Endogenous Mincerian Returns: Explaining Cross-Country Variation in the Returns to Schooling

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PRELIMINARY

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Abstract

This paper calibrates a model in which both schooling levels and returns to schooling are endogenous and examines the extent to which cross-country variation in Mincerian returns can be explained by technology and supply factors (i.e., variation in life expectancy, retirement ages, fertility, implied discount rates, and government funding of education in a cross-section of fifty-nine countries) alone. The returns from the calibrated model is highly correlated with the data and the model is able to explain twenty-five percent of the variation in the data. Variation in the direct costs of schooling caused by variation in government funding levels and fertility contribute the most to the explanatory power of the model. Nevertheless, high effective discount rates are needed to reconcile the high level of Mincerian returns in the data.

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1 Introduction

The return to education plays an important role in the study of both growth and inequality. Growth researchers and inequality researchers have taken quite different angles in studying the returns to education, however. Following the traditional growth accounting program, a recent growth literature has taken the observed returns to education as given in estimating the extent to which differences in education stocks can explain income differences across countries. In contrast, the literature on inequality has tried to model the determinants of the returns to education, but has focused primarily on secular within-country trends in these returns. This paper integrates these two approaches by: 1) developing a model with endogenous schooling and returns, 2) evaluating the models ability to explain the level and variation of the returns to schooling across countries, 3) quantifying the importance of supply and demand factors in explaining this variation, and 4) comparing measured returns to schooling with the true growth effects of schooling increases in the model.

Recently, several papers1 have looked toward micro-evidence on the private return to schooling from Mincerian2 regressions to quantify the role that schooling plays in explaining the vast disparities in income across countries. Bils and Klenow (2000) observe an inverse relationship between returns to schooling and average schooling levels in the cross-section of countries, and so they develop a model with diminishing returns to schooling in the production of human capital efficiency units at the individual level. While this approach is consistent with their cross-country observation, it is no longer consistent with within country observations: namely, 1) the linear relationship in the cross-section of individuals within a country (i.e., the relationship from which Mincerian returns are actually estimated), and 2) the evidence that returns to schooling fluctuate, while average schooling levels rise. In summary, although this cross-country literature has incorporated microevidence on the returns to schooling, the approach of modeling these returns as a technol-

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2Mincer (1974) proposed an efficiency units model, in which log wages were linearly related to years of schooling, and under certain conditions the return (i.e. the coefficient on schooling) equals the interest rate. A Mincerian regression is a regression of log wages on years of schooling, controlling for experience, experience squared, and possibly other factors.
ogy parameterization has difficulties reconciling both the within-country and cross-country evidence.

Nevertheless, examining cross-country evidence is a natural approach to studying the determinants of the return to schooling. The variation in the returns to schooling across countries is considerable larger, than the variation over time within a country. For example, in a cross-section of seventy-two countries, the lowest ten percent had Mincerian returns averaging 4.1 percent, while the top ten percent had returns averaging 17.3 percent. In comparison, the entire rise in the returns to college between 1950 and 1990 ranged from 7.7 percent in 1950 to 12.9 percent in 1990. A key question is the extent to which this variation can be thought of as the consequence of variation in supply and demand within a competitive labor market framework, and the extent to which the returns depend on institutional differences across countries.

I follow the lead of the literature on the time trend of the return to schooling, which has evaluated the extent to which the trends can be explained as the equilibrium outcome of a competitive labor market model with changes in the supply and demand of educated labor. This research has primarily focused on short-run fluctuations and so has typically taken the changes in the supply of education as exogenous. Since the bulk of cross-country variation in the returns to school appears to be long term structural variation, I endogenize the supply of schooling and link this endogenous supply to the available data on factors whose variation may more plausibly be taken as structural: variation in government funding of education; fertility rates; life expectancy/expected career lengths and discount rates. While these factors do indeed show trends and fluctuations over the period of interest, the time variation in the data is small relative the cross-country variation.

Mincerian returns are available for seventy-two countries, but only fifty-nine of these countries had all other data necessary for the analysis.

See Goldin and Katz (2000). Variation in the returns to high school was even less over this period.


The model is also appropriate in that years of schooling is a continuous choice variable for agents. This is preferable to a simple categorical choices (e.g. college-high school or educated-uneducated) used in the examination of short-term time trends for two important reasons. First, the empirical cross-country evidence on the returns to schooling is in the form of Mincerian returns from a collection of comparable country studies compiled
Variation in the demand for education across countries is also considered. The literature on skill-biased technical change argues that newer technologies are skill-biased. In harmony with this literature, I test a static variant of the model in Kaboski (2002), in which the demand for heterogeneous skills is positively related to the level of technology. The technology level (and hence the demand for skill) is characterized by two country-specific parameters calibrated to match the levels of income per worker and average years of education in each country.

Calibrated simulations were performed for the fifty-nine countries for which the appropriate data was available. The simulated returns are significantly correlated with the data at a 0.0001 significance level with a coefficient of 0.50. Nevertheless, the model is only able to explain the high Mincerian returns observed in the data for high rates of time preference that imply real interest rates that average 9.2 percent. At interest rates of six percent, the returns are only five percent. The gap between the model’s returns and returns in the data cannot plausibly be explained by unobserved costs to schooling. At the high real interest rates, the model is able to explain twenty-seven percent of the variation in the data.

Counterfactual simulations, in which countries were assumed to be identical to one another in all dimensions except one, suggest that direct costs variation plays a significant role in explaining the variation of returns to schooling. The variation in direct costs comes from variation in school funding per student, a result of both fertility rates and (moreso) other school funding factors. Variation in fertility rates alone explained nine percent of the variation in the data, while variation in other school funding factors explained eighteen percent. Variation in effective discount rate and career length played small, though positive roles in explaining the variation of returns. Technology played a perverse role in explaining returns to schooling because we tend to see high demand for schooling in low return countries. That is, the Mincerian returns in simulations with only technology variation were negatively correlated with observed Mincerian returns. Nevertheless,
technology was the most important factor for explaining income per worker, while technology and school funding factors (other than fertility rates) were the most important in explaining the variation in levels of schooling across countries.

The model and simulations emphasize several important factors related to the differences between measured Mincerian returns, the average private return to a marginal increase in schooling, and the predicted growth effects of schooling increases. First, without assuming utility costs to schooling (as in Bils and Klenow) or capital market constraints, the true marginal return to schooling are much smaller than measured returns, about four percent instead of nine percent. Second, because of a positive association between heterogeneous wages and the returns to schooling, applying Mincerian returns to a representative agent model will tend to underestimate the growth effects of schooling increases. Third, in models of heterogeneous human capital, where changes in relative supply effect changes in relative wages, the average marginal effect of additional schooling can substantially overestimate the effect of a discrete change in schooling levels. Using the cross-section of countries to calibrate this diminishing response to higher education levels supplied (as in Bils and Klenow), does not adequately account for this effect, since it ignores the effect that varying demands for education have on these prices. Quantitatively, however, the underestimation arising from return heterogeneity, and the overestimation from discrete changes nearly cancel each other out in the simulations.8

The rest of the paper is organized as follows. The model and equilibrium equations are developed in Section 2. Section 3 describes the data and calibration methodology, and presents the estimated values of key technology parameters. The simulation results, model performance, and predictions from counterfactual simulations are discussed in Section 4, and Section 5 concludes.

2 Model

I present a static variant of the model of endogenous choice of schooling level developed in Kaboski (2002). The model is a competitive equilibrium in

8Thus, Bils and Klenow's assertion that the direct (i.e. excluding possible externalities) growth effects coming from schooling do not explain a large fraction of growth is supported, since without using utility costs I find smaller true returns to schooling.
which agents choose their occupations and levels of schooling to maximize income, taking wage schedules as given. Likewise, a representative firm rents capital and hires workers, taking the rental rate and wage schedule as given. Within a country, a distribution of heterogeneous workers differ in their ability level. Across countries, economies will differ in their length of potential career (determined by entrance age, life expectancy and retirement age), levels of government expenditure per pupil (determined by levels of government funding for schooling and fertility rates), and technology levels. I first discuss the firm’s problem, followed by the agents’ problem, then the equilibrium, and finally the cross-country heterogeneity in the model.

