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Essays on Skilled Workers and Economic Development

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A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy

ESSAYS ON SKILLED WORKERS AND ECONOMIC DEVELOPMENT

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by

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Abstract

This thesis consists of three chapters on skilled workers and the roles they play in economic development. In the first chapter, I use an overlapping generations model of education choice and skilled migration to study conditions under which a low-skill economy can grow its skilled labor force in the presence of skilled emigration. This occurs when skill premiums are low, and there are individuals in the economy who can afford an education. The model is calibrated to data on 23 low and middle-income countries. For 22 of the 23 countries, any increase in the rate of skilled emigration leads to a net decline in the steady-state proportion of skilled workers. This is because increasing skilled emigration rates increases *future* expected benefits to skill, but leaves *current* schooling costs the same. So more people do not obtain an education because cost constraints are binding. I then provide empirical evidence that the cost of education is relatively high in developing countries, and that these costs are likely binding using information on the (un)availability of student loan programs. Poland is the only country which benefits from skilled emigration due to a combination of very low skill premiums and low costs of education. For brain drain to lead to a net increase in human capital, reducing education costs and relaxing credit constraints are important policy responses.

The second chapter studies the effects of education policies emphasizing basic education at the expense of higher levels of education. Larger estimates of the wage returns to basic education compared to higher levels of education, after adjusting for public costs, are often cited as evidence of over-investment in higher education. These estimates have provided a justification for the shift of public funding towards basic education in many developing countries. This paper shows that these estimates are not reliable for education policy when productivity depends on the proportion of higher educated workers (a productivity externality), and higher educated workers are an input in the production of basic education (a human capital externality). A methodological contribution is describing how the productivity and human capital externalities could be separately identified. Using data on cross-country agricultural productivity gaps, and returns to education for immigrants in the U.S. by country of origin, I show that the productivity and human capital effects of higher educated workers are quantitatively important. The productivity and human capital effects are equal to, and in some cases greater than, the oft-cited difference between estimates of the public-cost-adjusted returns to basic and higher education. For most countries in the dataset, the externalities are large enough to rationalize observed education investments as optimal.

The final chapter studies the relative productivities of skilled and unskilled workers across countries. I break down the cross-country ratio of the productivity of skilled to unskilled workers into two components: the human capital embodied in skilled workers, and the physical productivity of skilled and unskilled workers which reflect production techniques. I find that skilled workers from rich countries embody more human capital (compared to poor countries), and skilled workers in rich countries are also more physically productive. This is interpreted as skilled workers from high-income countries being of better quality, and firms in high-income countries adopting more technologies that are skilled-complementary. Furthermore, for most of the 49 countries in my dataset, I find their production techniques to be inappropriate; the estimated physical productivity of skilled workers, relative to the unskilled, is too low given the skilled-unskilled labour ratio. Most countries could increase output by increasing the physical productivity of skilled workers, and decreasing that of unskilled workers. I also find that poorer countries tend to be farther away from their appropriate technologies. I compute 7-fold and 4-fold increases in GDP-per-capita for countries in the 2 lowest income quartiles, just from increasing the relative physical productivity of skilled to unskilled workers. The results suggest large barriers to the adoption of skilled worker complementary technologies, and also present a rationale for why increases in schooling attainment have not led to growth in several countries.

Keywords: Macroeconomics, Skilled Workers, Economic Development

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Chapter 1

Introduction

Why is gross domestic product (GDP) per person only $2048 in Ghana compared to $48,112 in the U.S. (The World Bank, 2012)? The quest to understand why some nations are richer than others is as old as economics itself, and we know from this literature that GDP per person in the U.S. is over 20-times as large as it is in Ghana because the U.S. uses factors of production more productively, has accumulated more factors of production, or both. This thesis is concerned with understanding how cross-country differences in one particular factor of production, the proportion of skilled workers, contributes to differences in GDP per person.

Skilled workers are defined as individuals who have, at least, completed primary schooling. This broad definition includes high school graduates, and individuals with vocational, professional and university degrees. The data reveal that about 40% of individuals aged 15 and over in Ghana have not completed primary schooling, compared to less than 1% of individuals in the U.S (Barro and Lee, 2010). In this thesis, I study why the proportion of skilled workers is so low in Ghana, and how the low proportion of skilled workers in Ghana translates into a 20-fold difference in GDP per capita (compared to the U.S.). A second encompassing theme in the thesis is the use of macroeconomic models and data to study the process of economic development.

The thesis is organized into three chapters. The first chapter deals with challenges posed by a brain drain for the expansion of the skilled workforce in many developing countries. Recent studies argue that a brain drain could increase private investment in education. Individuals who hope to emigrate acquire more education but not everyone who intends to emigrate ends up leaving, so an increase in the rate of skilled emigration could lead to a net increase in the proportion of skilled workers. I test the quantitative significance of this "brain gain" effect using a model of skill acquisition and emigration that is calibrated to estimates of cross-country skill premiums. I find that a brain drain lowers the proportion of skilled workers in the set of developing countries that I examine. This is because at over 50% of GDP per capita, the cost of higher education is large relative to income in many of these countries. Binding credit constraints make further private investments in education difficult.

The second chapter studies how education policies that emphasize public investment in basic education at the expense of higher levels of education, may inhibit the growth of a skilled workforce and economic development. These policies have been partly driven by social return estimates showing that returns are larger for basic education. In the chapter, I show that the standard estimates of social returns are not suitable for education policy. The chapter presents a framework that can be used to quantify the importance of higher educated workers for the human capital of basic educated workers and aggregate productivity. I find that after accounting for non-wage effects of higher educated workers, the social return to higher levels of education is a lot larger than standard estimates indicate. Reducing investments in higher levels of education leads to significantly lower productivity, and even lower returns to basic education as quality declines. In the process, I also show how the low proportion of higher educated workers in developing countries accounts for the low education quality and productivity observed in these same countries.

The final chapter investigates the sources of low productivity in developing countries. I build on the finding that relative to skilled workers, unskilled workers are more productive in low-income countries (Caselli and Coleman, 2006). This finding is regularly seen as a result of low-income countries choosing production techniques which are more complementary with unskilled workers. To assess this claim, I first decompose the productivity of skilled workers (relative to the unskilled) into productivity arising from the human capital embodied in the worker, and productivity resulting from the greater availability of production techniques complementary with skilled workers (physical productivity). I find that skilled workers are relatively more productive in high income countries, because they have more embodied human capital and high-income countries also use production techniques which are complementary with skilled workers.

I then assess the appropriateness of the estimated physical productivities (production techniques). I argue that the estimated physical productivity of skilled workers in low-income countries are too low to be considered appropriate. In Ghana for example, skilled workers are 50 times less physically productive compared to unskilled workers, and in Venezuela they are 100 times less physically productive. These relative productivity numbers are too low given that skilled workers are just as numerous as the unskilled in these countries, and embody more human capital. I further compare the estimated physical productivities to what would be optimal if firms chose technologies appropriately. I find that low-income countries are systematically farther behind from their optimal physical productivities. The poorest countries in the dataset could quadruple GDP per capita by increasing the physical productivity of skilled relative to unskilled workers, leaving all else the same. This suggests significant barriers to the adoption of technologies complementary to skilled workers in low-income countries.

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Chapter 2

Can Brain Drain Be Good For Human Capital Growth? Evidence From Cross-Country Skill Premiums and Education Costs

2.1 Introduction

A brain drain is the emigration of high-ability skilled labor from developing to more developed countries. Skilled workers are attracted to developing countries by relatively higher wages and better working environments. Developed countries actively adopt policies to attract even more skilled workers. For example, Canada and Australia pursue policies which admit immigrants based on skill level, and adaptability to the working environment.[1] Skilled migrants and their destination countries benefit from the increased mobility of skilled workers, but skilled migrants remain the single largest beneficiaries from the brain drain (Gibson and McKenzie, 2010).

However, the emigration of skilled labor presents a major challenge to economic growth for developing countries. Brain drain is of economic interest because it limits the ability of a poor economy to retain and increase its stock of human capital, which is widely identified as an important driver of economic growth. Table 2.1 provides some evidence on the over-representation of skilled workers in the pool of migrants from developing to developed nations.[2] The share of skilled workers in the adult population for low income countries is estimated at 3.5%. This pales in comparison to the percentage of skilled workers in the pool of emigrants originating from this group, which stands at 45.1%. The trend has been one of increased

[1]See Commander et al. (2003) for a discussion. There is currently a bill on the floor of the U.S. Congress demanding automatic permanent residence to foreign postgraduates. This is part of an ongoing global competition between countries for skilled workers

[2]For the estimates in Table 2.1, skilled workers are defined as individuals who have completed tertiary education.

skilled emigration relative to the unskilled. The ratio of the skilled to unskilled emigration rate was 33.7 in 1975, but in the year 2000 this ratio stands at 55. These numbers indicate that the proportion of skilled workers among migrants is considerably high and increasing.

Table 2.1: Emigration rates by country and skill groups

	Rate of Emigration(%)		Share of Skilled Workers(%)	
By Country Size	**Total**	**Skilled**	**Among residents**	**Among migrants**
Large countries(Pop>25 million)	1.3	4.1	11.3	36.4
Upper-Middle(25>Pop>10)	3.1	8.8	11	33.2
Lower-Middle(10>Pop>2.5)	5.8	13.5	13	33.1
Small(Pop<2.5)	10.3	27.5	10.5	34.7
By Income Group	**Total**	**Skilled**	**Among residents**	**Among migrants**
High Income	2.8	3.5	30.7	38.3
Upper-Middle Income	4.2	7.9	13	25.2
Lower-Middle Income	3.2	7.6	14.2	35.4
Low Income	0.5	6.1	3.5	45.1
UN Least Developed	1	13.2	2.3	34

Source: Docquier and Marfouk (2004)

What is the impact of increasing skill-biased emigration rates on developing countries? Recent models of brain drain (Mountford, 1997; Stark et al., 1998; Vidal, 1998) emphasize the positive role an opportunity to emigrate could play on the decision to obtain an education. This positive effect of emigration on education decisions is known as the *brain effect* of brain drain. Nevertheless, skilled workers are simply lost to the home country when they emigrate, the impact of the loss of skilled workers is known as the *drain effect*. The theory of beneficial brain drain has been well developed over the years, but there remains a gap in the literature on the relative size of the brain and drain effects, and how they may differ across countries.

This paper attempts to fill this gap by constructing, and calibrating, an overlapping generations (OLG) model of endogenous skill formation with skilled emigration. The model can be used to quantify the size of the brain and drain effects, and investigate how and why they differ across countries. In particular, I solve for the steady state of the model, and use it to quantitatively investigate the relative sizes of the brain and drain effects given different emigration rates. Attention is paid to how these effects might vary across countries depending on costs of education. These costs broadly refer to the quality of education, teaching infrastructure (books, schools, teachers), borrowing constraints, basic health outcomes and other factors beyond an individual's ability which influence the decision to obtain an education.

There are three main results in the paper. First, I find that if skill levels are low in an economy due to high costs of an education, increased emigration rates only reduce the proportion of skilled workers in the economy. The cost of education is high if the marginal individual is not obtaining an education because they cannot afford it, and not because the benefits are not high enough. Such an economy is cost-constrained. An increase in the rate of skilled emigration does increase the expected skill premium, but since it does not alleviate the affordability problem, it cannot lead to an increase in the proportion of individuals obtaining an education. The brain effect is non-existent for these economies, and the drain effect reduces the proportion of skilled workers in the economy. The only economies that stand to benefit from a brain drain are those where skill premiums are low. Skill premiums are low when the marginal individual chooses not get an education, even when they can afford it.

Secondly, I calibrate parameters of the model to skilled-unskilled labor ratios and wage premiums for a cross-section of 23 low and middle-income countries. I find that with the exception of Poland, skill levels are low in most of these countries because the marginal individual is cost-constrained. Increased rates of emigration lower the proportion of skilled labor for most of the countries. If skilled-labor is interpreted as those having a tertiary education, there is no brain effect for all countries other than Poland. They all lose from the brain drain because even though skill premiums are higher, they just cannot afford to pay for the up-front cost of education. Lastly, I find that if skilled labor is interpreted as secondary-educated workers, then for most countries there is a quantitatively significant brain effect since secondary education is more affordable. However, the brain effect is not strong enough to prevent a decrease in the proportion of skilled workers brought about by the drain effect. It turns out that most countries are net-losers from the brain drain at the secondary school level as well.

Poland finds itself in a seemingly unique situation with relatively lower costs of schooling, but very low skill premiums for its skill level. Poland has an unusually low skill premium for an economy with its proportion of skilled workers – the wage premium for tertiary educated workers in Poland is lower than those for secondary educated workers in all countries in the dataset. An increase in the rate of emigration increases the skilled-unskilled labor force, because the marginal individual is constrained by the low skill premium, and the opportunity to emigrate relaxes this constraint.

This result is important given the literature on whether increased emigration can act as a substitute for education subsidies, as in Docquier et al. (2008). The results here show that the marginal student in a typical developing country is cost-constrained, thus increased emigration rates cannot act as a substitute for subsidies. Increased emigration only helps when the problem, at the margin, is one of low returns to education. I present evidence in Section 5 showing that, for many developing countries, current costs of education are high, and the lack of comprehensive student loan programs present significant barriers to education.[3] These results imply that a reduction in barriers to education, at all levels, could be an effective response to rising skilled emigration in developing countries.

The next section presents a brief survey of the literature on brain drain and its impact on sending countries. Then, I present the model of skill formation and emigration, and derive some properties of the steady state equilibrium. The fourth

[3]See Duflo (2001); Task Force on Higher Education and Society (2002); Glewwe and Kremer (2006); Gibson and McKenzie (2010) for more evidence that costs of schooling are the important constraints to improving the proportion of the educated in developing countries.

section describes how parameters of the model are calibrated, solves for the steady state, and backs out the brain and drain effects for the countries in the dataset. I then present some data which indicate that financial barriers to tertiary education exist in many developing countries, which would limit the size of the brain effect. The final section concludes, and suggests some areas for future research.

2.2 Related Literature

There are several channels through which skilled emigration can theoretically impact sending nations; it can result in a reshuffling of the labor market which affects wages and employment for those left behind (Bhagwati and Hamada, 1974; Miyagiwa, 1991). Brain drain has consequences for human capital accumulation and retention (Mountford, 1997; Stark et al., 1998; Vidal, 1998). Migrants can impact the sending country through network effects and remittances (Commander et al., 2004). In this section, I briefly summarize the key insights from classic models of brain drain, and the newer beneficial brain drain models which focus on the impact it can have on human capital accumulation.

Classic models of brain drain

Early models of brain drain pioneered by Bhagwati and Hamada (1974), with a modern reincarnation in Miyagiwa (1991), emphasize the impact of brain drain on employment levels and wages. Bhagwati and Hamada (1974) study the impact of the brain drain on developing countries in the context of sticky wage models. The general finding from this line of research is that in most circumstances, brain drain is bad for those left behind in the source country. Brain drain unambiguously denies an economy access to its human capital.[4]

The early literature also pointed out the fiscal imbalances a brain drain might create. Over 70% of the costs of education in developing countries is financed from public sources (The World Bank, 2009). This implies that the decision to invest in human capital is not an entirely private one, and the loss also generates externalities. If the government finances current education hoping to increase its future tax base, and possibly increase funding for education in the future, then emigration leads to a loss in the government's future revenues and a reduction in funding for future public education. This led Bhagwati and Dellalfar (1973) to propose a special income tax imposed on migrants by their countries of origin to make up for this fiscal loss. Egger et al. (2007) and Desai et al. (2004) study the welfare impacts and feasibility of such a taxation scheme. Skilled emigrant taxes schemes have not been widely adopted by sending countries.[5] Perhaps the fact that skilled emigrants can switch their country of citizenship renders the tax on emigrating human capital impractical.

[4] Commander et al. (2003) has a good summary of this class of models

[5] A reviewer kindly pointed out that Belarus adopts such a scheme, which makes it the only country I am aware of taxing skilled migrants.

Newer beneficial brain drain models

The exogeneity of the decision to invest in education is important for the negative effects of brain drain obtained in the early literature. The recent literature emphasizes the idea that the prospect of skilled emigration can induce greater skill formation (Mountford, 1997; Stark et al., 1998; Vidal, 1998). Key to these models is the assumption that individuals take the probability of migrating to a higher wage economy into account when investing in education. On a micro-level, there is empirical evidence in support of this assumption. Gibson and McKenzie (2010) using survey data from 5 high-emigration countries, find that individuals invest early on in skills which may aid emigration prospects. In Ghana, for example, they find that individuals take special English and SAT classes, and change their programs of study in school in order to improve their chances of working or studying overseas.

