted schooling level and the actual schooling level on the left axis. The model hits the general upward trend in schooling, but it has some difficulty in matching the exact levels. Figure 3b also plots the average education quality for each observation on the right axis. The predicted level of schooling tracks quality closely, so the inability of the model to fit the schooling data better is directly due to measured quality. In particular, the model has difficulty with the fact that measured quality shows little variation across the first three income quintiles while average years of schooling doubles.

Table 3: Income Differences Due to Schooling

	U.S.-Poorest	Top-Bottom Quintiles
Data	33	18.2
Baseline Model	4.99	2.67
Comparison Paper	HJ99[a]	EKR07[b]
Result	2.5	4

[a] Hall and Jones (1999), Table 1.

[b] Erosa, Koreshkova, and Restuccia (2007), Table 4. Their calculations are for two economies assumed to have an income ratio of 20, which corresponds well to the actual difference between the top and bottom quintiles.

Now that the model quantitatively replicates the returns to schooling and schooling attainment data, I back out the implied income differences. Table 3 gives two different possible ways of breaking down income differences. The model suggests that schooling accounts for a factor of 2.67 of the observed income differences between the top 20% and the bottom 20% of countries. The effect here is smaller than predicted in the most comparable paper from the endogenous school quality literature (Erosa, Koreshkova, and Restuccia 2007).[9] I also compare the implied income difference between the United States and the poorest country. To do so, I solve for the equilibrium in each country by inputting the country's actual (T_j, Q_j) into the calibrated model. I perform this exercise for each of the 105 countries with the data available, excluding those with fewer than 50 observations for the estimation of Q_j and those with negative estimated Q_j. The United States is predicted to have income 5 times the poorest country; Bosnia, Bolivia, and Laos are in a tight cluster at the bottom of the distribution, because of their low measured education quality. The effect is twice what was found in the literature that focuses on years of schooling, particularly Hall and Jones (1999).

[9] The effect is much smaller than in Manuelli and Seshadri (2005), who find that human capital accounts for almost all of the observed income differences. However, their model accommodates a broader definition of human capital. Bils and Klenow (2000) consider a wide range of human capital production functions with very different roles for human capital, so direct comparison is not possible.

5 Collapsing Heterogeneity for Aggregate Outcomes

The cross-sectional heterogeneity in the model is important for interpreting cross-section wage evidence in the form of Mincerian returns. Cross-sectional heterogeneity plays no substantive role in generating cross-country income predictions. To see this, consider the limiting case where $\bar{\gamma} \to 1$, $\underline{\gamma} \to 1$. Then relative schooling, human capital, and output per capita can be approximated as follows:

$$\frac{S_i}{S_j} \approx \left(\frac{Q_i}{Q_j}\right)^{\eta/(1-\eta)} \tag{15}$$

$$\frac{H_i}{H_j} \approx \exp\left(\frac{M}{\eta}(S_i - S_j)\right) \tag{16}$$

$$\frac{Y_i}{Y_j} \approx \exp\left(\frac{M}{\eta}(S_i - S_j)\right)\frac{T_j}{T_j - S_j}\frac{T_i - S_i}{T_i} \tag{17}$$

As mentioned in the introduction, a common empirical strategy for estimating human capital stocks due to Bils and Klenow (2000) is to value each year by the average Mincerian returns to that year. Hence, if M were constant, one would measure $\log(H) = MS$. Equations 16 and 17 yield an important insight about how to account for education quality in this procedure. Since years of schooling themselves reflect education quality, they contain all the information needed to account for differences in education quality. Given η, accounting for education quality consists of taking $1/\eta$ to be the markup that represents the additional education quality difference implied by the years of schooling difference. Since $\eta < 1$, accounting for education quality in this way has the effect of increasing the implied differences in human capital stocks across countries.

In the previous section η was calibrated to fit aggregate schooling data. However, equations (15) and (17) suggest an alternative strategy to estimate η and the importance of quality-adjusted schooling. In particular, use two steps: first, use data on schooling and education quality to estimate η from equation (15); then treat η as a known and back out income differences from equation (17). This approach has the virtue of showing that neither the calibration methodology nor the cross-sectional heterogeneity are driving the model's income predictions.