2.1 Production

A representative firm produces output using a technology that is Cobb-Douglas in capital $K$ and aggregate labor services $L$. Aggregate labor services $L$ are a function of the output $x(i)$ of a continuum of imperfectly substitutable tasks (or occupations) indexed by their level of complexity $i$. These tasks are performed by a continuum of workers indexed by their skill level $h$:

$$ Y = AK^{1-\alpha}L^\alpha $$

$$ L \equiv \left( \int_0^I x(i)^{1-\mu} di \right)^{\frac{1}{1-\mu}} $$

and

$$ x(i) = \int_{-\infty}^{\infty} a(i, h)l(i, h)dh \text{ where } a(i, h) \equiv \tilde{a}(i, h)^\alpha $$

Here $l(i, h)$ indicates the amount of labor of human capital (or skill) level $h$ at work in task (or occupation) $i$. $a(i, h)$ is a labor productivity parameter specific to both task and skill level, and $I$ is the maximum complexity level of any existing task. The output $x(i)$ of a given task is the sum of the outputs of agents of different skill levels $h$ who work in task $i$.

Kaboski (2001) derives these equations from a production function with heterogeneous human capital and physical capital that is both task- and human capital-specific. $A(i, h)$ can thus be thought of as not only a function of human capital productivities, but also the relative productivities and prices of complementary physical capitals.

Notice that the task outputs produced by labor with different skills are perfect substitutes, only if they are working in the identical task.
The positive function \( a(i, h) \) represents the productivity that a worker of human capital level \( h \) has in task of complexity level \( i \). It is assumed to be positive and twice differentiable. In addition, I make the following three assumptions:

Assumption 1: \( \frac{\partial a(i, h)}{\partial h} \geq 0 \)

Assumption 2: \( \frac{\partial^2 \log a(i, h)}{\partial i \partial h} > 0 \)

Assumption 3: \( \frac{\partial^2 \log a(i, h)}{\partial h^2} < 0 \)

Assumption 1 is an assumption that workers with higher levels of skills have an absolute advantage over less skilled workers, and ensures that wages will be increasing in skill level. Assumption 2, termed “log super-modularity”, is a statement of comparative advantage; workers with higher levels of skill have a comparative advantage in performing more complex tasks. The rationale is that while anyone can do simple tasks reasonably well, it is skill that enables workers to excel in more difficult or complex jobs. The assumption will lead to a sorting equilibrium, in which more skilled laborers work in more complex tasks. Assumption 3 is an assumption of log diminishing returns – in any given task, incremental gains in skill yield increasingly smaller percentage gains in productivity.

The following simple parameterization will be used in the quantitative analysis:

\[ a(i, h) = h^i \]

This parameterization is differentiable, continuous and can be easily shown to satisfy Assumptions 1-3.

The firm simply maximizes profits by choosing labor and capital taking wages \( w(i, h) \) and interest rates \( R \) as given:

\[
\max_{K, l(i, \ldots)} Y - RK - \int \int w(i, h)l(i, h) di dh
\]

The firm’s first-order conditions are therefore:

\[ R = (1 - \alpha)A \left( \frac{L}{K} \right)^{\alpha} \]  
(3)

\[ w(i, h) \geq \alpha \left( \frac{K}{L} \right)^{1-\alpha} L^\mu [x(i)]^{-\mu} a(i, h) \]  
(4)

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where condition (4) holds with equality for \( \forall (i, h) \) such that \( l(i, h) > 0 \).

### 2.2 Households

I assume a measure-one distribution of agents differing only in a heterogeneous parameter \( \theta \), which I will refer to as ability.\(^{11}\) The distribution of \( \theta \) follows \( g(\theta) \), a density function that is everywhere positive and finite along a bounded interval \([\overline{\theta}, \Bar{\theta}]\). Without loss of generality, I assume that all agents in a country have the same level of initial wealth \( B \). An agent’s level of skill \( h \) is simply the sum of years of schooling \( s \) and ability \( \theta \). Taking wages and schooling costs as given, agent \( \theta \)’s objective is to choose a level of schooling and an occupation to maximize lifetime income net of direct schooling costs. The agents’ problem is therefore:

\[
\max_{\forall (i, h) \in [1, I]} \int_0^s \{ \eta [z, e(z), F] \} w(i, h)dz
\]

where \( T \) is the agent’s “potential career” the number of total years that can be allocated toward schooling or work, \( r \) is the effective discount rate of future income, and \( \tau(s; T, r) \) is the amount of effective time spent in the labor force. \( R \) is both the gross interest rate and the rental rate of capital. \( \eta \) is the ratio of direct schooling costs (i.e. tuition) to indirect schooling costs (i.e. foregone wages). It is the difference between the true cost of schooling and the government subsidy per person, and is a function of the level of schooling \( s \), the level of government educational funding \( e(s) \) at each level of schooling, and the fertility rate \( F \) in the country. In sum, the first term of equation (5) is wage income, the second term is capital income, and the summation is the direct cost of schooling born by the agent.\(^{12}\)

\(^{11}\)This parameter \( \theta \) could represent inherent ability, family background characteristics, or any other heterogenous quality that is a complementary to education in increasing skill or wages.

\(^{12}\)This note addresses two features of the model that might appear peculiar at first glance.

First, the direct costs of schooling are proportional to the indirect costs (foregone earnings, i.e. wages) as is government funding. Schooling costs are not strictly related to the true foregone earnings, however, since the costs are proportional to the agents’ end wage,
I will assume that $w(i, h)$ is continuous and strictly concave in both $i$ and $h$ and later verify this in equilibrium. Given this assumption, the objective is strictly concave in $i$. Taking first order conditions, the optimality condition for the household’s choice of occupation $i$ is:

$$\left\{ \tau(s; T, r) - \int_0^s \{\eta[z, e(z), F]\} w(i, h) dz \right\} \frac{\partial w(i, h)}{\partial i} = 0$$

The term in brackets is necessarily positive, or agents would remain unschooled and not work, so this first-order condition simplifies to:

$$\frac{\partial w(i, h)}{\partial i} = 0$$

That is, given their skill level, agents work in the task that pays them the highest wage.

The first-order conditions for the household’s choice of schooling is:

$$\frac{\partial \ln w(i, h)}{\partial h} = \frac{1 + \eta[s, e(s), F]}{\tau(s; T) - \int_0^s \{\eta[z, e(z), F]\} w(i, h) dz}$$

The intuition behind the first-order conditions is clear. The left-hand side shows the benefit (i.e. the increase in wages) that comes from schooling, the right hand side shows the costs. The costs in the numerator are the foregone wage and the cost of an additional year of schooling, the implied increased not the foregone wage at each level of schooling. That is, not only does the cost of a marginal year of schooling increase with the years of schooling, but the costs of all years of schooling increase. One rationale for this assumption is that agents who eventually go on to secondary (or tertiary) need to attend higher quality primary schools than those who stop at primary school. The primary reason for this peculiarity is for mathematical tractability, however. Also, both the costs (relative to wages) and funding levels of schooling are allowed to differ across the level of schooling $j$.

Second, as noted in Kaboski (2001) since agents’ human capital level, $h$, is the sum of their inherent ability and their schooling level, schooling and ability appear to be oddly separable in producing “human capital”. This separability does not exist for human capital in the traditional sense of the word, however. The value $h$ is simply an index of skill. It cannot be thought of as an amount of embodied capital stock that receives a constant price per unit as standard human capital does. In simulations, schooling $s$ will be shown to be linearly related to log wages, as Mincer observed. Thus, defining $\tilde{h} \equiv e^h = e^{s+\theta}$ would produce this more traditional “capital” where $\tilde{h}$ would receive a constant observed price. Such a redefinition also illuminates the complementarity of ability and schooling in increasing productivity and wages.
costs of earlier years of schooling are the terms subtracted from \( \tau(s; T, r) \) in the right-hand side denominator.