The main finding from this line of research is that the prospect of emigration may induce additional human capital formation (*the brain effect*), and in certain situations, this can outweigh the loss in human capital brought about by skilled emigration (*the drain effect*). However, the literature on the net empirical effect of skilled emigration remains relatively sparse, and to the best of my knowledge, there is nothing on the relative sizes of the brain and drain effects across different economies.

Docquier et al. (2010) is closest in spirit to what I do here. They attempt to quantify the impact of the brain drain from a sending country's perspective. The authors construct and calibrate an overlapping generations (OLG) model of the world economy, divided into 10 regions. They find that the main impact of the brain drain lies in the inability of high skilled emigration nations to innovate. Their model differs from mine in that human capital (which is a crucial channel through which emigration can positively impact growth) is assumed to grow exogenously; this means that they cannot say much on the size of the "brain effect".

In Beine et al. (2008), the authors set out to uncover countries who have experienced a net increase in their human capital stocks due to increased migration prospects. To this end, they obtain estimates of the elasticity of human capital stock to changes in skilled emigration rates between 1990 and 2000. Every country is assigned the emigration rate of their unskilled, and the estimated elasticity is used to estimate what the human capital stock would have been had the skilled been allowed to migrate at the unskilled rate. The difference between this counterfactual and the observed human capital stock is interpreted as the effect of high skilled emigration. The results show that doubling the probability of emigration increases the stock of human capital by 5%. Similar to the result here, they also find that most countries are net losers from the brain drain.

Due to the fact that Beine et al. do not run their counterfactual within a richer model of migration and human capital formation, there is no clear idea of the size of the brain effect and how it relates to the drain effect across countries. The authors cannot say whether the cross-country difference in ex-post human capital stock is due to differences in the brain effect, or differences in the drain effect.

This distinction is important because understanding the factors which contribute to the net effect of brain drain (as opposed to the net effect itself) is more informative towards policy. Quantifying the brain and drain effects within a model not only allows us to uncover the winners/losers, but also uncover the mechanisms which produced the winners/losers. Given the recent literature on increased emigration as a possible alternative to education subsidies (see for example Stark et al. (1998) and Docquier et al. (2008)), an understanding of the size of the brain effect compared to education subsidies is important.

Zhang (2001) quantifies the size of the drain effect for the Chinese economy, while ignoring the brain effect. Using information on the number of emigrants and an estimate of their value to the Chinese economy, the numbers indicate that China has lost about 4-5 billion U.S. dollars annually due to increased emigration from 1978-1997. Desai et al. (2009) examine the fiscal loss associated with the brain drain in India's IT sector. They are mostly concerned with the loss in government revenue due to a reduced tax base. To this end, they estimate a conterfactual income distribution of the emigrants and calibrate the tax structure to match that of the Indian economy. They then back out the loss in government revenue due to emigration. They find that the loss is about one-half to one percent of India's gross national income.[6] A common problem with these papers is that if the brain effect is large, then they ignore the potential gains to government revenues from an increase in the proportion of skilled workers due to increasing brain drain.

This paper adds to the literature by focusing on the impact of skilled emigration on the skilled-unskilled labor ratio, and decomposing this impact into a brain and a drain effect. I also show that patterns of education costs and skill premiums, across countries, reveal important information regarding the potential impact of skilled emigration. These relationships, to the best of my knowledge, have not been quantitatively evaluated in the literature.

2.3 The Model

2.3.1 Economic Environment

The model is an OLG model of a small, open, infinitely-lived economy consisting of individuals who live for T periods. The finite-life of individuals in the model captures the life-cycle nature of education and migration decisions. The OLG structure of the model takes into account important inter-generational linkages to human capital formation (Glomm and Ravikumar (1992), Docquier et al. (2010)). At any given time, t, the economy is made up of individuals of different ages $a \in \{0, 1, 2..., T\}$ born at time $t - a$.

Individuals of a given cohort are born with different "ability" endowments, $\psi \in [0, \Psi]$; individuals born at any given time, draw their abilities from a continuous density function given by $g(\psi)$, which is associated with the continuous cumulative

[6]This loss is large, India's gross national income in 2008 is about 3.34 trillion purchasing power parity dollars (The World Bank, 2012)

density function $G(\psi)$. These endowments are meant to capture private ability to pay in order to acquire an education. A higher ability to pay, captured by a higher value of ψ, translates to a lower cost of education. Ability levels are commonly known, the only uncertainty in the model lies in whether a young individual who has chosen to obtain an education would emigrate.

Migration is only allowed after the first period of life provided individuals have obtained an education.[7] Skilled individuals who emigrate earn an exogenous wage premium given by $\rho > 1$, and the population of newborns grow exogenously at rate n. The rate at which the skilled emigrate is exogenously specified by π, which is assumed to be constant at every time period.[8] For tractability, it is assumed that when individuals emigrate, they take all of their human capital and savings along with them, which rules out network effects. Successful migrants pay cost m after emigrating; this captures the costs of transportation and settling down in the destination countries.

The interest rate on savings, r_t, is exogenously determined in the world economy, and the population of skilled migrants are assumed to be too small to influence wages in the receiving country. The last two assumptions are consistent with a small open economy where capital can flow freely, but labor flows are restricted. I abstract from labor-leisure decisions, return migration decisions, remittance decisions, and decisions to migrate later in life so as to isolate the "brain effect". Data on the nature of return migration are poor, making it infeasible to include in this study. Docquier et al. (2010) find that remittances are not a major factor in the impact of skilled migration on human capital formation.

The assumption that there are only 2 levels of education, skilled and unskilled (s, u), can be interpreted as capturing the level at which individuals become eligible to migrate as skilled workers - which in the case of developing to developed country migration, often corresponds to having a tertiary education. As it turns out, the interpretation of the level of education at which an individual becomes eligible to migrate may be important for the brain gain, and I explore this possibility further in Section 4. As a practical consideration, assuming only two skill types simplifies the production function and makes it comparable to those used in the literature. The unavailability of migration data for more than 3 levels of education makes a model with finer levels of eduction difficult to quantify.

2.3.2 Aggregate State Variables

In any given period t, the aggregate state is given by $\Omega_t = (K_t, \{\psi^*_{t-a}\}^T_{a=1})$, which consists of the aggregate capital stock K_t, and ψ^*_{t-a} denoting the ability level of the individual born in period $t-a$ who is just indifferent between obtaining and not obtaining an education. If everyone benefits from obtaining an education, then

[7] This is consistent with the data which show that unskilled workers migrate at very low rates.

[8] A constant rate of migration makes the model tractable but is not crucial for the steady-state results in the model. However, the endogeneity of π may be important especially when comparing two economies of very different sizes, but as a first attempt at the problem and given that most countries in the dataset are of comparable sizes, I take emigration rates as exogenous.

ψ^*_{t-a} = 0. It is assumed that parameters are such that the most able individual always finds it strictly beneficial to obtain an education, so that $\psi^*_{t-a} \in [0, \Psi)$ for all t and a. Finally, when solving their problems, individuals posit that the aggregate state evolves according to the functions: $K_{t+1} = \Gamma(\Omega_t)$ and $\psi^*_t = H(\Omega_t)$.

2.3.3 Consumer Problems

In this section, consumer problems are defined recursively beginning with the retired individuals of age T. Within a specific cohort, there are at most 3 types of individuals, the unskilled who always remain home $\{u, h\}$, the skilled who did not migrate $\{s, h\}$, and the skilled who migrated to a foreign country $\{s, f\}$. The consumer problem can be defined backwards beginning with age T individuals. In what follows, the wage rate, w, depends on the aggregate state Ω_t, and interest rate depends on time period t, the time subscript is suppressed for ease of exposition. Instantaneous utility is given by $U(\kappa) = \frac{\kappa^{1-\gamma}-1}{1-\gamma}$, where κ is current consumption and γ is the degree of relative risk aversion.

Age *T* individuals (Retired)

Given the aggregate state Ω_t, age T individuals only differ by their savings b, and location denoted by home, h, or foreign, f. These individuals are retired, and interest income is their only source of income. An age T individual with asset b consumes the income from his savings, and his continuation utility is given by:

$$V_T(b) = U(Rb) \quad \text{where,} \quad R = (1 + r).$$

Age *1 to T-1* individuals (Middle-aged)

All individuals of age $a \in \{1, 2...T - 1\}$ are endowed with 1 unit of time which they supply inelastically to the labor market. The individual state in this age group is summarized by savings $b \geq 0$, location $l \in \{h, f\}$, and skill level $j \in \{s, u\}$. The continuation utility of an individual in this group who is of age a is given by:

$$V^l_{a,j}(b, \Omega) = \max_{b'}\{U(w^l_j + Rb - b' - m\mathbb{1}_{\{a=1,l=f\}}) + \beta V^l_{a+1,j}(b', \Omega')\}$$

s.t.

$$\Omega' = (\Gamma(\Omega), H(\Omega)), \quad w^f_s = \rho w^h_s, \quad b' > 0, \quad \rho > 1.$$

Let their decision rule be denoted by $b^l_{a+1,j}(b, \Omega)$, where β is the discount factor. The migration premium on skilled wages is given by $\rho > 1$, and is exogenously specified. Lastly, note that if $a = 1$, and the individual has emigrated, the emigrant also has to pay migration costs m.

Age *0* individuals (Young)

Young age 0 individuals are endowed with E units of the consumption good, and they decide whether to acquire an education (become skilled) at cost $c(\psi_i)$.[9] They also decide on how much of their endowment to allocate towards savings $b \geq 0$, which imposes a strict borrowing constraint. The cost of becoming educated $c(\psi_i)$ is assumed to be strictly decreasing.

If they obtain an education, they emigrate with probability π at the end of the period, where they earn a wage rate which is directly proportional to the wage rate of the skilled who do not migrate. Individual state is represented by ability level ψ_i. For a young individual, investing in an education yields continuation utility given by:

$$V_0^s(\psi_i, \Omega) = \mathbf{max}_{b'}\{U(E - c(\psi_i) - b') + \beta[\pi V_1^f(b', \Omega') + (1-\pi)V_{1,s}^h(b', \Omega')]\}^{10}$$

$$\text{s.t. } \Omega' = (\Gamma(\Omega), H(\Omega)), \quad b' > 0.$$

If an individual does not invest in an education, his continuation utility is given by:

$$V_0^u(\psi_i, \Omega) = \mathbf{max}_{b'}\{U(E - b') + \beta V_{1,u}^h(b', \Omega')\}$$

$$\text{s.t. } \Omega' = (\Gamma(\Omega), H(\Omega)), \quad b' > 0.$$

Let the savings decision rule of a young individual be denoted by $b_{1,j}(\psi_i, \Omega)$, where $j \in \{s, u\}$. The young individual in deciding whether to invest in an education, solves:

$$V_0(\psi_i, \Omega) = \mathbf{max}_{s,u}\{V_0^u(\psi_i, \Omega), V_0^s(\psi_i, \Omega)\}.$$

A young individual will invest in an education if $V_0^s(\psi_i, \Omega) - V_0^u(\psi_i, \Omega) \geq 0$.

2.3.4 Firm Problem

Firms are perfectly competitive, country-specific, and live for just one period. They rent capital and labor, produce and then disappear. Production is governed by a constant returns to scale production function given by:

$$Y_t = A_0 K_t^{\alpha}(L_t)^{1-\alpha}.$$

[9]It is true that investment in human capital possibly occurs over the life cycle, but I am interested in human capital investment which is relevant to one's ability to migrate (these include investing in careers in high demand at probable destinations, ability to speak the foreign language, and knowledge of foreign cultures). As available data in Gibson and McKenzie (2010) and Beine et al. (2007) show, this type of human capital investment occurs relatively early in life.

[10]The skill type of migrants is suppressed since only those who get an education get to migrate.

Where, K_t is aggregate stock of capital in period t which completely depreciates every period. A_0 is a scale parameter which is exogenously specified. L_t is an aggregate of skilled and unskilled labor, I use the CES aggregator: $L_t = [\mu(L_t^s)^\eta + (1-\mu)(L_t^u)^\eta]^{1/\eta}$, where s and u stand for skilled and unskilled respectively.[11] The weight on skilled labor μ is restricted to be between zero and one.

Given $w^u(\Omega_t)$, r_t, $w^s(\Omega_t)$, the representative firm solves the profit maximization problem:

$$max_{\{Y_t, L_t^u, L_t^s, K_t\}} Y_t - w_t^u L_t^u - w_t^s L_t^s - r_t K_t$$
$$\text{subject to } Y_t = A_0 K_t^\alpha (L_t)^{1-\alpha}.$$

2.3.5 Definition of a Recursive Competitive Equilibrium

Given the population of initial old N_0, $g(\psi)$, $(n, \pi, \rho, \{\psi_{t-a}^*\}_{a=1}^{T}$[12], $\{r_t\}_{t=0}^{\infty})$, a recursive C.E. for every period t, consists of the value functions for all types of consumers, and their decision rules. Wage functions, $w_u^h(\Omega_t)$, $w_s^h(\Omega_t)$, aggregate laws of motion $\Omega_{t+1} = (\Gamma(\Omega_t), H(\Omega_t))$, and firm output Y_t and input decisions L_t^s, L_t^u and K_t such that:

1 Given prices and aggregate laws of motion, the value functions and decision rules solve the appropriate individual problems.

2 Taking pricing functions as given, firm input-output decisions maximize firm profits.

3 Markets clear in every period:

(i) Labor market:

$$L_t^u = \sum_{a=1}^{T-1} N_{0,t-a} \int_0^{\psi_{t-a}^*} g(\psi) d\psi,$$

$$L_t^s = \sum_{a=1}^{T-1} N_{0,t-a}(1-\pi) \int_{\psi_{t-a}^*}^{\Psi} g(\psi) d\psi.$$

The labor market consists of the market for skilled and unskilled labor for all middle-aged agents. The market clearing condition requires that the total number of employed unskilled labor be equal to the total number of unskilled in the population.

[11] I do not just add up skilled and unskilled labor because available evidence from U.S. data shows that the elasticity of substitution between skilled and unskilled labor lies somewhere between 1 and 2, which is far from perfect substitutability (Ciccone and Peri, 2005).

[12] The only restriction on ψ_{t-a}^* is that it is not equal to Ψ or zero for all age groups. This ensures that wages are well defined to begin. When I describe the steady state, then it becomes clear that on an equilibrium, it is never the case that everyone(or nobody) gets an education.

(ii) Goods market:

$$Y_t + N_{0,t}E = \chi_t + B_t + \int_{\psi_t^*}^{\Psi} c(\psi)g(\psi)d\psi.$$

Where $Y_t = r_tK_t + w_t^uL_t^u + w_t^sL_t^s$ and $N_{0,t}E$ is the total endowment of young agents. χ_t is total consumption for all agents in the economy, B_t is total savings for all agents, and the last term is the total consumption cost for those who obtain an education.[13]

4 Aggregate laws of motion are consistent with individual decisions. In particular, $H(\Omega_t)$ equals ψ_t^* which is the cut-off ability for the young born in period t.

2.3.6 The Decision Rules and Value Functions

In this section, I describe the decision rules and value functions for young agents. This would be useful in understanding how individual decisions change with prices, and in computing the steady state. First, let $X_{t,j}^{a,l} = w_{t,j}^{a,l} + Rb_t^a$ denote the individual's wage and rental income at period t. If $a = 1$, and the individual has successfully migrated, $X_{t,j}^{a,l}$ is net of migration cost m. Old, age T, individuals earn no wage income, and only consumer their savings with interest.

Savings and Continuation utility for $a > 0$, and young unskilled agents: Let $U(\kappa) = ln(\kappa)$ be the instantaneous utility function. Deriving the decision rules and value functions for this group of agents is straightforward. Since the interest rate is exogenous, with perfect credit markets and no borrowing constraints, for any skill level and location, individuals would consume a given fraction of their lifetime wealth in each period. However, with the no-borrowing constraint, if it turns out that the individual wants to consume more than the current income $X_{t,j}^{a,l}$, savings equal zero.[14]

The continuation utility for an individual at age $a \in \{1, 2..., T-1\}$, location $l \in \{h, f\}$, with skill level $j \in \{s, u\}$, as well as young unskilled agents will depend on their current and future wage and rental incomes. All unskilled individuals of a given age have the same lifetime utility regardless of ability. For skilled individuals and conditional on location, lifetime utility would vary by savings when young.

Continuation utility for young skilled agents: The continuation utility for young skilled agents will be increasing in ability. To see why, let $X_t(\psi) = E - c(\psi)$ denote the income of young agents net of education costs.

[13] K_t does not have to equal B_t since the interest rate is exogenously given, and capital is allowed to move freely across borders.

[14] I do not have to worry about precautionary savings for middle-aged and unskilled agents because there is no income risk.