I regress equation (15) in logs, studying every country relative to a constant benchmark

j. In this case, the regression has the form:

$$\log(S_i) = b_1 + b_2 \log(Q_i) \tag{18}$$

where $\eta = \frac{b_2}{1+b_2}$. S_i is the average years of schooling in the foreign country, taken from Barro and Lee data, while Q_i is the returns to schooling of immigrants constructed from the Census data. Table 4 presents the OLS estimates of b_2 for the 86 countries for which both variables are available.[10] The regression suggests an estimate of $\eta = 0.189$, much lower than the calibrated value. Such a low value of η would imply a very large income importance of education.

Table 4: Estimation of η

Method	Dep. Variable	b_1	b_2	R^2	N. Obs
OLS	$\log(S_i)$	2.456	0.233	0.114	86
		(0.226)	(0.071)		
IV	$\log(S_i)$	4.738	0.944	0.119	70
		(0.945)	(0.312)		

Expressing this exercise as a regression shows one likely problem, namely that the education quality measures on the right-hand side are imperfect. At a minimum they certainly suffer from measurement error (unless Tanzania does possess the world's highest quality education, and a few countries have schooling that lowers human capital), and quite likely they suffer from some bias due to immigrant selection. To correct for this, I re-run the regressions using log test scores as an instrument for the log of returns to schooling for immigrants. Table 4 presents the results of this regression. As expected with measurement error, the instrumental variable estimate is much higher. The estimate of b_2 implies $\eta = 0.486$, very close to the value from the calibrated model. The first-stage regression results are also of some interest, since they lend an economically significant scale to test scores. A one standard deviation increase in test scores leads to a 2.05-2.38 percentage point increase in human capital generated per year of schooling, evaluated at the mean. A given year of schooling in the highest education quality country (Singapore) yields as much human capital as 3.4 years of schooling in the lowest education quality

[10] All countries with fewer than 50 responses were excluded. South Africa was also excluded as an extreme outlier in all regressions.

country (Iran). Using other test scores as instruments produces lower but similar results.[11] These results may underestimate cross-country differences in education quality since many developing countries do not participate in the tests, meaning they are excluded from this exercise.

Taking $\eta = 0.486$ as the true value, I can then use equation (17) to estimate the income differences due to quality-adjusted schooling predicted by the model for the 96 countries with data on life expectancy and average schooling attainment (not just the countries used in the estimation of η). Here, the model predicts that the United States will be 6.45 times richer than the poorest country. It predicts a factor of 3.55 difference between the top and bottom quintiles of countries. Some care must be taken here and throughout when comparing across models, since analysis is always conditioned on countries for which data are available. However, the general results here are modestly higher than in the previous section. In the next section I augment the model to allow for ex-ante heterogeneity in education quality across workers in a country. The model then suggests a structural correction, which I view as a second way to address the concern of immigrant selection.

6 A Model with Heterogeneous Workers and Immigrant Selection

The baseline model assumes that all workers in a country are ex-ante identical, with schooling differences arising ex-post only because workers choose to be employed in different industries. Here, I introduce ex-ante worker heterogeneity into the model. Worker heterogeneity introduces two complications. First, Mincerian returns are not the private returns to schooling. Second, immigrants may have different unobservables than non-migrants.

6.1 Changes to the Model

I incorporate worker heterogeneity into the model through the human capital production function. A worker in dynasty d with $S_j(d,t)$ years of schooling now has human capital

[11] The Hanushek-Kimko results are preferred since many more countries are included, 70 against 40 for TIMSS or 37 for PISA, but they are also the most conservative. Using TIMSS test scores as an instrument yields an estimated $\eta = 0.461$. The fitted values suggest that a 1 year of Taiwanese schooling is worth 6.2 years of Ghanaian schooling. Using the PISA test scores yields an estimated $\eta = 0.365$. The fitted values suggest that 1 year of Finnish schooling is worth 4.7 of Peruvian schooling.

given by a dynasty-specific human capital production function:

$$H_j(d,t) = \exp\left[\frac{(S_j(d,t)Q_j(d))^\eta}{\eta}\right] \tag{19}$$

The rate of human capital formation per year of schooling is idiosyncratic to the dynasty. I will call the term $Q_j(d)$ the heterogeneous school quality of the dynasty, although conceptually it could also be thought of as ability heterogeneity. Although there are other ways to introduce heterogeneity in the model, this is the most interesting since school quality heterogeneity jointly affects the schooling decisions and wages of workers. It is convenient to disaggregate the dynasty quality into $Q_j(d) = \bar{Q}_j(1 + \tilde{Q}_j(d))$, where $\bar{Q}_j$ is the average school quality in country j, and $\tilde{Q}_j(d)$ is the dynasty's mean zero, nonnegative idiosyncratic component.