In the simulations, the function \( \eta(s, e(s), F) \) is a step function varying over primary, secondary and tertiary education and is therefore discontinuous over \( s \). The function therefore contains some kinks and the first-order conditions for \( s \) do not always hold with equality (see Appendix A).

### 2.3 Equilibrium

Solving for an equilibrium involves applying the market clearing conditions for labor inputs (of different skill level \( h \) and in different tasks \( i \)) and for capital and is quite similar to Kaboski (2001). Assumptions 1 and 2 produce a increasing mapping of abilities to occupations \( i(\theta) \), and skill levels to ability \( h(\theta) \). Since the unknown function \( i(\theta) \) is strictly increasing, and the unknown function \( i(h) \) is strictly increasing along relevant sections (i.e. regions where \( h \) has positive density), they can be inverted. The derivation that follows can be expressed more intuitively using these inverse functions, denoted \( \theta(i) \) and \( h(i) \).

Labor market clearing simplifies to:

\[
I(i, h) = \begin{cases} 
    g(\theta(i))\theta'(i)\tau[s(i); T, r] & \text{for } h = \theta(i) + s(i) \\
    0 & \text{otherwise}
\end{cases} \tag{8}
\]

In words, the demand for labor of type \( h \) working in task \( i \) must equal the supply. For task-skill combinations that satisfy \( h = h(i) \), the supply is the density of workers of the type \( \theta \) that choose task \( i \), times the number of years that these workers spend in the labor force, given their optimal level of schooling. The \( \theta'(i) \) term is the Jacobian term from transforming the density in terms of \( \theta \) to a density in terms of \( i \). For task-skill combinations that are not optimal, the supply is zero.

Given the amount of labor, the amount of task \( i \) produced is therefore\(^\text{13}\):

\[
x(i) = a[i, h(i)]\tau[h(i) - \theta(i); T, r]g(\theta(i))\theta'(i) \tag{9}
\]

\(^{13}\)Equation (2) assumed that the mass of tasks was distributed across a two-dimensional \( (h, i) \) plane. This density would need to be integrated across \( h \) in order to reduce the dimensionality to one (the \( i \) dimension). The existence of the function \( h(i) \) shows that the problem was already one-dimensional, and the mass is distributed along the line \( h(i) \). Hence no integration is needed.
Combining the expression for wages (4) that comes from firm optimization, with household optimality condition in the choice of $i$ (6), one can easily derive the constant elasticity of substitution expression:

$$\frac{a_1(i, h)}{a(i, h)} = \mu \frac{x'(i)}{x(i)}.$$  \hfill (10)

Taking logs and differentiating (9) and combining with (10) yields a second order differential equation in the matching function $\theta(i)$. Omitting functional dependencies, this equation is:

$$\theta'' + \left( \frac{g'}{g} - \frac{\tau'}{\tau} \right) \theta' + \left( \frac{a_2}{a} + \frac{\tau'}{\tau} \right) h' + \left( \frac{\mu - 1}{\mu} \right) \frac{a_1}{a} = 0$$  \hfill (11)

This differential equation\footnote{In the quantitative simulations, $\eta$ is a discontinuous function of $s$. Hence, the mapping $i(\theta)$ and $h(\theta)$ are only piece-wise differentiable, and a series of differential equations satisfying (11) define $i(\theta)$ and $h(\theta)$.} yields the optimal choice of $i$ given $\theta$. The corresponding optimal choice of $h$ (and therefore $s$) can be easily found by applying (??). These policy functions satisfy the labor market clearing conditions by construction.

The market clearing condition for capital is:

$$K = RB - \int CS(\theta)g(\theta)d\theta$$  \hfill (12)

Here $CS(\theta)$ is the total direct cost of schooling of agents of type $\theta$.\footnote{The total direct costs of schooling for agent $\theta$ is:}

For a given level of capital $K$, substituting the optimal policies $\theta(i)$ and $h(i)$ into (8), (9), (4), and (3), yields the equilibrium quantities of labor, levels of task production, wages and the interest rate, respectively.

## 2.4 Cross-Country Heterogeneity

Though the model presented above is for a single economy, the empirical exercise will involve multiple countries. Each economy is modeled as a closed
economy, i.e. using the model above, but having country-specific parameter levels.

On the production side, two key technology parameters \( (A \text{ and } I) \) are country-specific, and so subscripted by \( n \). \( I_n \) represents both the amount of available tasks, and the complexity level of the most complex task. While \( A \) is simply a skill-neutral productivity parameter, \( I \) is a skill-biased technology parameter and so effects both output and the demand for skill. First, \textit{ceteris paribus}, higher values of \( I \) translate into higher productivity and output levels via the Romer growth effect; a larger range of tasks allow increased specialization and higher marginal products of each task.\(^{16}\) Second, higher \( I \) values cause productivity gains from skill to be larger. This can be easily seen by looking at the marginal wage return to skill in the model:

\[
\frac{\partial \ln w(i, h)}{\partial h} = \frac{i}{h} 
\]

The return to skill is increasing in both \( i \) and increases in \( I \), translate into increases in \( i \) (for all but the measure zero least skilled worker), and higher returns to skill in the economy.

The relationship between higher productivity and higher demands for skill driven by \( I \) is in harmony with the large empirical and theoretical literature showing that technological innovation has been skill-biased both recently\(^{17}\) and across extended periods of the twentieth century.\(^{18}\)

In addition, cross-country heterogeneity in \( K \), like heterogeneity in \( A \), produces cross-country variation in output levels, but does not affect decisions on schooling levels.

There are three supply-side factors that are country-specific, and based on available data:

1. Potential career lengths, \( T_n \), which involves the the age of school entrance, and the minimum of either life expectancy or the retirement age;

\(^{16}\) Also, the increased average productivity coming from increased average values of \( i \) for most workers is a secondary way in which higher \( I \) values translate into higher output.


2. The effective rate for discounting future income, \( r_p \), which involves the real interest rate, the growth rate of wages, and the wage return to experience. Higher interest rates imply higher discount rates, while higher growth in wages imply lower discount rates because the present opportunity cost of time is smaller relative to the future opportunity cost of time.

3. The ratio of direct to indirect costs of schooling at various levels of schooling, \( \eta(s, c(s), F) \), which varies because the fraction of income spent on public educational funding \( c(s) \) at different levels of schooling varies across countries and because the fertility rate varies across countries. As a function \( c(s) \) varies across primary, secondary, and tertiary education. Both the durations of these levels and the public spending vary across countries. Fertility effects direct costs because countries with high fertility rates must divide funds across more people.

The distribution of inherent ability \( \theta \), labor’s share \( \alpha \), and \( \mu \), the parameter governing the elasticity of substitution between tasks, are additional parameters that are constant across countries.

3 Data and Calibration

This section briefly describes the data used, the methodology used to calibrate key technology parameters, and the resulting values. A more detailed description of the data and calibration methodology is given in Appendix B.

The simulations aim to match the international cross-section of economies in 1990, chosen because it was the year of best data availability. Although the model is static, because of trends in the data and the implicit timing in the model, relevant years for data must be chosen. For example, I use fertility and life expectancy data averaged over 1960-1970, since I am concerned with members of the labor force in 1990. Details of these decisions are again included in Appendix B. The target Mincerian returns are also averages over the period 1975 to 1995. The panel variation in these data is small relative to the cross-sectional variation.

The cross-country dataset, original data sources, and data programs are available at http://kaboski.econ.ohio-state.edu/ccmincerdata. Data variables in this dataset play three roles in the analysis, as either a direct input into the model as a parameter value, a target variable for estimating technology
parameters, and/or a variable for evaluating the model’s predictions. Table 1 presents the summary statistics of the crucial data variables used.