The cost of education $c(\psi)$ is given by the function $e^{-\psi} + C$. The cost function has a component which is general to all individuals in the economy, C, and a component which varies with ability, $e^{-\psi}$. C is meant to capture general barriers to education, such as limited class capacity, poor teachers, access to quality books, libraries and teaching facilities. These are direct costs of education, which the individual cannot borrow against, and the no-borrowing constraint is partly intended to capture the effects of these costs.

Higher ability simply acts as an increase in current income, an income effect, which increases savings (weakly), because a poorer individual cannot be saving more than a richer one with identical future income prospects.[15] Since higher ability skilled individuals have more assets at the completion of schooling, and face the same future income prospects as lower ability skilled individuals, they also have higher continuation utilities. Thus, the the continuation utility of a young skilled agent, $V_{t,s}(\psi)$, is increasing in ability. Further, $V_{t,s}(\psi)$ is set to equal $-\infty$ if education costs are greater than income, that is $X_t(\psi) \leq 0$.

Cut-off Ability: It is easy to see that for all t, and for all agents of $a \in \{0, 1, 2..., T\}$, location $l \in \{h, f\}$, skill level $j \in \{s, u\}$, continuation utility, $V_{t,j}^{a,l}$, is increasing in current income, $X_{t,j}^{a,l}$. Further, $V_{t,s}(\psi)$ is increasing in ψ, because if for any two individuals $\psi_1 > \psi_2$, then $X_t(\psi_1) > X_t(\psi_2)$. A similar argument leads to the conclusion that the continuation utility of young unskilled agents, $V_{t,u}$, is constant across all young types, since $X_{t,u} = E$. Therefore a cut-off ability ψ_t^* exists in equilibrium, and is given by:

$$\psi_t^* = \begin{cases} \{\psi \mid V_{t,s}(\psi) - V_{t,u} = 0\} \\ 0 \quad \text{if } V_{t,s}(\psi) - V_{t,u} > 0 \quad \forall \ \psi_i \ . \end{cases}$$

A young individual acquires an education if the value of becoming skilled is greater than the value of being unskilled, that is $V_{t,s}(\psi) > V_{t,u}$. As I discuss later, ψ_t^* is never zero (or Ψ) since decreasing marginal returns impose an upper bound on the proportion of educated and uneducated individuals, so an equilibrium exists with a mix of the skilled and unskilled. This upper bound is derived in Section 4 in the context of a steady-state equilibrium. Next, I describe the steady state of the model. In particular, it is shown that the unique steady state is such that there is a mix of the skilled and unskilled.

2.3.7 Steady State Equilibrium

Definition of a Steady State: Given a constant gross interest rate $R = (1 + r)$, a steady state of the model is defined as an equilibrium where all aggregate variables grow at a constant rate, and the wage pricing functions are constant. Equivalently, the economy is on a steady state if the cut-off ability ψ_t^* equals ψ^* in all time periods.

[15] A simple algebraic proof involving derivatives for the case where $\pi < .5$ is also available.

Given R^*, N_0, $g(\psi)$, and $\tilde{\psi}$, a steady state is determined by the prices from the firm's problem, and the cut-off ability which yields the proportion of skilled. The set of equations below from the firm's problem gives the prices:

$$w_u^* = (1-\mu)(1-\alpha)AoK_t^{\alpha}L_t^{1-\alpha-\eta}L_{t,u}^{\eta-1}, \tag{2.1}$$

$$w_s^* = \mu(1-\alpha)AoKt^{\alpha}L_t^{1-\alpha-\eta}L_{t,s}^{\eta-1}, \tag{2.2}$$

$$w_f^* = \rho w_s^*. \tag{2.3}$$

Taking prices as defined above, asset holdings and continuation values can be derived as described in Section 3.6 for every generation. In the steady state, the continuation values of the young skilled and unskilled will be independent of time since prices are assumed to be constant. This implies that the cut-off ability, ψ^*, is constant across generations.

The aggregate variables are given by:

$$K_t^* = \left(\frac{\alpha Ao}{R^*-1}\right)^{\frac{1}{(1-\alpha)}} L_t^*,$$

$$L_t^{*u} = \sum_{a=1}^{T-1} N_{0,t-a}\int_0^{\tilde{\psi}} g(\psi)d\psi,$$

$$L_t^{*s} = \sum_{a=1}^{T-1} N_{0,t-a}(1-\pi)\int_{\tilde{\psi}}^{\Psi} g(\psi)d\psi,$$

$$L_t^* = [\mu(L_t^{*s})^{\eta} + (1-\mu)(L_t^{*u})^{\eta}]^{1/\eta}.$$

The economy is on a steady state if ψ^* is consistent with the prices and $\psi^* = \tilde{\psi}$.

Now assume that $\psi_t^* = \psi^*$ in all time periods and the interest rate is constant, from the aggregate variables above, it is evident that all aggregate variables Y_t, N_t, L_t^s, L_t^u, and K_t grow at rate n. Accordingly, per-capita variables as well as wages are constant over time. To see why this is the case, notice that since ψ^* is constant, the share of the skilled and unskilled in the population will be a constant. This means that L_t^s and L_t^u grow with the newborns at constant rate n, and the rest of the aggregate variables follow. This implies that we are on a steady state if and only if the cut-off ability is constant across generations.

Result 1 ***(Existence and Uniqueness of the Steady State)*** *Given a set of parameters such that $(E-C) \in (e^{-\Psi}, 1]$, the probability of migration $\pi < .5$, and $m < M$ where M is a big positive number, the model yields a unique steady state. The steady state has the property that a positive fraction, but not all individuals in the economy get an education.*

The assumption on $E-C$ ensures that barriers to education C are not large enough to prevent top-ability individuals from obtaining an education. The restriction on π is technical and guarantees that savings by young individuals are well defined, however it is also consistent with data on the rate of skilled emigration. The assumption on m ensures that when wage premiums are sufficiently high, some people will choose to migrate. A few definitions are in order before I present a sketch of the proof.

Let $\tilde{\psi}$ be the cut-off ability for all generations who are already living in the economy, which includes all retired and middle-aged agents.[16] Define $\overline{G}(\tilde{\psi})$ as the proportion of those who chose to get educated for living generations. Due to emigration, this may not equal the proportion of skilled currently living in the economy. Let ψ^* be the cut-off ability for the newborns consistent with the prices implied by $\overline{G}(\tilde{\psi})$. Finally, $\overline{G}(\psi^*)$ is the proportion of newborns who choose to get an education given $\overline{G}(\tilde{\psi})$.

Define a "transition" function that maps elements of $\overline{G}(\tilde{\psi})$ into $\overline{G}(\psi^*)$. The function takes a given proportion of skilled in the population, and gives us the proportion of newborns in the population who will get an education. A fixed point of this function is a steady state of the model, since the cut-off ability will be the same across all generations. Technically, the function is undefined at 0 and 1 because from eqs. (2.1) to (2.3), wages are undefined at those points.

However, in the interval $(0, 1)$, the transition function depicted in Figure 2.1 has the property summarised below. Result 1 is true if the remark is true, so I present a proof of the statement.

Remark Given the conditions in Result 1, as $\overline{G}(\tilde{\psi})$ approaches zero, the transition function lies above the 45-degree line. It is continuous, decreasing, hits zero at some point in the interval, and remains at zero thereafter.

The function is decreasing in the interval $(0, 1)$: If $\overline{G}(\tilde{\psi})_1 < \overline{G}(\tilde{\psi})_2$, then $w_s(\overline{G}(\tilde{\psi})_1) > w_s(\overline{G}(\tilde{\psi})_2)$ from the definition of wages in eqs. (2.1) and (2.2). It follows that the skill premium is decreasing in the proportion of skilled. Since the cost of an education for individual i is independent of the proportion of skilled, $\overline{G}(\psi^*)$ is increasing as $\overline{G}(\tilde{\psi})$ is decreasing.

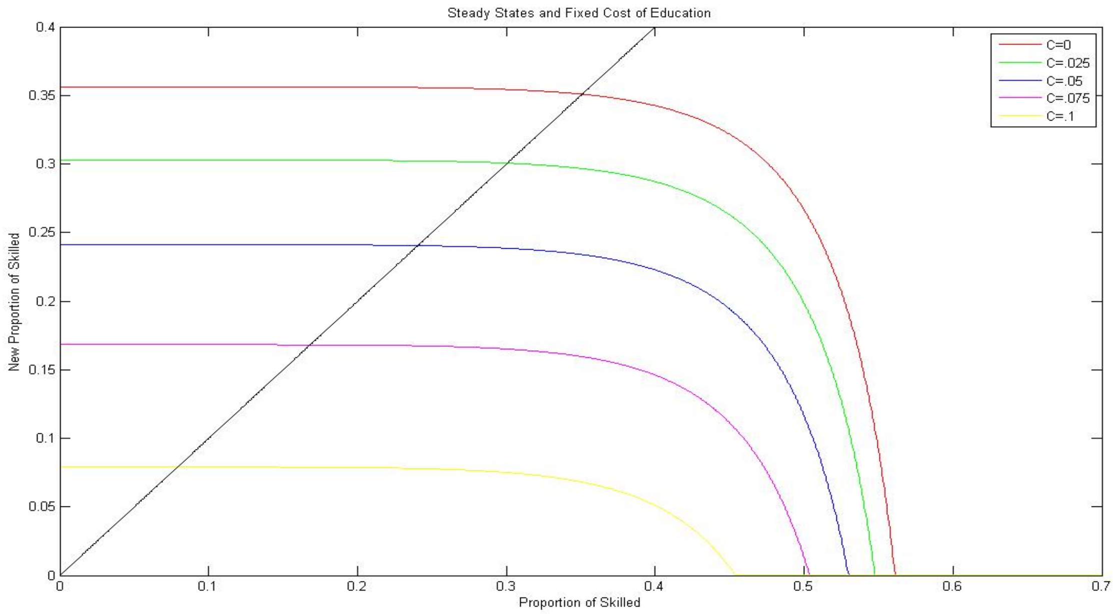
However, even when skill premiums are arbitrarily high, not everyone gets an education because education has to be prepaid from endowments. There is an upper-bound on the proportion of individuals in the population who can afford an education, given by $\overline{G}(\bar{\psi})$, where $\bar{\psi}$ is such that $E - C - e^{-\bar{\psi}} = 0$, or $\bar{\psi} = -ln(E - C)$. Given the restrictions on $E - C$, it is clear that $\bar{\psi} < \Psi$ and the function lies above the 45-degree line when skilled wages are sufficiently high.[17] The upper bound that is due to *cost constraints* explains why the function flattens out as the proportion of the skilled approaches to zero.

The function equals zero in the interval because there is a limit on the amount of people who will want to get skilled even if education was costless due to diminishing marginal returns. For a given individual with no cost constraints, an

[16]Since in a steady state the cut-off ability must be the same for all generations, it is sufficient to start off with a cut-off ability which is the same for all living generations. So finding a steady state is just finding a cut-off ability for the newborns which is equal to the one which the economy started off with, and is an equilibrium given the prices implied by the initial cut-off ability.

[17]Also notice that $\overline{G}(\bar{\psi})$ is decreasing with general barriers to education C.

Figure 2.1: The "Transition" Function



education cannot be worthwhile unless the wage of skilled migrants is at least as great as unskilled wages: $\rho w_s \geq w_u$. Substituting the expression for wages given in eqs. (2.1) to (2.3) into the inequality, and rearranging using the relationship between the proportion of educated and the proportion of skilled workers in the population, $\frac{(1-\pi)\overline{G}(\psi)}{1-\overline{G}(\psi)}=\frac{L_s}{L_u}$, we get that for anyone to be getting an education, it must be that:

$$\overline{G}(\tilde{\psi}) \leq \frac{x}{1-\pi+x} < 1 \quad \text{, where } x = \left[\frac{\mu\rho}{1-\mu}\right]^{\frac{1}{1-\eta}}. \tag{2.4}$$

The above condition restricts the proportion of individuals who will like to get an education even if it was costless because $\pi < 1$ and $x > 0$. It means that for $\overline{G}(\tilde{\psi}) \geq \frac{x}{1-\pi+x}$, nobody will choose to get an education because the wage premium is too small. For any proportion of educated workers such that $\overline{G}(\tilde{\psi}) \geq \frac{x}{1-\pi+x}$, nobody will choose to get an education, and $\overline{G}(\psi^*) = 0$. This upper-bound that is due to *skill-premium constraints* explains why the function touches zero and remains there in the interval $(0, 1)$.

Taken together, these properties of the function along with continuity(which is not shown) establish that it crosses the 45-degree line once in the interval, thus there always exists a unique steady state with a strictly positive mix of the educated and uneducated.

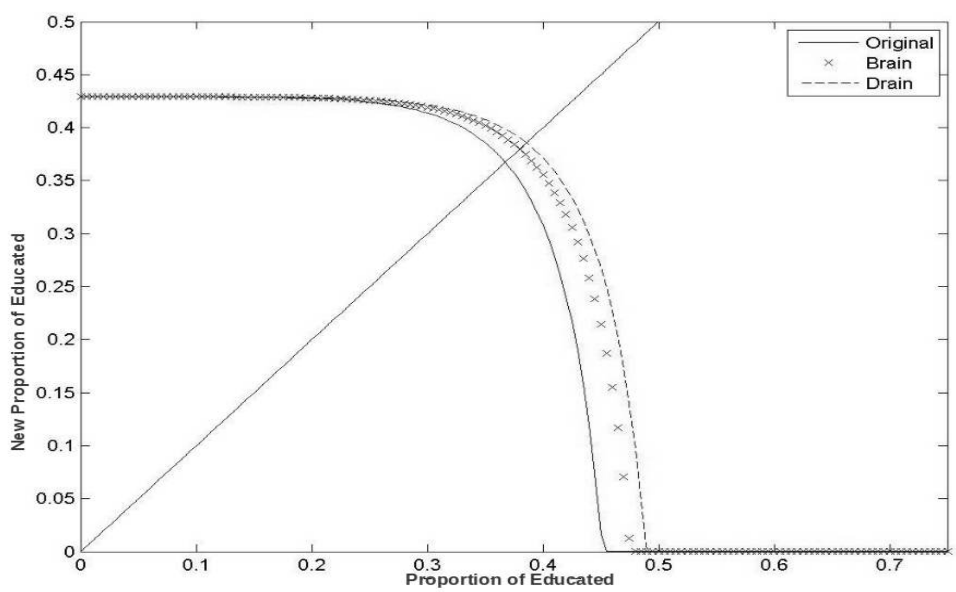
2.4 Analyses and Results

2.4.1 Qualitative Properties of The Brain and Drain Effects

This section examines how the steady-state proportion of skilled labor changes with the rate of skilled emigration. Consider the following thought experiment: Suppose prices are held fixed, what is the impact of a higher rate of emigration on the steady state proportion of individuals who obtain an education, and the skilled-unskilled labor ratio? The answer captures the brain effect, which is the impact of an increase in the probability of emigration on the proportion of skilled workers.

The drain effect captures the change in the proportion of skilled workers due to emigration. This also includes any changes in the proportion of skilled workers as a result of the impact of emigration on prices. Notice that the drain effect could also lead to an increase in the proportion of skilled as a result of increased scarcity of skilled labour. The brain and drain effects depend on important features of the economy that I elaborate upon.