The model has the same basic structure in terms of demographics, preferences, and industries. One change in notation is in order; since workers have different levels of education quality, different wages can be offered to two workers with the same schooling attainment. Hence, it is necessary to write the generalized wage schedule $W_j(S_j, Q_j, t)$. Similarly, the wage schedules posted by firms have the form $W_j(S_j, Q_j, \gamma_j, t)$. The workers' problem is still to maximize lifetime income:

$$\max_{\gamma_j(d,t), S_j(d,t)} \int_{\tau+S_j(d,t)}^{\tau+T_j} e^{-\int_\tau^t R_j(\theta)d\theta} W_j(S_j(d,t), Q_j(d), \gamma_j(d,t), t)dt \tag{20}$$

The worker's income maximization problem has the same first-order condition:

$$\int_{\tau+S_j(d,t)}^{\tau+T_j} e^{-\int_\tau^t R_j(\theta)d\theta} \frac{\partial W_j(S_j(d,t), Q_j(d), \gamma(d,t), t)}{\partial S_j(d,t)} dt = \\ e^{-\int_\tau^{\tau+S_j(d,t)} R_j(\theta)d\theta} W_j(S_j(d,t), Q_j(d), \gamma_j(d,t), S_j(d,t)+\tau) \tag{21}$$

6.2 Balanced Growth Path Adjustments

The balanced growth path of this model looks somewhat different from the model with identical workers. Again, for exposition I make the assumptions that $\sigma = 1$ and that $T_j - S_j$ is large. Workers still go to school until the private returns equal their internal discount rate:

$$\frac{\partial \log(W_j(S,Q,\gamma))}{\partial S} = R - g = \rho$$

The optimal schooling level for each worker is:

$$S_j(\gamma) = \left[\frac{\gamma_j(d)\,(Q_j(d))^{\eta}}{\rho}\right]^{1/(1-\eta)} \tag{22}$$

The heterogeneous quality of workers is the underlying driving force in explaining the cross-section of wages and schooling levels. Mincerian returns are no longer the private returns to schooling. Instead, a worker with higher observed schooling earns higher wages both because he has more schooling, and because he has a higher education quality and more human capital per year of schooling. Under the assumed human capital function, Mincerian returns can be related to the private returns to schooling:

$$M_j = \rho\left(1 + \frac{1-\eta}{\eta + \varepsilon_{\gamma(d),Q(d)}}\right)$$

Since ρ is the private return to schooling in this case, Mincerian returns are biased upward by quality heterogeneity. The size of the bias depends on the elasticity of industry of employment with respect to dynasty education quality, $\varepsilon_{\gamma(d),Q(d)}$, which is an equilibrium object in the model. Two special cases illustrate the bias in observed returns. If there is no quality heterogeneity, then in the limit $\varepsilon_{\gamma(d),Q(d)} = \infty$. In this case all the observed schooling heterogeneity is driven by industry heterogeneity, and the observed returns are an unbiased estimate of private returns, $M_j = \rho$, as in the previous model. If there is no industry heterogeneity, then in the limit $\varepsilon_{\gamma(d),Q(d)} = 0$. In this case all the observed schooling heterogeneity is driven by quality heterogeneity, and the observed returns are biased upward by a constant proportion of private returns, η^{-1}. The calibrated equilibrium falls in between these two extremes, with an intermediate bias in Mincerian returns.

The returns to schooling of immigrants can be evaluated as in Section 2:

$$M_j^i = \frac{Q_i(d)}{Q_j(d)} M_j = \left(\frac{\bar{Q}_i}{\bar{Q}_j}\right)\left(\frac{1+\tilde{Q}_i(d)}{1+\tilde{Q}_j(d)}\right) M_j \;\Big|_{H_j(d)=H_i(d)} \tag{23}$$

The average returns to schooling of immigrants are equal to the education quality of immigrants relative to the education quality of Americans with the same human capital. For example, the average Portuguese immigrant in the United States has 7 years of schooling. Then the returns to schooling measure the education quality of a Portuguese worker with 7 years of schooling relative to the education quality of an American worker with the same human capital. In the next section I use the structure of the model to decompose observed returns into differences in average education quality and selection effects.