The calibration involves four main components: 1) calibration of distribution of ability \( g(\theta) \), which is common to all countries; 2) calibration of effective working time \( \tau(s; T, r) \) as a function of potential career, schooling, and an effective discount rate; 3) calibration of the ratio of direct to indirect costs of schooling at various levels of schooling, \( \eta(s, e(s), F) \), as a function of government expenditures on education at different levels and fertility; and 4) calibration of both the common and country-specific technology parameters.

3.1 Distribution of Ability

The density of the distribution of ability \( g(\theta) \) is assumed constant across all countries. Given the human capital production function, inherent ability should be measured in year of schooling equivalents. Using a test score proxy for ability, Cawley, Heckman and Vytlacil (1999) estimate that in log wage terms, the gain from being in a higher ability quartile is about 1.5 times the gain from an additional year of school in the United States.\(^{19}\) Since the available evidence is on ability quartiles, the uniform distribution of ability \( \theta \) was used with a range of ability equal to six (i.e. \( \theta - \theta = 4 \times 1.5 = 6 \)). The lower bound \( \theta \) was chosen to match the model’s prediction of the average difference in years of schooling between the 25th and 75th percentile to the cross-country average in the data as close as possible. The highest value the model could produce, 4.4 years relative to 5.8 years in the data, was for \( \theta = 7 \). Since the model’s range is smaller than the data, the ability bias may be overstated in the model.

3.2 Effective Working Time

Effective working time is a function of length of schooling, potential career length, and a discount rate. Potential career length \( T \) is calculated as the difference between min(life expectancy, retirement age) and primary school entrance age.

I assume a simple parameterization of \( \tau(s; T) = T - s \), since the linearity in \( s \) allows me to analytically represent \( h(\theta) \). This functional form, however,

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\(^{19}\)Their results range from 1.3 to 2.3 for different race-gender groups. Since the numbers for white males and white females – the bulk of the labor force – are 1.4 and 1.4 respectively, I calibrate to a value of 1.5, which is intermediate but close to the mode.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Coeff. Of Variation</th>
<th>Min</th>
<th>Max</th>
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<td>2.5</td>
<td>0.40</td>
<td>2.29</td>
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<td>Avg. Mincerian Return</td>
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<td>2.7%</td>
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<td>10200</td>
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<td>0.37</td>
<td>0.5</td>
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<td>0.8%</td>
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<td>0.4%</td>
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<td>54.2</td>
<td>4.8</td>
<td>0.09</td>
<td>43.1</td>
<td>61.0</td>
</tr>
<tr>
<td>Effective Discount Rate</td>
<td>5.2%</td>
<td>0.3%</td>
<td>0.07</td>
<td>4.3%</td>
<td>6.4%</td>
</tr>
<tr>
<td>A (Skill Neutral Tech. Parameter)</td>
<td>36.9</td>
<td>20.5</td>
<td>0.56</td>
<td>6.5</td>
<td>87.9</td>
</tr>
<tr>
<td>I (Skill-Biased Tech. Parameter)</td>
<td>1.62</td>
<td>0.27</td>
<td>0.17</td>
<td>1.13</td>
<td>2.43</td>
</tr>
</tbody>
</table>

*Notes:* Fertility and life expectancy have been adjusted for infant mortality. Fertility data are divided by two to yield F (offspring per capita). Potential career length are values for T (i.e. before adjusting for discounting, growth and experience). Effective discount rates are for $\rho=0.067$, and I and A are the calibrated values for $\rho=0.067$ and $\mu=0.7$. 
does not account for the discounted effect of additional years of $T$ at the end of a person’s life. To incorporate this I rescale $^{20}$ $T$ values to account for discounting at a rate $r_n = \tilde{r}_n - \gamma_n - x$, which incorporates a country-specific real interest rate, $\tilde{r}_n$ and growth in wages, $\gamma_n$, and a linear $^{21}$ return to experience $x$ common across all countries.

The growth in output per worker (1960-1990) is used as a measure of $\gamma_n$. I use the real interest rate $\tilde{r}_n$ implied from the neoclassical growth model’s Euler equation given the growth rate of consumption (income per equivalent

$^{20}$A typical life-cycle approach would express lifetime earnings as:

$$\int_{s}^{T} e^{-\tilde{r}(t-s)} w(s + \theta; s)e^{\gamma(t-s)} e^{x(t-s)} dt$$

which, comparing to lifetime wage earnings in (5), would yield:

$$\tilde{\tau}(s; T, r) = \frac{e^{-r(T-s)} - 1}{-r}$$

where $r = \tilde{r} - \gamma - x$. The rescaled values $\tilde{T}$ equate effective working times:

$$\tau(s; \tilde{T}) = \tilde{T} - s = \frac{e^{-r(T-s)} - 1}{-r} = \tilde{\tau}(s; T)$$

$^{21}$My omission of a quadratic return to experience departs from the Mincerian model, but allows me to get a closed form expression for $\tau$. I do not view this as a crucial problem, however. For the average country for which we have returns to experience, they were positive over the first 38 years of experience, and workers worked on average only 48 years of experience. Given discounting these last ten years are already given quite small weight. A better way to account for this uncertainty is to evaluate the robustness of results to $(g + x - r)$. 

15
per capita, 1960-1990) in the data.\textsuperscript{22}

### 3.3 Direct Schooling Costs

The ratio of direct to indirect schooling costs $\eta(s,e(s),F)$ paid by students is calibrated as a step function varying across primary, secondary, and tertiary education. The length of schooling at each of these levels varies across countries according to the data. The direct costs paid by students are calibrated as the difference between true direct costs relative to indirect costs $\bar{\eta}$ (common to all countries) and $\bar{\eta}_{j,gov}$, which is paid by the government (country-specific).

The calculation of $\bar{\eta}_{j,gov,n}$ involves dividing total government expenditures at a certain level, by total direct costs at that level. Similar to Kaboski (2001), I assume that the government designates a fraction of output $e_j$ and divides it among the young generation.\textsuperscript{23} The ratio of direct costs paid by the government to indirect costs is therefore equal to the total government funding at level $j$ ($e_jY_j$) divided by the ratio of total costs of schooling (which depends on costs of schooling, number of students, and years in school of each

\textsuperscript{22}The Euler equation from a neoclassical growth model implies:

$$\gamma_c = \frac{1}{\theta}(r - \rho)$$

I calibrate the intertemporal elasticity of substitution to be to be unity, and therefore:

$$r = \gamma_c + \rho$$

We assume the discount rate to be common across all countries. For a standard value of $\rho = 0.04$, the implied discount rates $r_n$ are too small to reconcile the high level of Mincerian returns in the data. I therefore require a higher discount rate ($\rho = 6.7$) in order to produce $r_n$ high enough to match the average Mincerian return in the data. I view these high effective discount rates as likely the result of credit market imperfections.

\textsuperscript{23}The determination of this fraction, indeed the source of this bequest, is not described in the model above. In order to allow this to be mapped into available data, I assume that the funding is a bequest from an unmodeled previous period.
student) to indirect costs. The formula is:

\[
\tilde{\eta}_{j, \text{gov}, n} = \frac{e_{j-1}Y_{j-1}}{F_j \int s_j(\theta)\tilde{\eta}_j w(\theta)g(\theta)d\theta} \tilde{\eta}_j = \frac{e_{j-1}Y_{j-1}}{F_j \int s_j(\theta)w(\theta)g(\theta)d\theta}
\]  

(14)

where \(s_j\) is the number of years of schooling at level \(j\).

I calibrate the true cost of schooling \(\tilde{\eta}_j\) using the calculated values of \(\tilde{\eta}_{j, \text{gov}, n}\) by looking at the average value of the subsidy level \(\tilde{\eta}_{j, \text{gov}, n}\) across countries that fully funded education at level \(j\). For primary and secondary, fully funded countries were those with compulsory schooling at each level, while for tertiary schooling I used a subset of countries with no tertiary school tuition and at least 90 percent of total tertiary expenditures were publicly funded.