Figure 2.2: The Brain and Drain Effects with Low Costs of Education

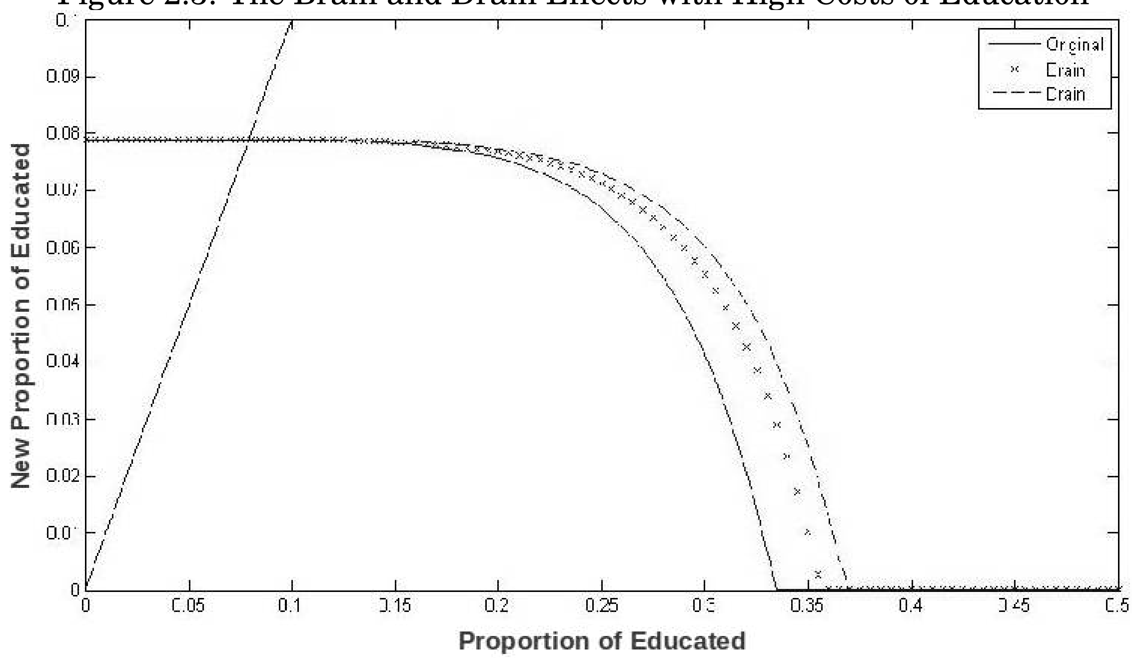


Consider the economy depicted in Figure effig:1.2, with the intersection of the solid line and the 45-degree line being the original steady state. As drawn, just less than 40% of the individuals in this economy obtain an education. With an increase in the rate of skilled emigration, the brain effect shifts the transition function right to the "xx-line". This follows from equation 2.4 above; an increase in π increases the upper bound on the proportion of individuals who can get an education(if it was free). The new steady state moves to the intersection of the "xx-line" and the 45-degree line.

Relative to the initial steady state, the brain effect encourages more people who can afford to get an education to do so. This increases the steady-state proportion of individuals getting an education. The drain effect accounts for the impact of increased rates of emigration on skill prices. Since relatively more skilled individuals are now leaving the economy, skilled wages rise relative to unskilled wages, so even more people are encouraged to get an education. The proportion of the educated in the new steady state is at the intersection of the dashed-line and the 45-degree line.

Even though relatively more individuals are now getting an education, the proportion of skilled individuals left behind after emigration may rise or fall. The proportion of skilled in the economy is given by $(1-\pi)\overline{G}(\psi^*)$, where ψ^* is the steady state cutoff ability. The change in the proportion of skilled individuals is equal to the change in the proportion of those who get an education less the change in the rate of emigration. If the change in the rate of emigration is relatively greater than the increase in the proportion of educated, the economy will end up with relatively less skilled people even though relatively more people get an education.

Figure 2.3: The Brain and Drain Effects with High Costs of Education



Increased emigration need not lead to an increase in the proportion of natives acquiring an education. Suppose we had an economy in the situation depicted in Figure 2.3 with its steady state in the relatively flat portion of the transition function. Recall that the transition function flattens out because there is a limit on the number of individuals who can prepay for an education even if skilled wages are arbitrarily high, as the initial proportion of skilled approaches zero. An upper bound is given by $\bar{\psi} = -ln(E-C)$. All else equal, an economy with a higher general barrier C will have a lower y-intercept.

In the economy of Figure 2.3 everyone who is able to pay for an education is already doing so. An increase in the rate of emigration has no impact on the proportion of those who get an education. There is no brain effect, and the drain effect just reduces the proportion of skilled labor in the population. The differential impact of the brain drain arises because education in the economy in Figure 2.2 is "skill-premium constrained", while that in Figure 2.3 is "cost-constrained".

Graphically,the economy in Figure 2.2 is on the downward sloping region of the transition function (Figure 2.1), and the one in 2.3 is on the flat portion (these are the only two possibilities, there cannot be a steady state where nobody gets an education by assumption). An economy is *skill-premium constrained* if the steady state proportion of higher educated workers is less than the upper-bound imposed by the general cost of education $E - C$. Thus a small increase in the expected skill premium is enough to induce the marginal individual to obtain an education. In a *cost-constrained* economy, small increases in the expected skill premium does not induce the marginal individual to obtain an education, because he cannot borrow to finance his education.

This leads to the result below outlining the conditions under which a brain drain can be beneficial:

Result 2 *In a steady state, the brain drain increases the proportion of skilled workers if and only if:*

- *The economy is initially skill-premium constrained, and*
- *The increase in the proportion of educated workers induced by an increase in the probability of emigration is greater than the increase in the outflow of skilled workers.*

All else equal, an economy is more likely to be skill-premium constrained if skilled labor is used inefficiently (μ is smaller), the foreign wage premium, ρ, is smaller, or the probability of emigration, π, is smaller. From equation 2.4, this means that holding the general cost of education C constant, the horizontal intercept of the skill-premium constrained economy is closer to zero. It follows that if an economy is skill-premium constrained, the *brain effect* is positive by definition since the probability of emigration increases the skill premium. However, the drain effect may still lead to a net decrease in the proportion of skilled workers. For a cost-constrained economy, a brain drain will unambiguously reduce the proportion of skilled workers. A cost-constrained economy has a high barrier to education C all else the same, and a brain drain will unambiguously reduce the proportion of skilled workers.

The next section uses the model to test for the presence and size of the brain and drain effect in a cross-section of 23 low and middle-income countries.

2.4.2 Data and Parameters

The steady-state of the model is calibrated to observed skilled-unskilled labor ratios and wage premiums. Data come from two primary sources: Data on skilled-unskilled labor ratios and wage premiums come from Caselli and Coleman (2006) who use the data to estimate skill weights across countries. Data on emigration rates come from Docquier and Marfouk (2004) and Beine et al. (2007) who provide cross-country estimates for secondary, and tertiary educated workers respectively. The data show that the proportion of tertiary educated workers is low for this group of countries, suggesting that a brain effect is unlikely in this case(high cost relative to observed skill premiums). I also investigate the possibility of a brain gain at the level of secondary educated workers since the proportion of secondary educated workers is relatively higher for countries in the dataset.

The paper by Caselli and Coleman has estimates of the skilled-unskilled labor ratio, as well as the skilled-unskilled wage premium for about 50 countries. From their dataset, I take the skilled-unskilled labor ratio and wage premium for countries with incomes below $10,000 excluding China and India.[18]

Table 2.2: General Parameters

Parameter (Baseline)	Value	Source(s)
β	0.95	
R	1.15	5-year U.S. Real Interest Rate
α	1/3	Gollin (2002)
η	0.375	Ciconne and Peri (2005); Caselli and Coleman (2006)
ρ	4	Clemens et al. (2010)
Ao	1	
T	9	
n	1.3	World Population Prospects: the 2008 Revision
Ψ	2.5	Chosen to ensure an interior solution in the steady state
m	1	Chosen to ensure an interior solution in the steady state
E	0.2	

General Parameters: Table 2.2 lists parameters which are general to all countries. I set the discount factor β equal to a conventional value of .99, a time period is equivalent to 5 years of life which makes β equal to .95. The steady state interest rate R^* is fixed at 1.15 which corresponds to the average annual U.S. real interest rate between 1981 and 2001 of 1.027. Following Gollin (2002) who has estimates of the capital and labor income shares in developing countries corrected for self-employment, I set the capital income share α to 1/3. Using U.S. data, Ciccone and Peri (2005) estimate the elasticity of substitution between skilled and unskilled labor. Their estimates imply that η lies somewhere between 0 and .5, η is set to .375 for an elasticity of substitution of 1.6.

Demographic parameters are chosen to match information available from World population prospects: the 2008 revision (WPP). The age groups are assumed

[18] I also exclude Jamaica because their wage premium appears to be an outlier at 50. The second highest wage premium is Botswana with a premium of 14.5. Indonesia was also excluded because the dataset shows they have 0 tertiary educated workers.

to be 5 year groups from age 20 to 65, which means that T=9, and all individuals die at 70. The steady-state population growth rate n is taken as the world average from 1995 to 2010, which is equal to 1.3. The top ability level Ψ, and the migration cost m are chosen to ensure that a steady-state cut-off ability exists in the interval $(0, \Psi)$;[19] Ψ is set to 2.5, and m is set to 1.

Endowment for the young E is fixed at $.2$.[20] The migration wage premium ρ is set to 4; it is taken from Clemens et al. (2010) who estimate wage premiums for immigrants in the U.S. compared to identical workers in their country of origin. Finally, ψ is assumed to be distributed on the interval $[0, \Psi]$, and follows a **Beta**(a, b) distribution; in the baseline parameterization, $a = b = 1$ corresponding to a uniform distribution. I tried other values for a, b with different implications for the shape of $g(\psi)$, but the results are not sensitive to a change in the shape of the ability distribution.

Country-Specific Parameters: There are three parameters which are country-specific —the skill weight in the labor aggregator function μ, the general costs of education C, and emigration rates π—which are used to match the skilled-unskilled labor ratio, and wage premiums observed in the data. In the first exercise, I interpret the skilled as those who have a tertiary education, and in the second as those who have a secondary education. These have different implications for μ and C.

To obtain the weight on skilled labor in the labor aggregator function, I follow the methodology outlined in Caselli and Coleman (2006). The ratio of skilled to unskilled wages on the steady state can be written as:

$$\frac{w_s^*}{w_u^*} = \frac{\mu}{1-\mu}\left(\frac{L_{t,s}}{L_{t,u}}\right)^{\eta-1}.$$

Given data on the wage-premium, and the skilled-unskilled labor ratio, the skill weights can be obtained from the above expression. For example, the countries in my dataset have an average tertiary educated skilled-unskilled labor ratio of .037, and wage premium of about 5.3, which implies a μ of .4010.[21]I repeat the same exercise with data for secondary educated workers in order to obtain their skill weights. The results for μ for the countries in my dataset follow the pattern of skill weights observed in Caselli and Coleman (2006) who find that poorer countries use less-skilled labour absolutely more efficiently. This is reflected in

[19]Migration costs do differ across countries, but in this model where migration rates are exogenous, it does not play a major role in the decision to obtain an education as long as it is not too high. A model with endogenous migration rates will need different costs of emigration across countries.

[20]Fixing the parameter E is not crucial because what matter for the impact of the brain drain is $E - C$, which is allowed to vary across countries. Moreover, most of the countries in the dataset have very similar income levels, so assuming a fixed E should not be problematic.

[21]The model was solved using different values for η, this changes the values for μ but the results are not very sensitive to these changes. I also cross-checked the data from Caselli and Coleman with those in Docquier and Marfouk (2004) for the share of secondary and tertiary-educated workers, and they closely correspond.

the higher value of μ when skilled workers are interpreted as those who have completed a secondary education.

As already mentioned, the migration rates for tertiary educated workers are taken from Beine et al. (2007), who correct for age-of-emigration when computing their estimates. Rates for secondary educated workers are taken from Docquier and Marfouk (2004). General barrier to education C is chosen to match the proportion of skilled workers in the economy. The results of the calibration, along with the wages and skill premiums obtained from the model are in Table 2.8.

The average cost of a tertiary-education is .1093 which is well over 50% of the endowments for young individuals. For a secondary education, the average cost is about 40% of endowments at .08, with a bit of variation between countries. It is difficult to comment on what these costs exactly translate to, but in Section 5 I present some evidence on the existence of general barriers to education which are not necessarily monetary in several developing countries. The evidence also offers several interpretations for C.

2.4.3 Quantitative Results

The Effect of the Brain Drain on The Proportion of Tertiary Educated Workers:

In this section, I solve the model for the steady state of the economies in my dataset for various rates of skilled migration. This is in order to understand how big the brain and drain effects are across different economies. From the dataset which is available in 2.8, the average skilled-unskilled labor ratio varies across the countries with an average of about 3.7%, and an average wage premium of 5.3. The earlier analysis suggests that with the low proportion of skilled workers, relative to the skill premium, these economies will be cost-constrained on average. Thus, the model will predict that increasing the rate of skilled emigration should have no effect on the proportion of individuals obtaining an education, and a reduction in the steady-state proportion of skilled workers.

This happens to be the case in the quantitative exercise: for tertiary educated workers, there is virtually no brain effect for most countries. Poland is the only country with a positive brain effect, and a brain gain at the tertiary-level. This occurs because Poland has an unusually low skill premium for a country with its skilled-unskilled labor ratio in the dataset. The skill premium for tertiary educated workers is 1.5 in Poland, and the second-lowest skill premium for secondary educated workers in the dataset is Sri Lanka at 1.88 (Poland also has the lowest skill-premium at the level of secondary-educated workers at 1.3).

The prominent effect of a brain drain on the steady-state proportion of tertiary educated workers comes from the drain effect; it does not increase the proportion of individuals getting an education, but reduces the skilled-unskilled labor ratio as more skilled workers leave the economy. Only the skilled workers who are left behind stand to benefit from increased emigration, as they become relatively scarce, and experience an appreciation in their steady-state wages. I report the results for the countries with the lowest and highest skilled-unskilled labor ratios respectively, as well as those for Poland, the full set of results are in Table 2.9.

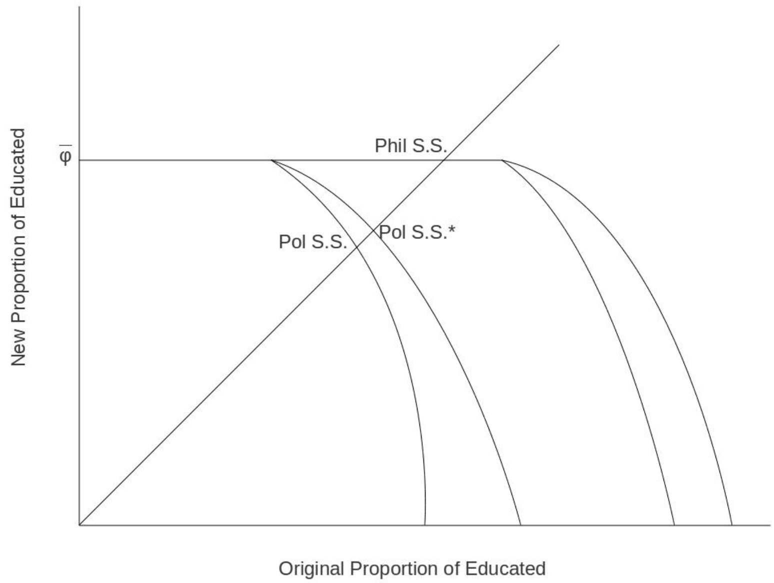
The Brain Effect: Table 2.3 presents the result from a situation where there is no emigration, to emigration rates as high as 20%. For each value of the rate of skilled migration (π), the table shows the steady-state proportion of the people who got an education, the skilled-unskilled labor ratio (L_s/L_u), the skill premium which is the home skilled-unskilled wage ratio, and the wages for skilled labor. These are reported for the brain effect which does not account for changing prices, and the final effect(from which the drain effect can be calculated). The results for Botswana and the Philippines are typical of all other countries in the dataset except for Poland. In most countries, there is no brain effect because they are relatively cost-constrained; skill premiums are high enough so that almost everyone who can afford to get an education is already doing so. Increasing the rate of skilled emigration, and the skill premium does not affect the cost constraint.

Table 2.3: Brain and Drain Effects for Tertiary Educated (Select Countries)

Botswana; C=.1168										
	Brain Effect:					**Final Effect:**				
π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
0	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0053	14.4859	0.3322	4.8126
0.04	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0051	14.8602	0.3316	4.928
0.07	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0049	15.158	0.3312	5.0198
0.1	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0048	15.4719	0.3307	5.1165
0.15	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0045	16.0346	0.3299	5.2896
0.2	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0042	16.6538	0.3291	5.48
Philippines; C=.097; μ=.4113										
	Brain Effect:					**Final Effect:**				
π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
0	0.0922	0.1015	2.919	0.3534	1.0316	0.0922	0.1015	2.919	0.3534	1.0316
0.04	0.0923	0.1017	2.9163	0.3535	1.0309	0.0923	0.0977	2.9906	0.3515	1.0511
0.07	0.0924	0.1018	2.9147	0.3535	1.0305	0.0924	0.0947	3.0486	0.35	1.0669
0.1	0.0924	0.1018	2.9136	0.3536	1.0302	0.0925	0.0917	3.1105	0.3484	1.0837
0.15	0.0925	0.1019	2.9122	0.3536	1.0298	0.0925	0.0867	3.2223	0.3457	1.114
0.2	0.0925	0.1019	2.9114	0.3536	1.0296	0.0926	0.0816	3.3461	0.3429	1.1474
Poland; C=.10; μ=.2033										
	Brain Effect:					**Final Effect:**				
π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
0	0.0498	0.0524	1.6122	0.5882	0.9483	0.0498	0.0524	1.6122	0.5882	0.9483
0.04	0.0527	0.0557	1.5521	0.59	0.9157	0.0542	0.055	1.5643	0.5896	0.9223
0.07	0.0549	0.0581	1.5106	0.5913	0.8931	0.0575	0.0567	1.5341	0.5905	0.9059
0.1	0.0571	0.0606	1.4719	0.5925	0.8721	0.0608	0.0582	1.5095	0.5913	0.8925
0.15	0.0607	0.0646	1.414	0.5945	0.8406	0.0659	0.06	1.4817	0.5922	0.8774
0.2	0.0641	0.0685	1.364	0.5963	0.8133	0.0703	0.0605	1.473	0.5925	0.8727

The different impacts of the brain drain in Poland and the Philippines in Figure 2.4 present a nice illustration of the difference between a skill-premium and a cost constrained economy. The calibrated general cost of education C in Poland (.1) is similar to that in the Philippines (.097) (similar vertical intercepts), but the weight on skilled workers in the production function μ is slightly more than half of that in the Philippines (different horizontal intercepts). This is reflected in differences in skill premium which is very low in Poland, even compared to the skill-premium for secondary educated workers for other countries in the dataset. This disparity in skill premiums results in Poland having slightly less than half the proportion of skilled workers compared to the Philippines, and thus skill-constrained.