7 Calibration and Selection

7.1 Immigrant Selection

U.S. immigration policy explicitly selects based on skills, including schooling. In this model, it is high education quality immigrants who go to school longer. Selecting on schooling is then equivalent to selecting on education quality. To measure the degree of selection, I compare the average years of foreign schooling of immigrants and non-migrants from a given country. Data on average years of schooling is available from Barro and Lee (2001) for 78 of 130 countries in the sample in Section 3. For every country except Mexico, immigrants have more schooling than non-migrants. The most extreme case is Sierra Leone, where immigrants have 13.2 years of schooling and non-migrants have 1.65 years, but the average amount of selection by this criteria is six years. I take these differences as evidence of large selection effects.[12]

For a given set of parameters, the calibrated model provides an exact relationship $S_j(Q_j(d))$. By inverting this relationship, it is possible to use the educational gap between migrants and non-migrants to measure the education quality gap between migrants and non-migrants. With this information I can correct for the bias in measured returns to schooling of immigrants. In the next section, I consider this structural approach to dealing with immigrant selection.

7.2 Calibration

Calibration of the model with ex-ante heterogeneity differs in three respects from the calibration done in Section 4. The first and most fundamental change is that there are now

[12] There is also a slight discontinuity since the Section 3 data measures average schooling among workers, while the Barro-Lee data is average schooling in the population over 25. Hence, the average American in my sample has 13.5 years of schooling, while Barro-Lee report an American average of 12.2, indicating that Americans are "selected" by 1.3 years. Still, only Mexican immigrants are less selected.

two possible sources of cross-sectional variation in schooling outcomes within a country: γ and $(1+\tilde{Q}_j(d))$. In general the model can accommodate arbitrary distributions for these variables, which leads to a complex matching problem. To simplify, I assume that the distributions are such that the matching function is one-to-one everywhere. This matching function implicitly defines a decomposition of observed schooling variation into the relative proportions from industry and education heterogeneity.

The second change is that observed Mincerian returns now overstate the true returns to schooling. There is a large labor literature that uses instrumental variable techniques to attempt to identify the true private returns to schooling; see Card (1999) for an overview. The basic finding in this literature is that IV estimates of the private returns to schooling are quantitatively similar to OLS estimates, suggesting that the private returns to schooling are close to OLS levels. I continue to calibrate the model to target the private returns to schooling of 9.1%, so that the measured Mincerian returns to schooling would be higher. This methodology has the virtue of isolating the effect of accounting for immigrant selection.

Finally, the returns to schooling of immigrants to the United States are no longer a valid measure of their source country education quality, because immigrants may be selected. Hence, it is no longer appropriate to treat M_j^i as a direct observation on $\bar{Q}_i$. Instead, I add $\bar{Q}_i$ to the set of parameters to be calibrated, and M_j^i to the set of moments to be matched. For each country j I simulate the $(\gamma_j, \tilde{Q}_j)$ pair of an immigrant whose schooling attainment corresponds to the average schooling attainment of immigrants from country j, and of an American worker who has the same human capital as the immigrant. I then calculate the implied returns to schooling for country j's immigrants using equation (23), and compare that moment to the data.

The result is that the calibration involves the same nine parameters as before ($\eta, \underline{\gamma}, \bar{\gamma}, \alpha, \rho$, g, δ, σ, and ψ), plus J additional parameters, $\left\{\bar{Q}_j\right\}_{j=1}^{J}$. I use the same restrictions and moments as before, plus the additional moments $\left\{M_{US}^j\right\}_{j=1}^{J}$. I construct a new data set of the 79 countries for which I also have the average schooling attainment of non-migrants from the Barro-Lee data. I aggregate the values into quintiles as before, but I also separate out the United States since American workers serve as an important denominator in the calibration process. I weight all moments in the calibration by the number of countries in the corresponding group. Table 5 gives the moments for the five quintiles, plus the United States for reference.

Overall, the data on life expectancy, income per capita, and Mincerian returns at home

Table 5: Representative Quintiles

	Quintile					
Observation	1	2	3	4	5	U.S.
M^j_{US}	4.44%	4.07%	4.42%	6.92%	10.3%	10.3%
M_j	9.14%	10.5%	10.8%	8.16%	7.50%	10.0%
Life Exp.	61.8	72.9	73.9	75.7	79.6	77.9
PPP GDP p.c.	1,904	4,258	7,618	18,386	29,122	36,465
Schooling	3.03	5.34	6.25	8.05	9.65	12.2
Immigrant Schooling	12.8	11.5	11.8	12.3	14.2	13.5

[a] M^j_{US} and M_j are the log-wage returns to schooling of immigrants to the U.S. and non-migrants. Life expectancy is age 5 life expectancy calculated as explained in the text; the value used for T_j is different, as reported. Schooling is average years schooling from Barro-Lee. Immigrant schooling is average schooling among immigrants to the United States who are in the sample in Section 3.