### 3.4 Technology Parameters

The production technology parameters in the model include the share of capital \(\alpha\), the 2\(N\) country-specific technology parameters \(I_n\) and \(A_n\), and \(\mu\), the inverse elasticity of substitution.

The share of capital is set at 2/3, which is consistent with Gollin (2002)’s finding that capital’s share ranges from 25 to 40 percent across countries and is uncorrelated with income levels.

For each country \(n\), \(I_n\) and \(A_n\) are calibrated to match GDP/worker and average education levels.25

---

24 Here \(e_{j-1}\) is the fraction of output that the government spent on education at level \(j\) in the previous period and \(Y_{j-1}\) is output per worker in that previous period. The numerator is therefore total government expenditures on education at level \(j\) per worker in the previous period. \(F_j\) is the ratio of agents in the modeled period to agents in the unmodeled previous period. The cost of a year of schooling at level \(j\) for agent \(\theta\) is \(\tilde{\eta}_j\) times the wage of agent \(\theta\). The total cost of schooling at level \(j\) for agent \(\theta\) is this cost times the number of years of schooling at level \(j\) that agent \(\theta\) attains. Integrating over all values of \(\theta\) yields the average total cost of schooling at level \(j\) per agent in the current period. The ratio of total government spending per previous period agent to total costs per previous period agent is clearly the fraction of total costs paid for by government funding. A ratio greater than one would indicate that governments give additional subsidies beyond the direct costs of schooling. Multiplying this by \(\tilde{\eta}_j\) yields the ratio of government subsidy to the wage \(\tilde{\eta}_{j, \text{gov}, n}\).

25 If data on average years of schooling and GDP/worker are taken to be the true values, the calibrated values correspond precisely to consistent point estimates from a method of moments estimation on a large, representative cross-section of workers.
The elasticity of substitution in the model is the elasticity of substitution between tasks, but most estimates are of the elasticity of substitution between workers of different skill levels. For example, Katz and Murphy (1993) use a college/high school elasticity of 1.4, which would yield an inverse elasticity of 0.7. Kaboski (2002) calibrates a similar model to match US variation in schooling levels over time also using a value of 0.7. However, in the model, workers of different skill levels work in different tasks, but they are perfect substitutes within tasks and any worker can potentially perform any task. In the context of the model, the elasticity of substitution between workers can be viewed as an upper bound estimate of the elasticity of substitution between tasks. We therefore check the robustness of our results to higher values of $\mu$.

Values for $\theta$, $\mu$, $I_n$, and $A_n$ cannot be solved analytically, and are instead solved via simulation, which involves solving the relevant differential equations in the policy function. The details of the computation/simulation are outlined in Appendix C.

The calibrated technology values, together with the Mincerian returns, for the sample of countries are listed in Appendix D.

4 Results

I discuss, first, the model’s predictions and fit of the model in predicting Mincerian returns, next the counterfactual simulation results, then the implications for the true returns and growth effects of education, and finally robustness checks on the calibration and findings.

4.1 Baseline Model Fit

For typical interest rates of 6.5 percent (implied by a 4 percent rate of time preference and 2.5 percent growth in consumption), the Mincerian returns in the model fall well short of the observed Mincerian returns. They average just 5.2 percent, relative to 9.0 percent in the data. This is true despite the inclusion of direct costs of schooling, true foregone earnings at all levels of schooling\(^{26}\), and an ability bias calibrated using results based on AFQT tests. Simulations measuring how large additional costs (e.g. transportation, utility

\(^{26}\)In Mincer (1974), schooling does not subtract from the length of one’s career, but only delays the career.
costs, other costs) would of schooling would have to be to produce Mincerian returns in the data at typical interest rates indicate that these costs would need to average about two and a half times foregone earnings. Such costs were viewed as unreasonable. Instead, as mentioned in the previous section, higher interest rates were calibrated to reconcile the model with the data.

The summary statistics of this baseline simulation with these preferred parameter values (a time preference of 6.7 percent implying average interest rates of 9.2 percent) is given in the second column of Table 2. The resulting estimates are positively correlated with the . The returns in the model are significantly (at a 0.0001 significance level) correlated with those in the data with a correlation of 0.50. However, the variation in the model is only half that in the data, so that the pseudo-\( R^2 \) is only 0.27. The \( R^2 \) values are “pseudo”, since they are merely the analog of a regression \( R^2 \), equal to one minus the ratio of unexplained variation in the data relative to the model to variation in the data relative to the mean. There is no \textit{ex ante} reason that this \( R^2 \) is positive, however, since the model might predict high returns in low return countries and vice versa, and hence do worse than mean in predicting observed returns.

Figure 1 is a scatterplot of the predicted Mincerian returns against actual Mincerian returns. One can see that the model can not explain the extremely high returns in the data, since the simulated values fall well below the forty-five degree line.

### 4.2 Counterfactuals

Counterfactuals simulations isolate the roles of different sources of variation in the simulated distribution of Mincerian returns, schooling levels, and income per capita. These counterfactuals were simulated by only allowing variation in a single factor (e.g. fertility, career lengths), and "turning off" (i.e. equalizing\(^{27}\)) all other factors across countries\(^{28}\), in order to see effect

\(^{27}\)The “equalized” constant value, \( Z \), for a given factor \( Z \) is the value that matches the average Mincerian return in the cross-section of countries in the data, when \( Z \) is the only factor equalized. \( A \) and \( K \) do not affect Mincerian returns, however, so \( K \) is cross-sectional average of \( K_n \) and \( \bar{A} \) is the corresponding average output per capita in the cross-section of countries in the data.

\(^{28}\)Simulations in which variation in a single factor was “turned off” relative to the baseline, were also run. The magnitude of the effects were both quantitatively similar and supported the claims made about the relative importance of different factors.
### Table 2: Simulations Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Actual Data</th>
<th>Baseline Model</th>
<th>No Variation Model</th>
<th>Only Technology (A &amp; I) Variation</th>
<th>Only Career Length (T) Variation</th>
<th>Only Discount Rate (r) Variation</th>
<th>Only η*Fertility Variation</th>
<th>Only Fertility (F) Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mincerian Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>9.0%</td>
<td>9.0%</td>
<td>9.0%</td>
<td>8.9%</td>
<td>9.0%</td>
<td>9.0%</td>
<td>9.0%</td>
<td>9.0%</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.7%</td>
<td>1.4%</td>
<td>0.0%</td>
<td>0.4%</td>
<td>0.2%</td>
<td>0.4%</td>
<td>1.1%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td>--</td>
<td>0.27</td>
<td>0.00</td>
<td>-0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.18</td>
<td>0.09</td>
</tr>
<tr>
<td>Correlation with Actual</td>
<td>1.00</td>
<td>0.51</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.36</td>
<td>0.19</td>
<td>0.43</td>
<td>0.46</td>
</tr>
<tr>
<td><strong>Years of Schooling</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>6.2</td>
<td>6.2</td>
<td>6.2</td>
<td>5.8</td>
<td>6.2</td>
<td>6.6</td>
<td>6.4</td>
<td>6.4</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.5</td>
<td>2.5</td>
<td>0.0</td>
<td>1.4</td>
<td>0.2</td>
<td>0.4</td>
<td>1.2</td>
<td>0.6</td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td>--</td>
<td>1.00</td>
<td>0.00</td>
<td>0.46</td>
<td>0.10</td>
<td>-0.07</td>
<td>0.68</td>
<td>0.25</td>
</tr>
<tr>
<td>Correlation with Actual</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.72</td>
<td>0.72</td>
<td>-0.16</td>
<td>0.94</td>
<td>0.62</td>
</tr>
<tr>
<td><strong>Income/Capita</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>15,400</td>
<td>15,400</td>
<td>15,400</td>
<td>14,700</td>
<td>15,400</td>
<td>15,400</td>
<td>15,500</td>
<td>15,500</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>10,200</td>
<td>10,200</td>
<td>-</td>
<td>5,300</td>
<td>100</td>
<td>300</td>
<td>800</td>
<td>400</td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td>--</td>
<td>1.00</td>
<td>0.00</td>
<td>0.69</td>
<td>0.02</td>
<td>-0.10</td>
<td>0.12</td>
<td>0.04</td>
</tr>
<tr>
<td>Correlation with Actual</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.93</td>
<td>0.73</td>
<td>-0.18</td>
<td>0.74</td>
<td>0.56</td>
</tr>
</tbody>
</table>