Figure 2.4: The Brain Effect: Poland and The Philippines



Increasing the rate of skilled emigration increases the expected skill-premium and moves Poland out to the new steady state (S.S*) as the economy can now support more educated workers. For the Philippines which is at the flat portion of its transition function, increasing the skill-premium shifts the curve out to the right as in Poland, but the steady state proportion of educated does not change. The increased rate of skilled emigration does not address the fact that the marginal individual is cost-constrained (the flat portion does not move with emigration rates), thus there is no brain effect.

This places Poland in a unique position amongst the set of countries in this study. The brain effect alone leads to an increase of about 2-percentage points in the steady-state skilled-unskilled labor ratio from .0498. This is a 40% rise in the steady-state proportion of skilled workers. However, since there is no transition in the model, there is no idea of *how long* it takes to converge to this new steady-state.

The Drain Effect: The drain effect takes into account the impact of increased migration on prices. The drain effect is the difference between the final effect and the brain effect in the skilled-unskilled labor ratio. The increased drain on the economy leads to a *decrease* in the proportion of skilled workers for all countries except Poland where the brain effect outweighs the drain effect. In the Philippines, an increase in the skilled migration rate from 4% to 20% leads to a drain effect of about 2 percentage-points decrease in the skilled-unskilled labor ratio. Since there is no brain effect, this is essentially a 2 percentage-point drop in the steady-state skilled-unskilled labor ratio from .1016. Again, a 16 percentage-point rise in the skilled-emigration rate is relatively large, most countries in the dataset have skilled emigration rates well below 10%. The model predicts that for a country like the Philippines, shutting down skilled migration from its current level of 10%

will increase the steady-state skilled-unskilled labor ratio by 1 percentage-point, from its current level of about .09.

In Poland, the brain effect leads to a 2.28 percentage-point rise in the skilled-unskilled labor ratio from .056 when the emigration rate increases from 4% to 20%. The drain effect leads to a decrease in the steady-state skilled-unskilled labor ratio of about .08 percentage-points over this range. The brain effect dominates the drain effect, and Poland experiences a net gain in the proportion of skilled-labor of about 2 percentage-points. Poland is the only country in the dataset with a brain effect, and consequently, the only one where the brain effect dominates the drain effect.

Overall, skilled emigration has a negative impact on the proportion of tertiary-educated workers for countries in the dataset. This particular result is not especially new; Beine et al. (2008) find that most developing countries are net losers of skilled labor due to the brain drain. The novel result in this analysis is that this negative effect of the brain drain on low skill economies can be explained by high general costs to acquiring an education. Returns to education in many developing countries are not the problem, the problem is one of affordability, which increased emigration rates do not address.

This is especially relevant given the recent debate as to whether increased emigration rates can act as a substitute for education subsidies in Docquier et al. (2008). As long as education subsidies are there to alleviate costs constraints in developing countries, the analysis above suggests that increased emigration rates can only complement but not act as a substitute to subsidies in an economy with low skill levels, and high skill premiums. Next, I look at the secondary education level where costs are lower to see whether a brain gain can result here.

The Effect of the Brain Drain on The Proportion of Secondary Educated Workers:

In this section, the model is calibrated to match skilled-unskilled ratios and wage premiums at the secondary education level. The main feature at the secondary school level is that for many countries, there is a brain effect because the marginal individual can afford to obtain a secondary education in the presence of increased skilled migration rates. However, this brain effect is very modest, and is a lot smaller than the drain effect which leads to a net loss in skilled workers. Again, Poland is the only net-gainer due to its really low skill-premium relative to proportion of skilled workers. Table 2.4 presents the results for Poland, the Philippines and Botswana; the rest of the results are in Table 2.10.

The result in Botswana is representative of that of countries with the lowest levels of secondary-educated workers (Kenya, Guatemala, Ghana), while the outcome in the Philippines is representative of that in the rest of the dataset with the exception of Poland. For the countries with the lowest levels of education, there is no brain effect even at the secondary education level. The outcome for these countries is no different from that in the tertiary case where there is no brain effect, and skilled emigration only lowers the steady-state skilled-unskilled labor ratio.

Table 2.4: Brain and Drain Effects for Secondary Educated (Select Countries)

Botswana; C=.1120										
	Brain Effect:					**Final Effect:**				
π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
0	0.0278	0.0286	5.5893	0.3408	1.905	0.0278	0.0286	5.5893	0.3408	1.905
0.04	0.0278	0.0286	5.5891	0.3408	1.9049	0.0278	0.0275	5.7334	0.3396	1.9473
0.07	0.0278	0.0286	5.5889	0.3408	1.9049	0.0278	0.0266	5.8481	0.3387	1.981
0.1	0.0278	0.0286	5.5888	0.3408	1.9049	0.0278	0.0258	5.9692	0.3378	2.0164
0.15	0.0278	0.0286	5.5888	0.3408	1.9048	0.0278	0.0243	6.1862	0.3362	2.0799
0.2	0.0278	0.0286	5.5887	0.3408	1.9048	0.0278	0.0229	6.425	0.3346	2.1496
Philippines; C=.0376										
	Brain Effect:					**Final Effect:**				
π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
0	0.2693	0.3685	2.0174	0.3371	0.68	0.2693	0.3685	2.0174	0.3371	0.68
0.04	0.2703	0.3705	2.0108	0.3375	0.6787	0.2707	0.3564	2.0602	0.3341	0.6883
0.07	0.2709	0.3715	2.0071	0.3378	0.678	0.2714	0.3465	2.0968	0.3316	0.6953
0.1	0.2713	0.3724	2.0043	0.338	0.6775	0.2719	0.3361	2.137	0.329	0.703
0.15	0.2719	0.3734	2.0009	0.3383	0.6768	0.2724	0.3182	2.2113	0.3243	0.7172
0.2	0.2722	0.3741	1.9987	0.3384	0.6764	0.2726	0.2998	2.295	0.3194	0.7331
Poland; C=.0391										
	Brain Effect:					**Final Effect:**				
π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
0	0.1924	0.2383	1.3224	0.4706	0.6223	0.1924	0.2383	1.3224	0.4706	0.6223
0.04	0.2013	0.252	1.2769	0.4746	0.606	0.2057	0.2486	1.288	0.4736	0.61
0.07	0.2078	0.2623	1.2454	0.4775	0.5947	0.2153	0.2552	1.267	0.4755	0.6024
0.1	0.2141	0.2724	1.2163	0.4803	0.5842	0.2245	0.2606	1.2506	0.477	0.5965
0.15	0.2241	0.2888	1.1728	0.4847	0.5685	0.2384	0.2661	1.2344	0.4785	0.5907
0.2	0.2332	0.3041	1.1355	0.4887	0.5549	0.2497	0.2662	1.2339	0.4786	0.5905

For the Philippines and other countries in the dataset, an increase in the rate of skilled emigration leads to a less than modest brain effect which levels off quickly with further increases in the rate of skilled emigration (as the supply of those who are able to afford an education runs out). Increasing the rate of migration from 0% to 20%, increases the steady state skilled-unskilled labor ratio by less than 1 percentage-point from an already high level of .3685. The force at work here is that the cost constraint begins to get even more severe. The drain effect is a lot stronger than the brain effect; more skilled workers are removed from the economy than unskilled workers who become skilled so most countries experience a net loss in steady-state skilled labor.

For each change in rate of skilled emigration, Poland experiences a strong brain effect which outweighs the drain effect at low levels of migration. At higher levels of emigration, the drain effect begins to outweigh the brain effect, and Poland experiences a net-loss in steady-state skilled-unskilled labor ratio. Increasing the rate of skilled migration from 0% to 4% for example, leads to a brain effect of a 1.4 percentage-point rise in the skilled-unskilled labor ratio from .2383. This outweighs the drain effect of less than .5 of a percentage-point decline in the skilled-unskilled. Increasing the rate of migration from 4% to 7% leads to no change in the steady-state skilled-unskilled labor ratio as both effects cancel out. Any further increase in the rate of skilled migration leads to a net-loss for Poland as the drain effect gets stronger(or the economy becomes more cost-constrained).

2.5 Evidence of Barriers to Education

2.5.1 Interpretation of Steady-state Cost

Increased skilled emigration fails to encourage greater investment in education in this model because the marginal individual is cost-constrained. This cost-constraint is reflected in calibrated high general barriers to education C. The high barrier to education for Botswana relative to Poland for example helps explain why less than 1% of its workforce is educated compared to Poland's 6%, even though it has a skill premium which is close to 10 times that of Poland. However, this steady state relationship need not be conclusive evidence for high costs of education. For example, because the model is calibrated to steady state variables, it cannot account for the possibility that the rate of education is rapidly increasing in Botswana in response to a higher skill premium.

Available data does support the hypothesis that enrollment is indeed rapidly increasing in several developing countries, but this increase is mostly due to rapid population growth, and is not reflected in enrollment ratios (UNESCO, 2006). For example, the report by UNESCO shows that from 1991-2004, enrollment in tertiary education has increased by 7.2% on average in Sub-Saharan Africa (SSA), and 1.9% for North America and Western Europe. However, enrollment ratios, which is the ratio of students in school relative to the school-age population, have only increased from 3% to 5% for the countries of SSA in the same time frame, compared to an increase from 52% to 71% for North America and Western Europe. The underwhelming rise in enrollment ratios is attributed to the higher growth rate of the tertiary-age population in SSA.[22]

Further data on tertiary school life expectancy (TSLE) between 1990-1993 and 2007-2009 presented in Table 2.5 shows that it is not the case that low-skilled, high returns to education, countries are quickly catching up. TSLE is defined as the number of years of tertiary education an individual who has completed secondary school can expect to receive. It provides some information on access to tertiary education, and changes over time gives us an idea of how access has improved with demand (UNESCO, 2006). The TSLE has increased from 1 year in Poland in 1990 to an impressive 3.5 in 2007, reflecting the rise in tertiary enrollment rates in Central and Eastern Europe, even with lower estimates of the returns to education in the 1990s. Given the more than 200% rise in TSLE in less than two decades, the 40% increase in the proportion of skilled workers appears quite reasonable. On the other hand, the countries of Sub-Saharan Africa, and South and West Asia for example continue to have low TSLEs even with higher measured returns. The slow or non-existent growth in TSLE over time, in many regions of the world, is not indicative of a world where countries with low levels of education and high returns to skill are catching up. The picture painted by TSLEs supports an interpretation of C as representing existing barriers (costs) to education.

[22] See Table 1 in UNESCO (2006) for more information.

Table 2.5: TSLE and Returns to Education

Country	TSLE(years)		Return to Tertiary Education
	1990-1993	2007-2009	(Annual, early 1990s)
Botswana	0.3	0.3	38.00
Chile	1.4	3.1	20.70
Colombia	0.7	1.9	21.70
Ecuador	1	2.2	12.7
El Salvador	0.8	1.3	9.5
Ghana	0.1	0.4	37
Guatemala	0.4	0.9	22.20
Honduras	0.4	1.1	25.90
Kenya	0.1	0.2	16**
Malaysia	0.4	2	34.50
Pakistan	0.1	0.3	31.20
Panama	1.1	2.2	21.00
Paraguay	0.4	2.1	13.70
Philippines	1.2	1.4	11.60
Poland	1	3.5	7**
Thailand	0.8	2.3	11.80
Tunisia	0.4	1.7	27.00
Region			
Arab States	0.6	1	18.8
Central and Eastern Europe	1.6	2.6	N/A
Central Asia	1.5	1.3	N/A
East Asia and the Pacific	0.4	1	N/A
Latin America and the Caribbean	0.8	1.3	19.5
North America an Western Europe	2.6	3.3	11.6
South and West Asia	0.3	0.5	N/A
Sub-Saharan Africa	0.1	0.2	27.8
World	0.7	1.1	19

Sources: UNESCO (2012); UNESCO (2009) for school expectancy data.
Psacharopoulos and Patrinos (2004), and Hendricks (2004) for returns to education data.
**Rate of return here is the average for all schooling levels.

2.5.2 Evidence from Tertiary Education Expenditure

Here, I present some evidence on significant barriers to tertiary education in developing countries which would limit the size of the brain effect. I begin with the observation that the cost of tertiary education represents a high proportion of income. Table 2.6 presents data on tertiary education expenditure-per-pupil, at the tertiary education level, as a proportion of GDP (Expperpup_tert in the table) across regions and income groups. Across income groups, these range from 227.12% for low-income countries and close to 28% for high-income countries. Most of the cross-regional estimates, with the exception of Eastern Europe/Former Soviet Union and OECD countries, show that most countries spend over 50% of per-capita GDP on tertiary education. These spending patterns correspond very well with the calibrated cost of education.

Table 2.6: Tertiary education expenditure-per-pupil by region and income

Region	**Expperpup_tert(%)**
Low-income	227.12
Middle-income	68.2
High-income	27.95
Sub-Saharan Africa	2092.38
Middle East/North Africa	103.35
Latin America	57.2
South Asia	72.6
East Asia	76.7
East Europe/FSU	28.65
OECD	34.2

Source: Author's calculations from Table 9 in Glewwe and Kremer (2006).

Table 2.7 presents data on total (public and private) expenditure-per-pupil as a percentage of GDP (Expperpup in the table), at the tertiary and secondary levels of education, when available for the 23 countries in my dataset (and including the U.S. for comparison). Expenditure-per-pupil at the tertiary level is adjusted for the fact that a significant proportion of expenditure on tertiary education is privately financed.[23] For more than half of the countries for which data is available, per-pupil expenditure on tertiary students exceeds 50% of GDP, which matches up well with the endowment-cost (E/C) ratios obtained from the calibration. Tertiary education expenditure is vastly underestimated in the sub-Sahara African countries (Botswana, Ghana and Kenya) where the tertiary education expenditure as a percentage of GDP exceed 200%.

Cross-country data on the cost of higher education (tuition and other expenses) available from the International Comparative Higher Education Finance Project (ICHEFAP, 2009) confirm the information given by aggregate expenditure data.

[23] The adjustment multiplies public tertiary education expenditure-per-pupil as a percentage of GDP, by the ratio of total tertiary education expenditure to public tertiary education expenditure obtained from various tables in UNESCO (2012).

Table 2.7: Expenditure-per-pupil at tertiary and secondary levels of education

Country	Year	Expperpup_GDP(%)	Expperpup_Sec(%)	Expperpup_Tert(%)		E/C_{tert}
				Public	Adjusted	
Bolivia	2003	17.89	13.04	35.97		53.7
Botswana	2007	27.91	38.30	256.32		58.4
Chile*	2005	12.51	13.23	11.64	64.01	54.65
Colombia*	2005	14.42	14.46	19.41	30.33	55.9
Costa Rica	2004	18.69	16.98	44		0.5195
Dominican Rep.	2007	N/A.	4.07	N/A.	N/A.	53.75
Ecuador	1995	N/A.	6.03	34		50.75
El Salvador	2005	8.55	9.17	15.06	45.18	56.05
Ghana	2005	22.84	33.22	204.88		57.75
Guatemala*	2007	10.14	5.92	18.95	51.67	56.6
Honduras	1995	N/A.	N/A.	61.66		57.3
Kenya	2004	22.78	22.20	273.63		57.95
Malaysia	2004	20.73	20.59	69.35		57.5
Nicaragua	2005	N/A.	3.85	N/A.	N/A.	52.75
Pakistan	2005	11.67	N/A.	N/A.	N/A.	57.15
Panama	2004	13.52	12.32	26.59		53.2
Paraguay*	2004	13.10	13.03	24.55	56.12	55.85
Peru*	2005	8.75	9.53	8.86	29.53	51.1
Philippines*	2005	8.89	8.82	11.10	23.20	48.25
Poland*	2005	22.70	22.17	21.43	28.57	50.05
Sri Lanka	1995	N/A.	N/A.	64		58.1
Thailand	2004	18.26	16.09	23.86		52
Tunisia	2005	22.71	21.71	50.13		56
United States*	2005	20.89	22.79	23.07	69.21	

Sources: UNESCO (2012); UNESCO (2009), and Task Force on Higher Education and Society (2002) for expenditure data. *Adjusted for the fact that a significant proportion of expenditure on tertiary education(Expperpup_Tert) is financed privately.