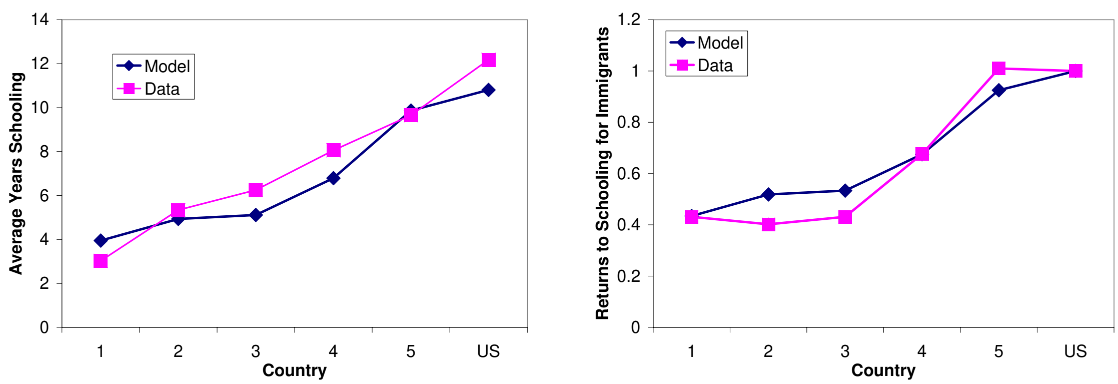
and abroad are similar for this group and the sample used for the previous calibration. Education levels are slightly higher in this group than before. The more striking fact is revealed in the last row. Despite large changes in average schooling attainment of non-migrants across income quintiles, there is no strong pattern in average schooling attainment of immigrants across income quintiles. This fact gives an estimate of the quantitative magnitude of the selection correction that needs to take place. Table 6 presents most of the re-calibrated parameters; those chosen based on outside evidence are the same as in the previous calibration and are not presented. The calibration results are presented in the next section.

Table 6: Alternative Model Calibrated Parameters

Parameter	Role	Value
Calibrated to Fit Data		
ρ	Time Discount Rate	0.065
η	$\varepsilon_{H,S}$	0.39
$\underline{\gamma}$	Least Skill-Intensive Match	0.86
$\bar{\gamma}$	Most Skill-Intensive Match	1.14
ψ	Substitution Across Varieties	0.036

7.3 Results

The model does a reasonable job on several of the moments. It predicts a lower world Mincerian returns of 8.3%, against 9.22% in the data. It predicts within-U.S. variation in schooling of 1.86, against 1.82 in the data. The elasticity of substitution between college and high school workers is predicted to be 1.48, against 1.4 in the data. Figure 4a plots the model predicted and actual schooling values for the five quintiles, while Figure 4b plots the predicted and actual returns to schooling for immigrants. The model fits these moments reasonably well, but there is a tension between fitting both. Take Quintile 3: a higher education quality would improve the fit with the average schooling data, but would imply higher returns to schooling for emigrants, worsening the fit along the second dimension.



(a) Predicted vs. Actual S_j

(b) Predicted vs. Actual M_{US}^{j}

Figure 4: Calibrated Model with Heterogeneity vs. Data

Correcting for immigrant selection makes a large difference in the quality measures used in the calibration. Based on differences in years of schooling between migrants and non-migrants, it seems that immigrants from developing countries are more selected than those from developed countries. Figure 5 confirms this intuition. For each quintile, it decomposes returns to schooling (relative to U.S.) into two portions: that due to average school quality (relative to U.S. average school quality) and that due to selection. Selection accounts for a higher portion of the observed returns to schooling of first income quintile countries, whether measured in absolute or relative terms. The model predicts that all immigrants are positively selected. However, immigrants from developing countries are more selected, suggesting again that accounting for selection will increase the implied importance of quality-adjusted schooling. The implied education quality differences across countries are large: a given year of schooling in the richest income quintile yields the same human capital as five years of schooling in the poorest income quintile.