*Notes:* The baseline model matches average years of schooling and income/capita country by country in the data by construction. The constant parameters in the no variation counterfactual were chosen individually to match the average Mincerian returns in the cross-section of countries to the baseline model. "Only η*fertility variation" has no fertility variation, but only variation in η, the ratio of direct costs to indirect costs, independent of fertility. "Pseudo-$R^2$" of variable X is $1-(\Sigma(X_{data}-X_{model})^2/\Sigma(X_{data}-X_{mean})^2)$. 
Figure 1: Mincerian Returns - Model vs. Data
on the distributions of Mincerian returns, schooling levels, and income per capita across countries. The value of the isolated factor was chosen to leave the average Mincerian returns in the cross-section of countries unchanged. Since technology involves two parameters ($A$ and $I$), this counterfactual also leaves average output unchanged. Two types of counterfactuals were used that affect $\eta_j$, the ratio of indirect to direct schooling costs. The first of these counterfactuals is the effect of fertility variation, keeping $\eta_j \times F_j$ constant. The second counterfactual is the effect of $\eta_j$ variation independent of fertility, that is, allowing variation in $(\eta_j \times F_j)$, while keeping $F_j$ constant. I report the total effect of variation at the primary, secondary, and tertiary levels.

Returning attention to Table 2, one can see the results of the counterfactual simulations. We compare the counterfactual results to both the no variation and the baseline results. In terms of explaining the variation in Mincerian returns, variation in the direct costs of schooling (caused by variation in funding per student relative to wages) plays the largest explanatory role. Within this category fertility variation alone produces a pseudo-$R^2$ of 0.09, while $\eta_j \times F_j$ alone produces a pseudo-$R^2$ of 0.18. The correlations for the two variables are similar, but the extra explanatory power comes from the higher standard deviation in returns caused by $\eta_j \times F_j$ variation.

Compared to these school funding variables, career length and discount rate variation play relatively small roles. The discount rate has a small effect because it does not vary much in the data (see Table 1). Career length plays a relatively small role because of the high calibrated discount rate needed to match average returns. At this discount rate, additional years at the end of a career have only small effects on discounted lifetime earnings.

Technology variation actually produces perverse variation in the model. This is because demands for schooling ($I$) is negatively correlated with returns (in both the data and the model). That is, although high education countries have lower returns to school, as Bils and Klenow note, they are nevertheless countries with high demands for schooling.

Technology does play a large role in explaining variation in output per capita explaining seventy percent of the variation (much of the remainder comes from variation in capital stocks per worker which is not shown). Technology also, together with $\eta_j \times F_j$ play the largest roles in explaining variation

\footnote{Note that because of different distributions of schooling $s$ across countries, equalized values of $\eta_j \times F_j$ may imply very different government spending levels $e_j$.}
in schooling attainment.

4.3 “True” Returns to Schooling

Several “true” measures of the average gains to schooling can be drawn from the model. The three measures differ from each other, but are all lower than the measured Mincerian returns (in both the data and simulations). The resulting predictions for these returns are presented in Table 3. I compare each of these returns with those implied by efficiency units models that use Mincerian returns, using Bils and Klenow (2000) as an example.

The “average marginal return” in the first column represent the average marginal log wage return:

$$E \left[ \frac{\partial \ln w(i, h)}{\partial s} \right] = \int \frac{i(\theta)}{h(\theta)} g(\theta) d\theta$$

(15)

In Table 3, this measure averages only 5.8 percent across countries, which is much lower than the Mincerian return averages of 8.9 in the data, respectively. The reason for this can be seen by examining (15) together with a heuristic version of the household’s first-order condition for choosing schooling (??):

$$\frac{i}{h} = \frac{1 + \eta}{\tau - \eta s} = \frac{(w + \eta w)}{(\tau w - \eta sw)}$$

After multiplying by $\frac{w}{w}$, the numerator in the right hand side is obviously the indirect and direct cost of an additional year of schooling, while the denominator is lifetime income net of direct schooling costs. This must equal the marginal return to schooling on the left hand side. Direct costs of schooling are small relative to foregone earnings (i.e., $\eta$ is highest at the tertiary level and still averages just 0.44), and so the total cost of a year of schooling is small relative to discounted lifetime earnings net of schooling costs, not more than five percent (see Section 4.4 below). This holds even given the fact that we add an additional 2.7 percent to the rate of time preference ($\rho$) in order to match the high returns in the data.\(^{30}\)

\(^{30}\)Realizing this issue, Bils and Klenow added utility costs to schooling in order to reconcile observed Mincerian returns and observed schooling levels within a representative agent model.

21
<table>
<thead>
<tr>
<th>Variable</th>
<th>Average Marginal Return</th>
<th>Average Marginal Wage Gain</th>
<th>Average Discrete Wage Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>5.8%</td>
<td>6.9%</td>
<td>6.0%</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.7%</td>
<td>0.9%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Correlation with Mincerian Return in Model</td>
<td>0.49</td>
<td>0.54</td>
<td>0.47</td>
</tr>
<tr>
<td>Correlation with Mincerian Return in Data</td>
<td>0.27</td>
<td>0.28</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Table 3: Measures of Returns to Schooling in Model
The “average marginal wage gain” in the second column is the average percent wage gain coming from a marginal increase in schooling:

\[
\frac{E \left[ \frac{\partial w(i,h)}{\partial s} \right]}{E[w]} = \frac{\int w(\theta) \left( \frac{i(\theta)}{w(\theta)} \right) g(\theta) d\theta}{\int w(\theta) d\theta}
\]

Equivalently, it would be the percentage change in wages per capita that would result from a marginal increase in schooling for the entire distribution of workers. The average marginal wage gain differs from the average marginal return in that it is wage-weighted average of the marginal returns, while the average marginal return is an unweighted average. Since high wage agents are those with high levels of schooling and high marginal returns in the model, the wage-weighted average exceeds the unweighted average, 6.9 percent relative to 5.8 percent. The distinction is only present in a model of heterogeneous agents with heterogeneous returns to schooling.\(^{31}\)

The “average discrete wage gain” in the third column is the average percent wage gain coming from a discrete additional year increase in schooling:

\[
\frac{E [w(i,h) - w(i,h+1)]}{E[w(i,h)]}
\]

The distinction here is that productivities suffer from log diminishing returns by Assumption 3, so that discrete gains will be smaller than marginal wage gains. Again, the assumption of diminishing returns was necessary in order allow for the possibility that returns to schooling decrease as levels of schooling increase, which is observed empirically.

Bils and Klenow observed this relationship in the cross-section of countries and so posited that the production function for efficiency units of human capital exhibited diminishing returns. They calibrate the amount of diminishing returns using the international data. My theory suggests that this would not adequately account for the true diminishing returns in the production function, since countries with higher levels of average schooling also have higher demands for average schooling (higher \(I\) in the model). Essentially, Bils and Klenow estimate a demand curve for years of schooling. By

\(^{31}\) The microliterature on the returns to schooling has also emphasized the importance of heterogeneity in the returns to schooling (see Heckman and Vytlacil (2000), Heckman, Tobias and Vytlacil (2001)). Naturally, heterogeneity also produces the issue of how increases in average schooling are distributed across the population. Here I measure the effect of a uniform increase.
assuming that the price per unit of human capital is fixed by a perfectly elastic demand, they can impute the way that the marginal units of human capital implied by marginal increases of schooling varies across different levels of schooling. The assumption is that the demand curve for schooling is constant across countries, and so shifts in the supply of schooling identify demand. In my model, the demand for skills varies across countries (through \( I \)) and the calibration implies that countries with higher average quantities of schooling are those with greater demand for skills. Without the higher demand for schooling, high schooling countries would have returns even lower than observed.