Take Ghana for example, the total of a year at a Ghanaian fee paying public university is $4,636. Given a per-capita GDP of $1854, this implies that Ghana spends 250% of per-capita income on a typical tertiary educated student. Taken together, these data imply that tertiary education is expensive, and costs easily exceed 50% of per-capita GDP in many countries as found in the preceding calibration exercise. However, they do not directly imply that there are high barriers to education (cost constraints) which restrict access.

Evidence for high barriers to education come from the malfunctioning, and in most cases unavailable student loan programs in most developing countries (Task Force on Higher Education and Society, 2002). Since the mid-1980s, there has been a shift in the financing of higher education from a fully public (tuition and living expenses) model, to one in which costs are shared between the student and the Government through tuition and user fees (cost-sharing). This change is due to a combination of a rise in per-student cost, increased enrollment, and declining or stagnant Government revenues (Johnstone and Marcucci, 2007).

A solution to the change from a public to a public-private model of higher education funding is the expansion of student loan programs, which aims to ensure that students still have access to higher education even if they cannot afford the up-front costs. Still many developing countries do not have the capacity, and well developed financial markets to administer these programs. As Johnstone (2004) and Ziderman (2002) find in their study of student loan programs, when functional in many developing countries, they face substantial challenges in meeting student needs as demand greatly exceeds supply. Most student loan programs in developing countries also find it difficult recovering previously disbursed loans, and staying solvent. In many others, they just do not exist, and students are forced to meet the up-front costs of education.

In sub-Saharan Africa for example, Burkina Faso has a means-tested student loans program established in 1994, however the per-student amounts disbursed are very small and there is little or no recovery to date (Johnstone, 2004). In Kenya and Ghana, the student loans programs have failed due to low recovery rates, and new programs are being set up which face similar challenges to that in Burkina Faso. In the other African countries surveyed, with the exception of South Africa surveyed, student loan programs do not exist. Coupled with poorly functioning financial markets, this means that students have no access to loans at reasonable rates with which to finance schooling (Task Force on Higher Education and Society, 2002).

Problems with access to student loans are not limited to countries of sub-Saharan Africa. The Philippines for example has a variety of student loan programs targeted at poor students in different institutions and regions. However, the program only covers tuition expenses which according to data available from ICHEFAP (2009), constitutes a little less than 50% of the annual cost of a tertiary education in the Philippines. In addition to this, the program has very limited coverage, covering less than 1% of all enrolled students (Ziderman, 2002), which implies that most poor students do not have access to these loans.

The evidence presented here shows that higher education is expensive, and in most developing countries, the cost exceeds 50% of per-capita GDP. Taken together with evidence on low, and in many cases non-existent access to student loans (public and private), this presents significant barriers to higher education. Significant financial barriers to higher education remain in many developing countries, especially for the poorest. This implies that even though an increase in the probability of emigration increases the benefits of a higher education, the presence of cost constraints means that there is unlikely to be an increase in the proportion of individuals getting an education. While the evidence here focuses on financial barriers to education, it is worth mentioning that there exists other barriers to access prior to university age which are not discussed. This includes amongst other things, the challenges facing primary education in many developing countries discussed comprehensively in Glewwe and Kremer (2006).

2.6 Conclusion

I use an OLG model of education choice and skilled emigration to derive conditions under which a low-skill economy can grow its skilled labor with an increase in the brain drain. This occurs when on the steady state there are individuals in the economy who can afford an education but are not doing so due to low skill premiums, and the increase in the proportion of educated workers dominate the increase in the rate of emigration. The model is calibrated to data on 23 low and middle-income countries in order to investigate the possibility of a net brain-gain at both the secondary and tertiary levels of schooling.

For 22 out of the 23 countries in the dataset, at any rate of skilled emigration, they experience a net decline in the steady-state proportion of skilled labor. A combination of high costs of education and already high skill premiums imply that increasing migration rates do not induce more people to obtain an education since they cannot afford the up-front costs of education. The only exception is Poland which has a unique combination of relatively low cost and low skill premiums, which means that improved outside opportunities encourage a lot of people on the margin to become skilled. Finally, I present some data on financial barriers to education, and changes in tertiary education which support the quantitative results of the model.

Additional cross-country data on skill premiums and skilled-unskilled labor ratios are needed to see if the result here is generalizable; is it typical for most countries, and are there other countries similar to Poland? If most developing economies are unlike Poland, then reducing obstacles to education is a necessary response to the brain drain.

2.7 Other Tables and Figures

Table 2.8: Labor Ratios, Wage Premiums, Migration Rates, and Parameters

Tertiary-Educated Workers

Country	Income(PPP $)	Skill Premium	Lu	Ls	Ls/Lu	π_{90}	μ	C
Bolivia	4953	2.70	125.00	6.00	0.0480	0.044	0.2881	0.1074
Botswana	3316	14.50	190.00	1.00	0.0053	0.016	0.3541	0.1168
Chile	9323	5.37	203.00	8.00	0.0394	0.0477	0.4171	0.1093
Colombia	9360	7.10	180.00	5.00	0.0278	0.0632	0.4307	0.1118
Costa Rica	9118	4.60	156.00	10.00	0.0641	0.0473	0.4524	0.1039
Dom. Rep.	7314	3.73	134.00	6.00	0.0448	0.1061	0.3469	0.1075
Ecuador	8388	5.22	171.00	13.00	0.0760	0.032	0.5095	0.1015
El Salvador	5548	3.89	136.00	3.00	0.0221	0.209	0.2647	0.1121
Ghana	1854	3.29	130.00	1.00	0.0077	0.3386	0.1361	0.1155
Guatemala	7431	8.05	151.00	3.00	0.0199	0.1229	0.4119	0.1132
Honduras	4597	11.75	217.00	3.00	0.0138	0.14	0.4480	0.1146
Kenya	1998	9.93	166.00	1.00	0.0060	0.3799	0.2880	0.1159
Malaysia	9472	3.73	169.00	2.00	0.0118	0.161	0.1875	0.1150
Nicaragua	4453	3.89	126.00	6.00	0.0476	0.1999	0.3677	0.1055
Pakistan	4552	3.89	120.00	2.00	0.0167	0.0498	0.2321	0.1143
Panama	7898	6.81	227.00	11.00	0.0485	0.1246	0.5064	0.1064
Paraguay	6015	5.00	170.00	5.00	0.0294	0.0241	0.3555	0.1117
Peru	8387	3.11	139.00	10.00	0.0719	0.0413	0.3743	0.1022
Philippines	4473	3.06	141.00	13.00	0.0922	0.0965	0.4113	0.0965
Poland	8439	1.50	119.00	7.00	0.0588	0.1129	0.2033	0.1001
Sri Lanka	5476	2.66	149.00	1.00	0.0066	0.2309	0.1048	0.1162
Thailand	5558	4.29	152.00	8.00	0.0656	0.0161	0.4393	0.1040
Tunisia	7696	3.06	122.00	3.00	0.0246	0.1294	0.2343	0.1120
Averages	**—**	**5.2665**	**156.2174**	**5.5652**	**0.0369**	**0.1188**	**0.4011**	**0.1093**

Secondary-Educated Workers

Country	Income(PPP $)	Skill Premium	Lu	Ls	Ls/Lu	π_{90}	μ	C
Bolivia		1.89	105.00	20.00	0.1905	0.019	0.4014	0.0748
Botswana		5.58	174.00	5.00	0.0287	0.001	0.3775	0.112
Chile		2.94	143.00	35.00	0.2448	0.019	0.5495	0.0647
Colombia		3.53	138.00	22.00	0.1594	0.039	0.5284	0.0828
Costa Rica		2.67	126.00	28.00	0.2222	0.075	0.5105	0.0667
Dom. Rep.		2.33	116.00	17.00	0.1466	0.236	0.4124	0.0772
Ecuador		2.89	126.00	39.00	0.3095	0.087	0.5813	0.0454
El Salvador		2.39	123.00	10.00	0.0813	0.385	0.3324	0.0901
Ghana		2.15	123.00	5.00	0.0407	0.009	0.2252	0.1086
Guatemala		3.82	133.00	11.00	0.0827	0.189	0.4458	0.0965
Honduras		4.87	152.00	21.00	0.1382	0.132	0.5857	0.0843
Kenya		4.38	159.00	4.00	0.0252	0.008	0.3050	0.1127
Malaysia		2.33	127.00	22.00	0.1732	0.011	0.4378	0.0804
Nicaragua		2.39	114.00	15.00	0.1316	0.239	0.4022	0.0813
Pakistan		2.39	107.00	9.00	0.0841	0.006	0.3371	0.0998
Panama		3.43	142.00	47.00	0.3310	0.096	0.6322	0.0396
Paraguay		2.82	141.00	19.00	0.1348	0.008	0.4463	0.0892
Peru		2.07	106.00	30.00	0.2830	0.026	0.4847	0.0549
Philippines		2.05	103.00	37.00	0.3592	0.031	0.5195	0.0376
Poland		1.30	98.00	24.00	0.2449	0.025	0.3505	0.0391
Sri Lanka		1.88	117.00	18.00	0.1538	0.015	0.3685	0.0829
Thailand		2.55	143.00	16.00	0.1119	0.015	0.3935	0.0938
Tunisia		2.05	104.00	14.00	0.1346	0.034	0.3692	0.0876
Averages		**2.8130**	**126.9565**	**20.3478**	**0.1657**	**0.0741**	**0.4777**	**0.0799**

Sources: Data on skill premiums and skilled-unskilled labour ratios come from Caselli and Coleman (2006). Data on emigration rates in 1990(π_{90}) come from Beine et. al (2007) and Docquier and Marfouk(2004).
Note: C and μ are chosen to match proportion of skilled workers and skill premiums as explained in the text.

Table 2.9: Brain and Drain Effects for Tertiary Educated Workers

		For Tertiary Educated Brain Effect:					**For Tertiary Educated Drain Effect:**				
Country	π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
Bolivia											
	0	0.0474	0.0498	2.6396	0.4676	1.2343	0.0474	0.0498	2.6396	0.4676	1.2343
	0.04	0.0477	0.0501	2.6294	0.4678	1.2301	0.0478	0.0482	2.6935	0.4665	1.2566
	0.07	0.0478	0.0502	2.6238	0.4679	1.2278	0.048	0.0469	2.7405	0.4656	1.276
	0.1	0.048	0.0504	2.6195	0.468	1.226	0.0481	0.0455	2.7924	0.4646	1.2974
	0.15	0.0481	0.0505	2.6144	0.4681	1.2239	0.0482	0.0431	2.8889	0.4629	1.3372
	0.2	0.0482	0.0506	2.6111	0.4682	1.2226	0.0483	0.0406	2.9979	0.461	1.382
Botswana											
	0	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0053	14.4859	0.3322	4.8126
	0.04	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0051	14.8602	0.3316	4.928
	0.07	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0049	15.158	0.3312	5.0198
	0.1	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0048	15.4719	0.3307	5.1165
	0.15	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0045	16.0346	0.3299	5.2896
	0.2	0.0053	0.0053	14.4859	0.3322	4.8126	0.0053	0.0042	16.6538	0.3291	5.48
Chile											
	0	0.0398	0.0414	5.2354	0.3098	1.622	0.0398	0.0414	5.2354	0.3098	1.622
	0.04	0.0398	0.0414	5.2352	0.3098	1.622	0.0398	0.0397	5.3704	0.3084	1.6564
	0.07	0.0398	0.0414	5.2351	0.3098	1.6219	0.0398	0.0385	5.4779	0.3074	1.6837
	0.1	0.0398	0.0414	5.235	0.3098	1.6219	0.0398	0.0373	5.5912	0.3063	1.7124
	0.15	0.0398	0.0414	5.2349	0.3098	1.6219	0.0398	0.0352	5.7945	0.3044	1.7639
	0.2	0.0398	0.0414	5.2348	0.3098	1.6219	0.0398	0.0331	6.0182	0.3025	1.8204
Colombia											
	0	0.0288	0.0296	6.8263	0.2851	1.9461	0.0288	0.0296	6.8263	0.2851	1.9461
	0.04	0.0288	0.0296	6.8262	0.2851	1.946	0.0288	0.0284	7.0026	0.2839	1.9878
	0.07	0.0288	0.0296	6.8262	0.2851	1.946	0.0288	0.0275	7.1429	0.2829	2.021
	0.1	0.0288	0.0296	6.8262	0.2851	1.946	0.0288	0.0266	7.2908	0.282	2.056
	0.15	0.0288	0.0296	6.8262	0.2851	1.946	0.0288	0.0252	7.556	0.2804	2.1185
	0.2	0.0288	0.0296	6.8262	0.2851	1.946	0.0288	0.0237	7.8477	0.2787	2.1871
Costa Rica											
	0	0.0631	0.0673	4.4606	0.293	1.3068	0.0631	0.0673	4.4606	0.293	1.3068
	0.04	0.0631	0.0673	4.4603	0.293	1.3067	0.0631	0.0647	4.5754	0.2913	1.3326
	0.07	0.0631	0.0673	4.4601	0.293	1.3066	0.0631	0.0626	4.6669	0.2899	1.3531
	0.1	0.0631	0.0673	4.46	0.293	1.3066	0.0631	0.0606	4.7634	0.2886	1.3748
	0.15	0.0631	0.0674	4.4598	0.293	1.3066	0.0631	0.0573	4.9365	0.2863	1.4135
	0.2	0.0631	0.0674	4.4597	0.293	1.3066	0.0631	0.0539	5.127	0.284	1.4559
Dom. Rep											
	0	0.0476	0.05	3.4553	0.3945	1.363	0.0476	0.05	3.4553	0.3945	1.363
	0.04	0.0476	0.05	3.4531	0.3945	1.3623	0.0477	0.048	3.5416	0.393	1.392
	0.07	0.0477	0.0501	3.452	0.3945	1.3619	0.0477	0.0466	3.6112	0.3919	1.4154
	0.1	0.0477	0.0501	3.4511	0.3945	1.3616	0.0477	0.0451	3.685	0.3908	1.4401
	0.15	0.0477	0.0501	3.4501	0.3946	1.3613	0.0477	0.0426	3.818	0.3889	1.4847
	0.2	0.0477	0.0501	3.4495	0.3946	1.3611	0.0477	0.0401	3.965	0.3868	1.5338
Ecuador											
	0	0.0728	0.0785	5.0959	0.247	1.2587	0.0728	0.0785	5.0959	0.247	1.2587
	0.04	0.0728	0.0785	5.0958	0.247	1.2587	0.0728	0.0754	5.2275	0.2452	1.2819
	0.07	0.0728	0.0785	5.0957	0.247	1.2587	0.0728	0.073	5.3321	0.2439	1.3003
	0.1	0.0728	0.0785	5.0957	0.247	1.2587	0.0728	0.0707	5.4425	0.2425	1.3196
	0.15	0.0728	0.0785	5.0956	0.247	1.2586	0.0728	0.0667	5.6404	0.2401	1.3542
	0.2	0.0728	0.0785	5.0956	0.247	1.2586	0.0728	0.0628	5.8581	0.2376	1.3921
El Salvador											
	0	0.027	0.0277	3.3841	0.4819	1.6307	0.027	0.0277	3.3841	0.4819	1.6307
	0.04	0.027	0.0278	3.3798	0.4819	1.6288	0.0271	0.0267	3.4655	0.4809	1.6666
	0.07	0.0271	0.0278	3.3774	0.482	1.6278	0.0271	0.0259	3.5321	0.4801	1.6959
	0.1	0.0271	0.0278	3.3757	0.482	1.627	0.0271	0.0251	3.6033	0.4793	1.7272
	0.15	0.0271	0.0279	3.3736	0.482	1.6261	0.0271	0.0237	3.7324	0.4779	1.7839
	0.2	0.0271	0.0279	3.3723	0.482	1.6255	0.0271	0.0223	3.8755	0.4765	1.8467
Ghana											
	0	0.0106	0.0107	2.6883	0.6685	1.7972	0.0106	0.0107	2.6883	0.6685	1.7972
	0.04	0.0108	0.0109	2.6524	0.6688	1.7739	0.0109	0.0106	2.7066	0.6684	1.8091
	0.07	0.0109	0.0111	2.631	0.6689	1.76	0.0111	0.0104	2.7329	0.6682	1.8262
	0.1	0.0111	0.0112	2.6135	0.6691	1.7486	0.0112	0.0102	2.7688	0.668	1.8496
	0.15	0.0112	0.0113	2.5919	0.6692	1.7346	0.0113	0.0098	2.8471	0.6675	1.9004
	0.2	0.0113	0.0114	2.5774	0.6693	1.7252	0.0114	0.0092	2.9448	0.6669	1.9638
Guatemala											
	0	0.0223	0.0228	7.4326	0.2971	2.208	0.0223	0.0228	7.4326	0.2971	2.208
	0.04	0.0223	0.0228	7.4325	0.2971	2.208	0.0223	0.0219	7.6246	0.296	2.2568
	0.07	0.0223	0.0228	7.4325	0.2971	2.208	0.0223	0.0212	7.7774	0.2951	2.2955
	0.1	0.0223	0.0228	7.4325	0.2971	2.208	0.0223	0.0206	7.9384	0.2943	2.3363
	0.15	0.0223	0.0228	7.4325	0.2971	2.208	0.0223	0.0194	8.227	0.2928	2.4092
	0.2	0.0223	0.0228	7.4324	0.2971	2.208	0.0223	0.0183	8.5447	0.2913	2.4894
Honduras											
	0	0.0158	0.016	10.7389	0.2518	2.7041	0.0158	0.016	10.7389	0.2518	2.7041
	0.04	0.0158	0.016	10.7387	0.2518	2.704	0.0158	0.0154	11.0162	0.2509	2.7636
	0.07	0.0158	0.016	10.7387	0.2518	2.704	0.0158	0.0149	11.237	0.2501	2.8109
	0.1	0.0158	0.016	10.7387	0.2518	2.704	0.0158	0.0144	11.4697	0.2494	2.8607
	0.15	0.0158	0.016	10.7387	0.2518	2.704	0.0158	0.0136	11.8868	0.2482	2.9499
	0.2	0.0158	0.016	10.7387	0.2518	2.704	0.0158	0.0128	12.3458	0.2469	3.0478
Kenya											
	0	0.0095	0.0096	7.3922	0.4267	3.1546	0.0095	0.0096	7.3922	0.4267	3.1546
	0.04	0.0095	0.0096	7.3919	0.4267	3.1545	0.0095	0.0092	7.583	0.426	3.2306
	0.07	0.0095	0.0096	7.3919	0.4267	3.1545	0.0095	0.0089	7.7349	0.4255	3.2911
	0.1	0.0095	0.0096	7.3919	0.4267	3.1545	0.0095	0.0086	7.8951	0.4249	3.3549
	0.15	0.0095	0.0096	7.3919	0.4267	3.1545	0.0095	0.0081	8.182	0.424	3.4689
	0.2	0.0095	0.0096	7.3917	0.4268	3.1544	0.0095	0.0077	8.4979	0.423	3.5945