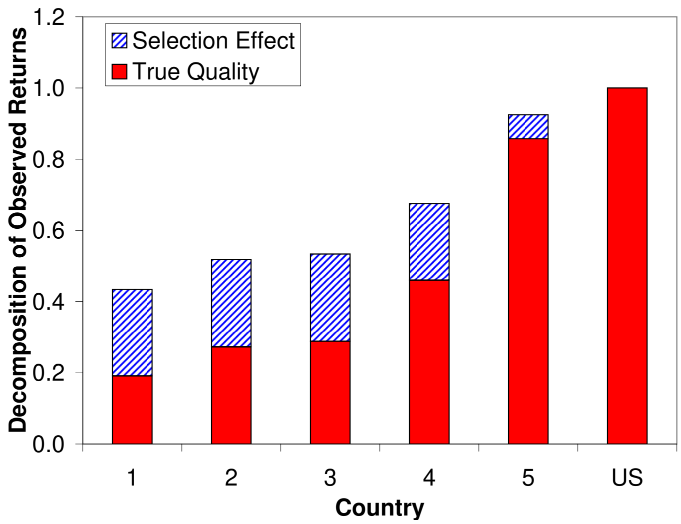


Figure 5: Decomposed Education Quality and Selection Effects

The structural correction makes predictions about the relative importance of quality-adjusted schooling that are similar to those from the reduced form correction. The model accounts for a factor of 3.43 of the income difference between the top and bottom quintiles. I also compare the United States to the poorest country. Again, I feed in the data (T_j, Q_j) for each of the 105 countries for which it is available; I also feed in the immigrant selection measure of the appropriate income quintile. The model predicts that schooling accounts for nearly a factor of 8 income difference between the United States and the poorest country. Results for the benchmark model and both corrections for immigrant selection are summarized in Table 7. Two different methods of controlling for immigrant selection both suggest that if anything, the returns to schooling of immigrants underestimate education quality and human capital differences across countries. Hence, controlling for immigrant selection leads to a larger role for quality-adjusted schooling. The results are now about 3 times larger than in the accounting exercises using only years of schooling, and only slightly smaller than in the most comparable paper in the endogenous school quality literature.

Table 7: Income Differences Due to Schooling

	U.S.-Poorest	Top-Bottom Quintiles
Data	33	18.2
Baseline Model	4.99	2.67
Reduced-Form Correction	6.45	3.55
Structural Correction	7.91	3.43
Comparison Paper	HJ99[a]	EKR06[b]
Result	2.5	4

[a] Hall and Jones (1999), Table 1.

[b] Erosa, Koreshkova, and Restuccia (2007), Table 4. Their calculations are for two economies assumed to have an income ratio of 20, which corresponds well to the actual difference between the top and bottom quintiles.

8 Conclusion

This paper develops a model of labor markets where education quality varies exogenously across countries. Education quality differences are treated as exogenous to students and measured using the returns to schooling of immigrants to the United States. The implied education quality differences are large. After controlling for noise, a given year of schooling in the highest education-quality countries is estimated to yield the same human capital as 3.4-6.7 years of schooling in the lowest education-quality countries. Differences in education quality may be the cause of cross-country schooling differences, since high returns offer students incentives to stay in school. The consequences of joint differences in years of schooling and education quality are large. The model suggests that quality-adjusted schooling accounts for a factor of 5 of the income difference between the richest and poorest countries; controlling for selection makes this number larger. Overall, the accounting importance of quality-adjusted schooling is 2-3 times larger than the number suggested in Hall and Jones for years of schooling alone.

By design, this paper has little to say about the source of these evidently important education quality differences. Rather, it is hoped that these estimates will be useful outside evidence for future research.

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A Model Details

A.1 Final Goods Producer

I assume a zero-profit final-goods producer who purchases $X_j(\gamma, t)$ of each of the intermediate goods and aggregates them into the final good, which she sells to the consumers. The producer uses a CES aggregator with elasticity ψ:

$$Y_j(t) = \left[\int_{\underline{\gamma}}^{\bar{\gamma}} (X_j(\gamma, t))^{1-1/\psi} d\gamma \right]^{\psi/(\psi-1)} \tag{24}$$

I express all time t intermediate good and factor prices in terms of the time t final goods price so that the prices of intermediate goods, capital, and labor are all real. Then the final goods producer's problem is:

$$\max \left[\int_{\underline{\gamma}}^{\bar{\gamma}} (X_j(\gamma, t))^{1-1/\psi} d\gamma \right]^{\psi/(\psi-1)} - \int_{\underline{\gamma}}^{\bar{\gamma}} P_j(\gamma, t) X_j(\gamma, t) d\gamma \tag{25}$$