Quantitatively, for a one year increase in schooling, the downward bias from heterogeneity almost exactly cancels out the upward bias from diminishing returns. That is, the average discrete wage gain, which accounts for both diminishing returns and heterogeneity, equals 6.0 percent, while the average marginal return, which accounts for neither is 5.8 percent. All three measures are well below the average Mincerian returns in the data used by Bils and Klenow.

4.4 Robustness

The robustness of the results presented were checked to variations in the parameters \( \mu \) (equal to 0.99, 0.9, and 0.8) and \( r \). The results were remarkably robust to variations in \( \mu \).

For reasonable values of discount rates and therefore real interest rates (i.e., \( \rho = 0.04 \) and \( \tilde{r} = 0.065 \)), the models Mincerian returns were much lower (averaging about five percent). In addition, lower values of \( \tilde{r} \) produced lower discount rates and therefore life expectancy, and retirement rates became somewhat more important in explaining variation in the returns, together playing almost as large a role as fertility.

5 Conclusions

The simple model incorporating in supply and demand variation, but no major institutional differences (e.g. differences in labor markets/institutions, credit markets, inequality, or school quality) yielded reasonable simulated results able to explain about twenty five percent of the variation in the data. The major findings are 1) at typical real interest rates, the model can not
explain the high level of Mincerian returns in the data and 2) variation in the
direct costs of schooling resulting from different fertility rates and funding
rates are the major causes of variation in the data that the model incorpo-
rates.

The model also produced refinements in understanding the growth effects
of educational investments in relation to the Mincerian return. The results
only serve to support the argument of Bils and Klenow (2000) that the direct
growth effects of schooling increases are a small fraction of total growth.
While their work underestimates the growth effect because of heterogeneous
returns, they overestimate the return because of diminishing returns. Overall,
these two effects approximately cancel out, and given the relatively small
costs of schooling, wage gains from schooling are much smaller than observed
Mincerian returns.
References


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[34] Sattinger, M. “Comparative Advantage and the Distribution of Earnings and Abilities.” *Econometrica*, 43 (May 1975): 455-468


[38] Winter-Ebmer, R. "Public Funding and Enrollment into Higher Education in Europe", IZA Discussion Series Paper #503, 2002


[40] World Development Indicators 2002, cd-rom, 2002
6 Appendix A

The necessary first-order conditions for the household’s choice of schooling is:

\[
\frac{\partial \ln w(i,h)}{\partial h} \leq \frac{1+\eta_1}{\tau(0;T,r)} \text{ for } s = 0
\]

\[
\frac{\partial \ln w(i,h)}{\partial h} \in \left( \frac{1+\eta_1}{\tau(s;T,r)-\eta_1 s}, \frac{1+\eta_2}{\tau(s;T,r)-\eta_2 s} \right) \text{ for } 0 < s < \bar{s}_1
\]

\[
\frac{\partial \ln w(i,h)}{\partial h} \in \left( \frac{1+\eta_2}{\tau(s;T,r)-[(\eta_1-\eta_2)\bar{s}_1+\eta_2 s]}, \frac{1+\eta_3}{\tau(s;T,r)-[(\eta_1-\eta_2)\bar{s}_2+\eta_3 s]} \right) \text{ for } \bar{s}_1 < s < \bar{s}_2
\]

\[
\frac{\partial \ln w(i,h)}{\partial h} \geq \frac{1+\eta_3}{\tau(s;T,r)-[(\eta_1-\eta_3)\bar{s}_1+(\eta_2-\eta_3)(\bar{s}_2-\bar{s}_1)+\eta_3 \bar{s}_2]} \text{ for } s = \bar{s}_2
\]

\[
\frac{\partial \ln w(i,h)}{\partial h} \geq \frac{1+\eta_3}{\tau(s;T,r)-[(\eta_1-\eta_3)\bar{s}_1+(\eta_2-\eta_3)(\bar{s}_2-\bar{s}_1)+\eta_3 \bar{s}_2]} \text{ for } s = \bar{s}_3
\]

(16)

7 Appendix B

7.1 Imputed Data

The three modification or imputations that were made involved: 1) the government educational expenditure data, 2) the fertility and life expectancy data, and 3) indicators for countries with fully funded primary, secondary, and/or tertiary education.

1. The government expenditures at a given level of education as a fraction of output \( e_j \) are calculated from data on expenditures per pupil by level of education, enrollments at different levels, and the government educational expenditures as a fraction of GDP. That is, for each level of education \( j \), I multiply the expenditures per pupil at level \( j \) by enrollment at level \( j \), to yield total expenditures at level \( j \). I then use these values of total expenditures to get the relative split of total expenditures between primary, secondary, and tertiary education. I then

---

32In the case where \( \eta_1 \leq \eta_2 \leq \eta_3 \), the problem is concave in \( s \) and these conditions are sufficient conditions. Otherwise, these conditions are only necessary conditions, and it is possible that the above conditions hold for multiple values of \( s \). The maximum can be found by comparing the objective function across the finite number of potential \( s \) values satisfying \((??)\).
multiply these by educational expenditures as a fraction of GDP, to yield $e_j$ values.\footnote{For two countries, West Germany and Indonesia, I had missing data and could only get the relative split of expenditures between primary and secondary levels. For these values, I use the sample average to get the split between tertiary and non-tertiary spending, then used the primary-secondary split to subdivide non-tertiary expenditures.} Finally, higher education expenditures were adjusted downward to account for the fact much of higher education expenditures are for research services, not educational services. The downward adjustment factor of 0.5 is consistent with available data on the relative fraction of expenditures used for education and research.\footnote{Available data (NCES, 2001) are for the U.S. in 1996-97: obvious educational services (instruction and student services) totaled $72.3$ billion, while obvious non-educational services (i.e. research, hospital services and independent operations, auxiliary services, and public services) totaled $68.1$ billion. Other services that are less easily categorized (i.e. libraries and other academic services, plant and operations, and institutional support) totaled $31.1$ billion.}

2. Since the choice between work and education in the model begins at the primary school entrance age, I adjust fertility (downward) and life expectancy (upward) to eliminate variation associated with infant mortality variation. Thus, I use total fertility of children that survive beyond the first year, and life expectancy of children that survive beyond the first year.

3. Countries with compulsory primary and/or secondary education were assumed to fully fund those levels of education, respectively. The list countries with fully funded tertiary education was based on meeting at least one of two criteria: 1) over 90 percent of tertiary expenditures were public based in 1995 or 1999 based on an OECD data of all OECD and some non-OECD countries (OECD, 2002), and 2) having no tuition costs for European countries (Winter-Ebmer, 2002). This data on which countries have fully funded education is only used to calibrate the cost of schooling parameters $\eta_j$, as discussed in Section 3.2.2, and so need not be a complete.

7.2 Timing

The exercise aims to match the international cross-section of economies in 1990, which was chosen because it was the year of best data availability. A summary of other timing decisions in the data:
• 1990 values were used for output/worker, capital/worker, and educational attainment distributions.

• For fertility, life expectancy, earlier years are used, namely the averages for the years 1960, 1965 and 1970.

• For the duration of primary and secondary schooling, the averages for the years 1965, 1970 and 1975 are used. These data are relatively stable over time.

• For retirement ages, the available data is for 1990 and 1999. Since, I am modeling the labor force that is working in 1990, I use the 1999 values.