Brain and Drain Effects for Tertiary Educated Workers (Continued)

Country	π	For Tertiary Educated Brain Effect: % Educated	Ls/Lu	Skill Premium	Unskilled Wage	Skilled Wage	For Tertiary Educated Drain Effect: % Educated	Ls/Lu	Skill Premium	Unskilled Wage	Skilled Wage
Malaysia											
	0	0.0136	0.0138	3.3538	0.584	1.9587	0.0136	0.0138	3.3538	0.584	1.9587
	0.04	0.0137	0.0139	3.3448	0.5841	1.9537	0.0137	0.0133	3.4279	0.5835	2.0001
	0.07	0.0137	0.0139	3.3399	0.5841	1.9509	0.0137	0.013	3.4904	0.583	2.035
	0.1	0.0137	0.0139	3.336	0.5842	1.9488	0.0138	0.0126	3.5586	0.5825	2.0729
	0.15	0.0138	0.014	3.3317	0.5842	1.9464	0.0138	0.0119	3.6838	0.5817	2.1427
	0.2	0.0138	0.014	3.3289	0.5842	1.9448	0.0138	0.0112	3.8239	0.5808	2.2208
Nicaragua											
	0	0.056	0.0593	3.3981	0.3769	1.2806	0.056	0.0593	3.3981	0.3769	1.2806
	0.04	0.0561	0.0594	3.3961	0.3769	1.28	0.0561	0.057	3.4831	0.3753	1.3073
	0.07	0.0561	0.0594	3.395	0.3769	1.2797	0.0561	0.0553	3.5516	0.3741	1.3287
	0.1	0.0561	0.0594	3.3942	0.3769	1.2794	0.0561	0.0535	3.6243	0.3729	1.3514
	0.15	0.0561	0.0595	3.3933	0.377	1.2791	0.0562	0.0506	3.7552	0.3708	1.3923
	0.2	0.0561	0.0595	3.3927	0.377	1.279	0.0562	0.0476	3.8998	0.3686	1.4373
Pakistan											
	0	0.0174	0.0177	3.7663	0.5187	1.9537	0.0174	0.0177	3.7663	0.5187	1.9537
	0.04	0.0174	0.0177	3.7627	0.5187	1.9519	0.0174	0.017	3.8586	0.5179	1.9985
	0.07	0.0174	0.0177	3.7608	0.5188	1.9509	0.0174	0.0165	3.9335	0.5173	2.0349
	0.1	0.0174	0.0177	3.7592	0.5188	1.9502	0.0174	0.016	4.0134	0.5167	2.0737
	0.15	0.0174	0.0177	3.7576	0.5188	1.9494	0.0174	0.0151	4.1578	0.5156	2.1438
	0.2	0.0174	0.0177	3.7565	0.5188	1.9489	0.0174	0.0142	4.3175	0.5145	2.2213
Panama											
	0	0.0524	0.0553	6.2624	0.2354	1.4742	0.0524	0.0553	6.2624	0.2354	1.4742
	0.04	0.0524	0.0553	6.2623	0.2354	1.4742	0.0524	0.0531	6.4241	0.2339	1.5025
	0.07	0.0524	0.0553	6.2622	0.2354	1.4742	0.0524	0.0515	6.5528	0.2327	1.5249
	0.1	0.0524	0.0553	6.2622	0.2354	1.4742	0.0524	0.0498	6.6884	0.2315	1.5485
	0.15	0.0524	0.0553	6.2622	0.2354	1.4742	0.0524	0.047	6.9317	0.2295	1.5906
	0.2	0.0524	0.0553	6.2622	0.2354	1.4742	0.0524	0.0443	7.1993	0.2274	1.6368
Paraguay											
	0	0.0294	0.0303	4.9098	0.3678	1.8058	0.0294	0.0303	4.9098	0.3678	1.8058
	0.04	0.0294	0.0303	4.9094	0.3678	1.8056	0.0294	0.0291	5.0361	0.3666	1.8462
	0.07	0.0294	0.0303	4.9091	0.3678	1.8055	0.0294	0.0282	5.1368	0.3657	1.8783
	0.1	0.0294	0.0303	4.909	0.3678	1.8055	0.0294	0.0273	5.2429	0.3647	1.9122
	0.15	0.0294	0.0303	4.9088	0.3678	1.8054	0.0294	0.0257	5.4334	0.3631	1.973
	0.2	0.0294	0.0303	4.9087	0.3678	1.8054	0.0294	0.0242	5.6431	0.3615	2.0397
Peru											
	0	0.0696	0.0748	3.0247	0.3791	1.1466	0.0696	0.0748	3.0247	0.3791	1.1466
	0.04	0.0697	0.0749	3.0216	0.3791	1.1456	0.0697	0.072	3.0985	0.3774	1.1694
	0.07	0.0697	0.075	3.0199	0.3792	1.1451	0.0698	0.0698	3.1585	0.3761	1.1879
	0.1	0.0698	0.075	3.0186	0.3792	1.1447	0.0698	0.0676	3.2225	0.3747	1.2076
	0.15	0.0698	0.0751	3.0171	0.3793	1.1443	0.0699	0.0639	3.3383	0.3724	1.2432
	0.2	0.0699	0.0751	3.0162	0.3793	1.144	0.0699	0.0601	3.4665	0.37	1.2825
Philippines											
	0	0.0922	0.1015	2.919	0.3534	1.0316	0.0922	0.1015	2.919	0.3534	1.0316
	0.04	0.0923	0.1017	2.9163	0.3535	1.0309	0.0923	0.0977	2.9906	0.3515	1.0511
	0.07	0.0924	0.1018	2.9147	0.3535	1.0305	0.0924	0.0947	3.0486	0.35	1.0669
	0.1	0.0924	0.1018	2.9136	0.3536	1.0302	0.0925	0.0917	3.1105	0.3484	1.0837
	0.15	0.0925	0.1019	2.9122	0.3536	1.0298	0.0925	0.0867	3.2223	0.3457	1.114
	0.2	0.0925	0.1019	2.9114	0.3536	1.0296	0.0926	0.0816	3.3461	0.3429	1.1474
Poland											
	0	0.0498	0.0524	1.6122	0.5882	0.9483	0.0498	0.0524	1.6122	0.5882	0.9483
	0.04	0.0527	0.0557	1.5521	0.59	0.9157	0.0542	0.055	1.5643	0.5896	0.9223
	0.07	0.0549	0.0581	1.5106	0.5913	0.8931	0.0575	0.0567	1.5341	0.5905	0.9059
	0.1	0.0571	0.0606	1.4719	0.5925	0.8721	0.0608	0.0582	1.5095	0.5913	0.8925
	0.15	0.0607	0.0646	1.414	0.5945	0.8406	0.0659	0.06	1.4817	0.5922	0.8774
	0.2	0.0641	0.0685	1.364	0.5963	0.8133	0.0703	0.0605	1.473	0.5925	0.8727
Sri Lanka											
	0	0.0072	0.0072	2.5539	0.7229	1.8462	0.0072	0.0072	2.5539	0.7229	1.8462
	0.04	0.0074	0.0075	2.4967	0.7232	1.8056	0.0075	0.0073	2.537	0.723	1.8342
	0.07	0.0076	0.0077	2.4602	0.7234	1.7796	0.0078	0.0073	2.538	0.723	1.8349
	0.1	0.0078	0.0078	2.4289	0.7236	1.7574	0.008	0.0072	2.5507	0.7229	1.8439
	0.15	0.008	0.008	2.3872	0.7238	1.7279	0.0082	0.007	2.5962	0.7227	1.8762
	0.2	0.0081	0.0082	2.3571	0.724	1.7065	0.0083	0.0067	2.6684	0.7223	1.9275
Thailand											
	0	0.0626	0.0668	4.2506	0.3055	1.2986	0.0626	0.0668	4.2506	0.3055	1.2986
	0.04	0.0626	0.0668	4.2502	0.3055	1.2985	0.0627	0.0642	4.3598	0.3038	1.3246
	0.07	0.0627	0.0668	4.2499	0.3055	1.2984	0.0627	0.0622	4.4469	0.3025	1.3452
	0.1	0.0627	0.0668	4.2498	0.3055	1.2984	0.0627	0.0602	4.5388	0.3012	1.367
	0.15	0.0627	0.0669	4.2495	0.3055	1.2983	0.0627	0.0568	4.7037	0.2989	1.4059
	0.2	0.0627	0.0669	4.2494	0.3055	1.2983	0.0627	0.0535	4.8852	0.2965	1.4486
Tunisia											
	0	0.0271	0.0278	2.8694	0.5255	1.5079	0.0271	0.0278	2.8694	0.5255	1.5079
	0.04	0.0272	0.028	2.8583	0.5256	1.5025	0.0273	0.027	2.928	0.5247	1.5364
	0.07	0.0273	0.0281	2.8521	0.5257	1.4995	0.0274	0.0262	2.979	0.5241	1.5612
	0.1	0.0274	0.0282	2.8474	0.5258	1.4972	0.0275	0.0254	3.0354	0.5234	1.5886
	0.15	0.0275	0.0283	2.8419	0.5259	1.4945	0.0276	0.0241	3.1404	0.5221	1.6396
	0.2	0.0275	0.0283	2.8383	0.5259	1.4927	0.0276	0.0227	3.2589	0.5207	1.697
Averages											
	0	0.0401	0.0417	4.8767	0.3269	1.5943	0.0401	0.0417	4.8767	0.3269	1.5943
	0.04	0.0401	0.0417	4.8764	0.3269	1.5943	0.0401	0.0401	5.0023	0.3255	1.6284
	0.07	0.0401	0.0417	4.8762	0.3269	1.5942	0.0401	0.0388	5.1023	0.3245	1.6555
	0.1	0.0401	0.0417	4.8761	0.3269	1.5942	0.0401	0.0376	5.2078	0.3234	1.6841
	0.15	0.0401	0.0417	4.8759	0.3269	1.5941	0.0401	0.0355	5.3971	0.3215	1.7352
	0.2	0.0401	0.0417	4.8758	0.3269	1.5941	0.0401	0.0334	5.6054	0.3196	1.7914