This problem leads to the standard demand equation:

$$X_j(\gamma, t) = Y_j(t) \left(\frac{1}{P_j(\gamma, t)} \right)^{\psi} \tag{26}$$

A.2 Market Clearing Conditions

There are market clearing conditions in this model for the final goods market, the capital market, the intermediate goods market for each good, and the labor market for each schooling level. These conditions are:

$$Y_j(t) = \int_0^1 \left[c_j(d, t) + \dot{a}_j(d, t) + \delta a_j(d, t) \right] dd \ \forall j, t \tag{27}$$

$$K_j(t) = \int_{\underline{\gamma}}^{\bar{\gamma}} K_j(\gamma, t) d\gamma = \int_0^1 a(d, t) dd \ \forall t \tag{28}$$

$$X_j(\gamma, t) = Y_j(\gamma, t) \ \forall j, t, \gamma \tag{29}$$

$$L_j(\gamma, t) = \int_0^1 I\left(S_j(d) = S_j(\gamma) \right) \frac{T_j - S_j(d)}{T_j} dd \ \forall j, t, \gamma \tag{30}$$

Here, $K_j(t)$ is the aggregate capital stock, which is equal to the sum of all the asset savings of the workers in the standard way. $I(S_j(d) = S_j(\gamma))$ is an indicator function. Then the first three market clearing conditions are entirely standard. The fourth requires that in equilibrium, the employment of industry γ equals the fraction of workers who have the appropriate level of schooling, $I(S_j(d) = S_j(\gamma))$, times the labor supply of those workers, $\frac{T_j - S_j(\gamma,t)}{T_j}$.

A.3 Definition of Equilibrium

An equilibrium consists of prices $(R_j(t), W_j(S,t), P_j(\gamma,t))_{t\in[0,\infty)}$ and allocations for intermediate industries
$(K_j(\gamma,t), L_j(\gamma,t), Y_j(\gamma,t), S_j(\gamma,t))_{t\in[0,\infty)}$, for the final goods producer $(X_j(\gamma,t), Y_j(t)_{t\in[0,\infty)}$, and for the dynasties $(a_j(d,t), c_j(d,t)S_j(d,t))_{t\in[0,\infty)}$, for each country j. These variables must satisfy:

1. The intermediate goods producers' production function, (5) and their FOCs, (6) - (8).

2. The final goods producer's CES production function (24) and its FOC, (26).

3. The dynasties' budget constraints (1), Euler equations (2), and FOCs for schooling,, (3).

4. The market clearing conditions, (27)-(30).

A balanced growth path is an equilibrium such that the variables $R_j, P_j(\gamma), L_j, L_j(\gamma), S_j(\gamma)$,and $S_j(d)$ are constant, while $W_j, W_j(\gamma), K_j, K_j(\gamma), Y_j, Y_j(\gamma), X_j(\gamma), a_j(\gamma,t)$, and $c_j(\gamma)$ grow at the same rate g as technology. Crucially, the schooling decision is unaffected by the level of aggregate TFP so that schooling decisions are stationary.

B Country Quality Estimates

Table 8: Quality Estimates

Country	Obs	Returns	S.E.
Afghanistan	227	6.42	1.01
Albania	343	-0.95	0.86
Algeria	82	5.88	1.66
Antigua-Barbuda	131	10.96	2.05
Argentina	797	7.62	0.62
Armenia	325	2.82	0.92
Australia	464	11.57	1.06
Austria	153	8.78	1.46
Azerbaijan	115	8.23	1.75
Azores	183	0.42	1.16
Bahamas	108	6.67	2.20
Bangladesh	602	2.76	0.59
Barbados	441	3.99	0.96
Belgium	133	13.89	1.70
Belize/British Honduras	246	4.82	1.16
Bermuda	65	9.17	2.36
Bolivia	371	0.78	0.99
Bosnia	1135	0.70	0.57
Brazil	1572	4.76	0.40
Bulgaria	308	4.74	1.06
Burma (Myanmar)	332	4.95	0.72
Byelorussia	314	5.44	1.22
Cambodia (Kampuchea)	1038	1.31	0.36
Cameroon	61	6.96	3.06
Canada	4137	10.39	0.34
Cape Verde	247	1.99	0.97
Chile	532	6.37	0.77
China	8576	5.34	0.13
Colombia	3667	3.07	0.25
Costa Rica	475	2.03	0.69
Croatia	263	3.32	1.02
Cuba	4842	2.53	0.24
Cyprus	46	0.16	1.88
Czech Republic	109	7.94	2.13