• Data on educational expenditures is not available for all countries in earlier years. Therefore, in calculating subsidies, I use time averages of the fraction of government educational expenditures as a share of output, as well as the relative distribution of these expenditures across primary, secondary and tertiary levels. Total government expenditures as a fraction of output do not show a strong trends within countries during this period. The distributions of these trends across primary, secondary and tertiary education do exhibit small trends whose direction varies from country to country. Estimating either a global trend or country-specific trends is problematic because of missing observations and compositional changes in the sample. In the case of both total government expenditures and the distribution of expenditures across schooling levels, the time variation within a country is small compared to the cross-country variation, however.

• The years of available Mincerian return estimates is much more sporadic and country-specific. Again, the time variation is small-compared to the cross-country variation, so I again use time averages of the available data.

• The only available data on years of compulsory schooling and the age of entrance into primary school were for 1993 and 1997. If available, I used the 1993 value. Otherwise, the 1997 value was used.
7.3 Calibration of Schooling Costs

I calculate the expectation in (14) by transforming this equation into an equivalent integral in $s$:

$$
\tilde{\eta}_{j,\text{gov}} = \frac{e_{j-1}Y_{-1}}{F_j \int s_jw(s)v(s)ds}
$$

The distribution of schooling levels in the data is used to form a density of schooling levels $v(s)$ and $s_j$ is easily calculated directly from schooling duration and attainment data. Given the Cobb-Douglas technology, wages are proportional to income per worker, and so the $\frac{w(s)}{Y}$ relationship is approximated using the Mincerian return data.

That is, given the Mincerian return $m$, wages can be expressed:

$$
w(s) = w(0)e^{ms}
$$

where $w(0)$ is an unknown constant. Given the Cobb-Douglas technology, labor is a constant share we can see that it is proportional to income we use the following relationships:

$$
\frac{\int_0^{T-s}w(0)e^{ms}v(s)ds}{Y} = \alpha
$$

$$
\frac{\int_0^{T-s}e^{ms}v(s)ds}{\alpha} = \frac{w(0)}{Y}
$$

The formula for calibrating $\tilde{\eta}_j$ is: I therefore calibrated:

$$
\tilde{\eta}_j = \frac{\sum_n FF_{j,n}\tilde{\eta}_{j,\text{gov};n}}{\sum_n FF_{j,n}}
$$

where $FF_{j,n}$ represents the country indicator variable for fully funded education at level $j$.

8 Appendix C

The approach used to compute the endogenous simulations was to discretize the ability space $[\theta, \bar{\theta}]$. Sixty equally spaced points were chosen. The actual differential equation solved is not (11), but its equivalent equation in terms
of the inverse $i(\theta)$. Using the chain rule, I first substitute $h'(i) = h'(\theta)\theta'(i)$ into (11):

$$
\frac{\theta''}{\theta'} + \left( \frac{g'}{g} - \frac{\tau'}{\tau(h-\theta; \bar{T})} \right) \theta' + \left( \frac{a_2}{a} + \frac{\tau'}{\tau(h-\theta; \bar{T})} \right) h'(\theta) + \left( \frac{\mu - 1}{\mu} \right) \frac{a_1}{a} = 0
$$

Substituting in for $\tau$, using the inverse rule for derivatives, and again ignoring functional dependency, we can write:

$$
\frac{-i''(\theta)}{[i'(\theta)]^2} + \left( \frac{g'(\theta)}{g} + \frac{[1-h'(\theta)]}{T-h+\theta} + \frac{a_2}{a} h'(\theta) \right) \frac{1}{i'(\theta)} + \left( \frac{\mu - 1}{\mu} \right) \frac{a_1}{a} = 0
$$

$$
\left( \frac{g'(\theta)}{g} + \frac{[1-h'(\theta)]}{T-h+\theta} + \frac{a_2}{a} h'(\theta) \right) i'(\theta) + \left( \frac{\mu - 1}{\mu} \right) \frac{a_1}{a} [i'(\theta)]^2 = i''(\theta)
$$

Given the uniform distribution for $\theta$, the derivative of the density function will be zero and $\frac{g'}{g}$ drops out of the equation. $a$ has the functional form:

$$
a(i, h) = h^{i+\phi}
$$

Differentiation yields:

$$
\frac{a_1}{a} (i, h) = \ln(h)
$$

$$
\frac{a_2}{a} (i, h) = \frac{i}{h}
$$

Finally, I use optimality in the choice of schooling (equation (16)) to solve for $h$:

$$
h = \begin{cases} 
\frac{\theta}{1+i} \left[ \frac{\bar{T}}{1+\eta_1} + \theta \right] & \text{for } s = 0 \\
\frac{i}{1+i} \left[ \frac{\bar{T} - (\eta_1 - \eta_2)s_1}{1+\eta_2} + \theta \right] & \text{for } 0 < s < \bar{s}_1 \\
\frac{i}{1+i} \left[ \frac{\bar{T} - (\eta_1 - \eta_2)s_1 + (\eta_2 - \eta_3)(s_2 - s_1)}{1+\eta_3} + \theta \right] & \text{for } s = \bar{s}_1 \\
\frac{i}{1+i} \left[ \frac{\bar{T} - (\eta_1 - \eta_2)s_1 + (\eta_2 - \eta_3)(s_2 - s_1) + (\eta_3 - \eta_4)(s_3 - s_2)}{1+\eta_4} + \theta \right] & \text{for } \bar{s}_1 < s < \bar{s}_2 \\
\frac{i}{1+i} \left[ \frac{\bar{T} - (\eta_1 - \eta_2)s_1 + (\eta_2 - \eta_3)(s_2 - s_1) + (\eta_3 - \eta_4)(s_3 - s_2) + (\eta_4 - \eta_5)(s_3 - s_2)}{1+\eta_5} + \theta \right] & \text{for } s = \bar{s}_2 \\
\theta + \bar{s}_3 & \text{for } \bar{s}_2 < s < \bar{s}_3 \\
\theta + \bar{s}_3 & \text{for } s = \bar{s}_3
\end{cases}
$$
and taking a derivative and realizing the unwritten functional dependence $i$ on $\theta$ yields $h'(\theta)$

$$h'(\theta) = \begin{cases} 
    1 & \text{for } s = 0, \bar{s}_1, \bar{s}_2, \bar{s}_3 \\
    \frac{i}{1+i} + \frac{1}{(1+i)^2} \left[ \frac{T}{1+\eta_1} + \theta \right] i' & \text{for } 0 < s < \bar{s}_1 \\
    \frac{i}{1+i} + \frac{1}{(1+i)^2} \left[ \frac{T-(\eta_1-\eta_2)s_1}{1+\eta_2} + \theta \right] i' & \text{for } \bar{s}_1 < s < \bar{s}_2 \\
    \frac{i}{1+i} + \frac{1}{(1+i)^2} \left[ \frac{T-(\eta_1-\eta_3)s_1+(\eta_2-\eta_3)(\bar{s}_2-\bar{s}_1)}{1+\eta_3} \right] + \theta \right] i' & \text{for } \bar{s}_2 < s < \bar{s}_3 
\end{cases}$$

(19)

Using these expressions, the differential equation above is numerically solved using Matlab’s ode15s function. A simple shooting algorithm is used to solve for the boundary conditions: $i(\theta) = 0$ and $i(\bar{\theta}) = I$. 

34
## Appendix D: Calibrated Technology Parameters and Mincerian Returns

<table>
<thead>
<tr>
<th>Code</th>
<th>Country</th>
<th>$A$</th>
<th>$I$</th>
<th>Mincerian Return in Data</th>
<th>Mincerian Return in Model</th>
<th>Code</th>
<th>Country</th>
<th>$A$</th>
<th>$I$</th>
<th>Mincerian Return in Data</th>
<th>Mincerian Return in Model</th>
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Notes: Calibrated values are for $\rho=0.067$ and $\mu=0.7$. 

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### Notes: Calibrated values are for $\rho=0.067$ and $\mu=0.7$. 

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