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Table 8: Quality Estimates

Country	Obs	Returns	S.E.
Czechoslovakia	159	5.68	1.55
Denmark	152	6.80	1.65
Dominica	129	2.44	1.76
Dominican Republic	4343	1.52	0.22
Ecuador	2121	1.15	0.33
Egypt/United Arab Rep.	751	6.86	0.77
El Salvador	7502	1.13	0.17
Eritrea	127	1.97	1.22
Ethiopia	493	1.65	0.76
Fiji	311	2.59	0.99
Finland	135	6.36	1.54
France	716	8.15	0.61
Germany	2736	10.44	0.39
Ghana	659	4.22	0.76
Greece	738	4.53	0.59
Grenada	207	3.61	1.46
Guatemala	4497	1.04	0.21
Guyana/British Guiana	1913	5.30	0.41
Haiti	3707	2.87	0.26
Honduras	2532	1.23	0.30
Hong Kong	1177	7.95	0.45
Hungary	302	9.47	1.09
India	6378	6.89	0.21
Indonesia	366	6.75	1.04
Iran	1480	8.39	0.52
Iraq	541	1.82	0.53
Ireland	762	8.84	0.83
Israel/Palestine	589	7.94	0.70
Italy	1625	4.61	0.33
Jamaica	4834	6.14	0.30
Japan	2269	11.44	0.45
Jordan	178	2.54	1.30
Kenya	229	8.33	1.30
Korea	4549	3.31	0.72
Kosovo	70	-1.60	1.78
Kuwait	44	13.90	2.64
Laos	1475	0.75	0.28

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Table 8: Quality Estimates

Country	Obs	Returns	S.E.
Latvia	91	5.09	2.36
Lebanon	468	7.07	0.71
Liberia	315	1.14	1.13
Lithuania	89	7.16	2.46
Macedonia	143	-0.90	1.33
Malaysia	325	7.48	0.78
Mexico	71406	0.85	0.06
Moldavia	164	4.53	1.52
Morocco	264	5.74	0.95
Nepal	81	2.35	1.66
Netherlands	347	12.22	1.06
New Zealand	209	12.45	1.58
Nicaragua	1580	2.34	0.36
Nigeria	913	4.88	0.62
Norway	120	12.08	1.90
Pakistan	1320	5.45	0.41
Panama	560	5.98	0.88
Paraguay	68	3.46	2.09
Peru	2307	3.50	0.38
Philippines	12283	5.80	0.18
Poland	3657	3.05	0.31
Portugal	1531	1.89	0.37
Puerto Rico	4886	4.68	0.22
Republic of Georgia	62	8.88	2.55
Romania	1071	5.50	0.54
Saudi Arabia	42	0.37	2.77
Senegal	74	3.22	1.42
Serbia	81	0.92	1.60
Sierra Leone	188	4.13	1.47
Singapore	104	11.36	1.61
Slovakia	94	8.98	2.56
Somalia	180	0.42	0.82
South Africa (Union of)	506	11.55	0.99
Spain	469	6.42	0.64
Sri Lanka (Ceylon)	248	7.53	1.10
St. Kitts-Nevis	98	5.88	2.25
St. Lucia	118	6.00	1.85

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Table 8: Quality Estimates

Country	Obs	Returns	S.E.
St. Vincent	159	6.98	1.28
Sudan	115	2.92	1.44
Sweden	240	14.50	1.41
Switzerland	210	10.43	1.49
Syria	315	3.76	0.82
Taiwan	1618	6.88	0.47
Tanzania	73	15.41	2.52
Thailand	851	3.05	0.46
Tonga	111	-0.80	1.60
Trinidad & Tobago	1567	5.53	0.54
Turkey	437	5.24	0.72
Uganda	100	4.35	1.81
Ukraine	1989	6.73	0.45
United Kingdom	4449	11.45	0.35
United States	4122274	10.25	0.01
Uruguay	188	3.29	1.28
Uzbekistan	150	4.05	1.75
Venezuela	536	5.18	0.70
Vietnam	8276	2.51	0.15
Western Samoa	86	1.85	1.56
Yemen Arab Republic (North)	93	2.13	1.12
Yugoslavia	542	2.66	0.65
Zimbabwe	78	7.84	2.03

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.