Table 2.10: Brain and Drain Effects for Secondary Educated Workers

		For Secondary Educated Brain Effect:					For Secondary Educated Drain Effect:				
Country	π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
Bolivia											
	0	0.1612	0.1921	1.8799	0.4009	0.7537	0.1612	0.1921	1.8799	0.4009	0.7537
	0.04	0.1632	0.195	1.8627	0.4019	0.7486	0.164	0.1883	1.9038	0.3996	0.7607
	0.07	0.1644	0.1967	1.8526	0.4025	0.7457	0.1655	0.1844	1.9288	0.3982	0.7681
	0.1	0.1653	0.1981	1.8445	0.403	0.7433	0.1665	0.1798	1.9592	0.3966	0.777
	0.15	0.1665	0.1998	1.8346	0.4035	0.7403	0.1677	0.1712	2.0203	0.3935	0.7949
	0.2	0.1673	0.2009	1.828	0.4039	0.7384	0.1683	0.1618	2.0928	0.3899	0.8161
Botswana											
	0	0.0278	0.0286	5.5893	0.3408	1.905	0.0278	0.0286	5.5893	0.3408	1.905
	0.04	0.0278	0.0286	5.5891	0.3408	1.9049	0.0278	0.0275	5.7334	0.3396	1.9473
	0.07	0.0278	0.0286	5.5889	0.3408	1.9049	0.0278	0.0266	5.8481	0.3387	1.981
	0.1	0.0278	0.0286	5.5888	0.3408	1.9049	0.0278	0.0258	5.9692	0.3378	2.0164
	0.15	0.0278	0.0286	5.5888	0.3408	1.9048	0.0278	0.0243	6.1862	0.3362	2.0799
	0.2	0.0278	0.0286	5.5887	0.3408	1.9048	0.0278	0.0229	6.425	0.3346	2.1496
Chile											
	0	0.1996	0.2494	2.9061	0.2786	0.8098	0.1996	0.2494	2.9061	0.2786	0.8098
	0.04	0.1997	0.2495	2.905	0.2787	0.8096	0.1997	0.2396	2.9796	0.2757	0.8216
	0.07	0.1998	0.2496	2.9044	0.2787	0.8095	0.1998	0.2322	3.0386	0.2735	0.8311
	0.1	0.1998	0.2497	2.9039	0.2787	0.8094	0.1998	0.2248	3.101	0.2712	0.8411
	0.15	0.1998	0.2498	2.9033	0.2788	0.8093	0.1999	0.2124	3.2132	0.2673	0.859
	0.2	0.1999	0.2498	2.903	0.2788	0.8093	0.1999	0.1999	3.337	0.2633	0.8786
Colombia											
	0	0.1423	0.1659	3.443	0.2696	0.9283	0.1423	0.1659	3.443	0.2696	0.9283
	0.04	0.1423	0.1659	3.4423	0.2696	0.9282	0.1423	0.1593	3.531	0.2672	0.9434
	0.07	0.1423	0.166	3.442	0.2697	0.9281	0.1424	0.1544	3.6014	0.2653	0.9554
	0.1	0.1424	0.166	3.4417	0.2697	0.9281	0.1424	0.1494	3.6757	0.2634	0.9681
	0.15	0.1424	0.166	3.4414	0.2697	0.9281	0.1424	0.1411	3.809	0.2601	0.9907
	0.2	0.1424	0.166	3.4412	0.2697	0.928	0.1424	0.1328	3.956	0.2567	1.0155
Costa Rica											
	0	0.1931	0.2394	2.5487	0.3101	0.7904	0.1931	0.2394	2.5487	0.3101	0.7904
	0.04	0.1934	0.2398	2.5461	0.3103	0.7899	0.1935	0.2303	2.6109	0.3073	0.8024
	0.07	0.1935	0.24	2.5446	0.3103	0.7896	0.1937	0.2233	2.6614	0.3051	0.8121
	0.1	0.1936	0.2401	2.5436	0.3104	0.7894	0.1938	0.2163	2.7153	0.3029	0.8224
	0.15	0.1938	0.2403	2.5423	0.3104	0.7892	0.1939	0.2044	2.8129	0.299	0.8409
	0.2	0.1938	0.2404	2.5415	0.3105	0.789	0.1939	0.1925	2.9208	0.2949	0.8614
Dom. Rep											
	0	0.1563	0.1853	2.0125	0.3871	0.779	0.1563	0.1853	2.0125	0.3871	0.779
	0.04	0.1577	0.1872	1.9999	0.3878	0.7755	0.1582	0.1804	2.0465	0.3853	0.7886
	0.07	0.1584	0.1883	1.9927	0.3881	0.7734	0.1591	0.176	2.0783	0.3837	0.7975
	0.1	0.1591	0.1891	1.987	0.3884	0.7718	0.1598	0.1712	2.1148	0.382	0.8078
	0.15	0.1598	0.1902	1.9802	0.3888	0.7699	0.1605	0.1625	2.1849	0.3787	0.8274
	0.2	0.1603	0.1909	1.9757	0.389	0.7686	0.1608	0.1533	2.2656	0.3751	0.8499
Ecuador											
	0	0.2529	0.3384	2.733	0.2753	0.7524	0.2529	0.3384	2.733	0.2753	0.7524
	0.04	0.253	0.3387	2.7318	0.2753	0.7522	0.253	0.3252	2.802	0.272	0.7622
	0.07	0.2531	0.3388	2.7312	0.2754	0.7521	0.2531	0.3152	2.8573	0.2695	0.7701
	0.1	0.2531	0.3389	2.7306	0.2754	0.752	0.2532	0.3051	2.9159	0.2669	0.7783
	0.15	0.2532	0.339	2.7301	0.2754	0.7519	0.2532	0.2883	3.0213	0.2625	0.7932
	0.2	0.2532	0.3391	2.7297	0.2754	0.7519	0.2533	0.2713	3.1377	0.258	0.8095
El Salvador											
	0	0.1077	0.1207	1.867	0.45	0.8401	0.1077	0.1207	1.867	0.45	0.8401
	0.04	0.1099	0.1234	1.8409	0.4512	0.8305	0.1108	0.1196	1.8776	0.4495	0.844
	0.07	0.1112	0.1252	1.8251	0.4519	0.8247	0.1125	0.1179	1.8942	0.4488	0.8501
	0.1	0.1124	0.1266	1.812	0.4525	0.8199	0.1139	0.1156	1.9175	0.4478	0.8587
	0.15	0.1138	0.1285	1.7956	0.4533	0.8138	0.1153	0.1108	1.9698	0.4456	0.8778
	0.2	0.1149	0.1298	1.7842	0.4538	0.8097	0.1161	0.1051	2.036	0.443	0.902
Ghana											
	0	0.0391	0.0407	2.1502	0.5487	1.1797	0.0391	0.0407	2.1502	0.5487	1.1797
	0.04	0.0401	0.0417	2.1169	0.5493	1.1629	0.0404	0.0405	2.1578	0.5485	1.1836
	0.07	0.0407	0.0424	2.0965	0.5498	1.1526	0.0412	0.04	2.174	0.5482	1.1917
	0.1	0.0412	0.0429	2.0797	0.5501	1.1441	0.0418	0.0393	2.1986	0.5477	1.2041
	0.15	0.0418	0.0436	2.0584	0.5506	1.1333	0.0425	0.0377	2.2558	0.5466	1.233
	0.2	0.0423	0.0441	2.0437	0.5509	1.1259	0.0428	0.0358	2.3303	0.5452	1.2704
Guatemala											
	0	0.0924	0.1019	3.3534	0.3186	1.0683	0.0924	0.1019	3.3534	0.3186	1.0683
	0.04	0.0925	0.1019	3.3522	0.3186	1.068	0.0925	0.0979	3.4384	0.3166	1.0885
	0.07	0.0925	0.102	3.3515	0.3186	1.0679	0.0925	0.0948	3.5065	0.315	1.1046
	0.1	0.0925	0.102	3.351	0.3186	1.0678	0.0926	0.0918	3.5785	0.3134	1.1216
	0.15	0.0926	0.102	3.3505	0.3187	1.0676	0.0926	0.0867	3.7081	0.3107	1.1521
	0.2	0.0926	0.102	3.3501	0.3187	1.0675	0.0926	0.0816	3.851	0.3079	1.1857
Honduras											
	0	0.1372	0.1591	4.4603	0.2197	0.9797	0.1372	0.1591	4.4603	0.2197	0.9797
	0.04	0.1372	0.1591	4.4602	0.2197	0.9797	0.1372	0.1527	4.5754	0.2174	0.9945
	0.07	0.1372	0.1591	4.4601	0.2197	0.9797	0.1372	0.1479	4.667	0.2156	1.0062
	0.1	0.1372	0.1591	4.46	0.2197	0.9797	0.1372	0.1432	4.7635	0.2138	1.0185
	0.15	0.1372	0.1591	4.46	0.2197	0.9797	0.1373	0.1352	4.9367	0.2108	1.0404
	0.2	0.1373	0.1591	4.4599	0.2197	0.9797	0.1373	0.1273	5.1273	0.2076	1.0644
Kenya											
	0	0.0247	0.0253	4.3702	0.4252	1.8582	0.0247	0.0253	4.3702	0.4252	1.8582
	0.04	0.0247	0.0253	4.3692	0.4252	1.8578	0.0247	0.0243	4.4817	0.4241	1.9009
	0.07	0.0247	0.0253	4.3686	0.4252	1.8576	0.0247	0.0235	4.5708	0.4233	1.9349
	0.1	0.0247	0.0253	4.3682	0.4252	1.8574	0.0247	0.0228	4.665	0.4225	1.9709
	0.15	0.0247	0.0253	4.3677	0.4252	1.8572	0.0247	0.0215	4.8343	0.4211	2.0355
	0.2	0.0247	0.0253	4.3675	0.4252	1.8571	0.0247	0.0203	5.0207	0.4196	2.1066

Brain and Drain Effects for Secondary Educated Workers (Continued)

		For Tertiary Educated Brain Effect:					For Tertiary Educated Drain Effect:				
Country	π	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**	**% Educated**	**Ls/Lu**	**Skill Premium**	**Unskilled Wage**	**Skilled Wage**
Malaysia											
	0	0.1488	0.1748	2.3164	0.3574	0.828	0.1488	0.1748	2.3164	0.3574	0.828
	0.04	0.1494	0.1756	2.3103	0.3577	0.8264	0.1496	0.1688	2.3676	0.3552	0.841
	0.07	0.1497	0.176	2.3069	0.3579	0.8255	0.1499	0.164	2.4108	0.3534	0.8519
	0.1	0.1499	0.1763	2.3042	0.358	0.8249	0.1502	0.159	2.4577	0.3515	0.8638
	0.15	0.1502	0.1767	2.3011	0.3581	0.8241	0.1504	0.1505	2.5441	0.3481	0.8856
	0.2	0.1503	0.1769	2.2991	0.3582	0.8236	0.1505	0.1418	2.6407	0.3445	0.9098
Nicaragua											
	0	0.1432	0.1672	2.0579	0.3911	0.8048	0.1432	0.1672	2.0579	0.3911	0.8048
	0.04	0.1444	0.1688	2.0456	0.3917	0.8012	0.1449	0.1627	2.0935	0.3894	0.8151
	0.07	0.1451	0.1697	2.0386	0.392	0.7991	0.1457	0.1586	2.1265	0.3878	0.8247
	0.1	0.1456	0.1705	2.033	0.3923	0.7975	0.1463	0.1542	2.1642	0.3861	0.8356
	0.15	0.1463	0.1714	2.0264	0.3926	0.7956	0.1469	0.1464	2.2363	0.383	0.8564
	0.2	0.1467	0.172	2.022	0.3928	0.7943	0.1472	0.1381	2.3191	0.3796	0.8803
Pakistan											
	0	0.0779	0.0845	2.3828	0.4273	1.0181	0.0779	0.0845	2.3828	0.4273	1.0181
	0.04	0.0784	0.0851	2.3721	0.4276	1.0143	0.0786	0.0819	2.4293	0.4259	1.0346
	0.07	0.0787	0.0855	2.3661	0.4278	1.0121	0.079	0.0798	2.4704	0.4247	1.0492
	0.1	0.079	0.0857	2.3614	0.4279	1.0105	0.0792	0.0774	2.5163	0.4234	1.0655
	0.15	0.0792	0.0861	2.3559	0.4281	1.0085	0.0795	0.0734	2.6024	0.4211	1.0959
	0.2	0.0794	0.0863	2.3524	0.4282	1.0072	0.0796	0.0692	2.7001	0.4187	1.1304
Panama											
	0	0.2679	0.366	3.2213	0.2396	0.772	0.2679	0.366	3.2213	0.2396	0.772
	0.04	0.268	0.3661	3.2209	0.2397	0.7719	0.268	0.3514	3.3039	0.2364	0.781
	0.07	0.268	0.3661	3.2206	0.2397	0.7719	0.268	0.3405	3.3699	0.2339	0.7882
	0.1	0.268	0.3661	3.2205	0.2397	0.7719	0.268	0.3295	3.4394	0.2314	0.7958
	0.15	0.268	0.3662	3.2202	0.2397	0.7719	0.268	0.3113	3.5643	0.2271	0.8093
	0.2	0.268	0.3662	3.2201	0.2397	0.7718	0.2681	0.293	3.7019	0.2226	0.824
Paraguay											
	0	0.1196	0.1359	2.8059	0.3337	0.9363	0.1196	0.1359	2.8059	0.3337	0.9363
	0.04	0.1198	0.1361	2.8032	0.3338	0.9357	0.1198	0.1307	2.8747	0.3315	0.953
	0.07	0.1199	0.1362	2.8018	0.3338	0.9354	0.1199	0.1268	2.9305	0.3298	0.9664
	0.1	0.1199	0.1363	2.8007	0.3339	0.9351	0.12	0.1227	2.99	0.328	0.9807
	0.15	0.12	0.1364	2.7995	0.3339	0.9348	0.1201	0.116	3.0976	0.3249	1.0064
	0.2	0.1201	0.1364	2.7987	0.3339	0.9346	0.1201	0.1092	3.2165	0.3217	1.0348
Peru											
	0	0.2241	0.2888	2.0437	0.3485	0.7122	0.2241	0.2888	2.0437	0.3485	0.7122
	0.04	0.2252	0.2906	2.0361	0.349	0.7105	0.2256	0.2796	2.0856	0.3459	0.7214
	0.07	0.2257	0.2916	2.0318	0.3492	0.7096	0.2263	0.272	2.122	0.3437	0.7293
	0.1	0.2262	0.2923	2.0284	0.3495	0.7088	0.2268	0.264	2.1621	0.3413	0.738
	0.15	0.2268	0.2933	2.0244	0.3497	0.708	0.2273	0.25	2.2368	0.3372	0.7542
	0.2	0.2271	0.2939	2.0218	0.3499	0.7074	0.2275	0.2356	2.3211	0.3328	0.7724
Philippines											
	0	0.2693	0.3685	2.0174	0.3371	0.68	0.2693	0.3685	2.0174	0.3371	0.68
	0.04	0.2703	0.3705	2.0108	0.3375	0.6787	0.2707	0.3564	2.0602	0.3341	0.6883
	0.07	0.2709	0.3715	2.0071	0.3378	0.678	0.2714	0.3465	2.0968	0.3316	0.6953
	0.1	0.2713	0.3724	2.0043	0.338	0.6775	0.2719	0.3361	2.137	0.329	0.703
	0.15	0.2719	0.3734	2.0009	0.3383	0.6768	0.2724	0.3182	2.2113	0.3243	0.7172
	0.2	0.2722	0.3741	1.9987	0.3384	0.6764	0.2726	0.2998	2.295	0.3194	0.7331
Poland											
	0	0.1924	0.2383	1.3224	0.4706	0.6223	0.1924	0.2383	1.3224	0.4706	0.6223
	0.04	0.2013	0.252	1.2769	0.4746	0.606	0.2057	0.2486	1.288	0.4736	0.61
	0.07	0.2078	0.2623	1.2454	0.4775	0.5947	0.2153	0.2552	1.267	0.4755	0.6024
	0.1	0.2141	0.2724	1.2163	0.4803	0.5842	0.2245	0.2606	1.2506	0.477	0.5965
	0.15	0.2241	0.2888	1.1728	0.4847	0.5685	0.2384	0.2661	1.2344	0.4785	0.5907
	0.2	0.2332	0.3041	1.1355	0.4887	0.5549	0.2497	0.2662	1.2339	0.4786	0.5905
Sri Lanka											
	0	0.1338	0.1545	1.8745	0.4226	0.7922	0.1338	0.1545	1.8745	0.4226	0.7922
	0.04	0.1359	0.1573	1.8535	0.4237	0.7853	0.1368	0.1521	1.8927	0.4217	0.7982
	0.07	0.1372	0.159	1.841	0.4243	0.7812	0.1384	0.1494	1.9143	0.4206	0.8052
	0.1	0.1383	0.1605	1.8309	0.4249	0.7779	0.1396	0.146	1.9418	0.4193	0.8142
	0.15	0.1396	0.1622	1.8183	0.4255	0.7738	0.1409	0.1394	1.9994	0.4166	0.833
	0.2	0.1405	0.1635	1.8098	0.426	0.771	0.1415	0.1319	2.0694	0.4135	0.8558
Thailand											
	0	0.1019	0.1134	2.5286	0.3781	0.956	0.1019	0.1134	2.5286	0.3781	0.956
	0.04	0.1022	0.1138	2.5229	0.3783	0.9543	0.1023	0.1094	2.5858	0.3762	0.9728
	0.07	0.1024	0.1141	2.5197	0.3784	0.9533	0.1025	0.1063	2.6337	0.3747	0.9868
	0.1	0.1025	0.1142	2.5172	0.3784	0.9526	0.1027	0.103	2.6855	0.3731	1.002
	0.15	0.1027	0.1144	2.5144	0.3785	0.9518	0.1028	0.0974	2.7805	0.3703	1.0297
	0.2	0.1028	0.1146	2.5126	0.3786	0.9513	0.1029	0.0918	2.8864	0.3674	1.0605
Tunisia											
	0	0.1206	0.1372	2.026	0.4149	0.8406	0.1206	0.1372	2.026	0.4149	0.8406
	0.04	0.122	0.1389	2.01	0.4156	0.8354	0.1225	0.134	2.0555	0.4136	0.8502
	0.07	0.1228	0.1399	2.0007	0.416	0.8324	0.1235	0.131	2.0848	0.4123	0.8596
	0.1	0.1234	0.1408	1.9934	0.4164	0.83	0.1242	0.1276	2.1194	0.4109	0.8708
	0.15	0.1242	0.1418	1.9844	0.4168	0.8271	0.1249	0.1213	2.1875	0.4082	0.8928
	0.2	0.1247	0.1425	1.9786	0.4171	0.8252	0.1253	0.1146	2.2671	0.4051	0.9185
Averages											
	0	0.1515	0.1785	2.6853	0.3201	0.8596	0.1515	0.1785	2.6853	0.3201	0.8596
	0.04	0.1517	0.1788	2.6827	0.3202	0.859	0.1517	0.1717	2.751	0.3176	0.8738
	0.07	0.1518	0.1789	2.6813	0.3203	0.8587	0.1519	0.1665	2.8044	0.3157	0.8853
	0.1	0.1518	0.179	2.6802	0.3203	0.8585	0.1519	0.1612	2.8613	0.3137	0.8975
	0.15	0.1519	0.1792	2.679	0.3204	0.8582	0.152	0.1524	2.9642	0.3102	0.9196
	0.2	0.152	0.1792	2.6782	0.3204	0.8581	0.1521	0.1435	3.078	0.3066	0.9438

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Chapter 3

Education Policy And Rate of Return Estimates

3.1 Introduction

Standard cross-country estimates of the social return to education, shown in Figure 3.1, appear to show that social returns to basic education are greater than social returnsm to higher levels of education.[1] The standard social rate of return estimates (ROREs), summarised in Figure 3.1, are often viewed as "...a diagnostic tool with which to start the process of setting priorities and considering alternative ways of achieving objectives" ((World Bank, 1995), pg. 94). The estimates prompted a shift of focus to basic levels of education, often at the expense of higher education. The World Bank in its "Priorities and Strategies for Education" concludes: "Consequently, basic education should usually be given priority for public spending on education in those countries that have yet to achieve near-universal enrollment in basic education" (World Bank (1995), pg. 56; see Section 5 in Psacharopoulos and Patrinos (2007)).

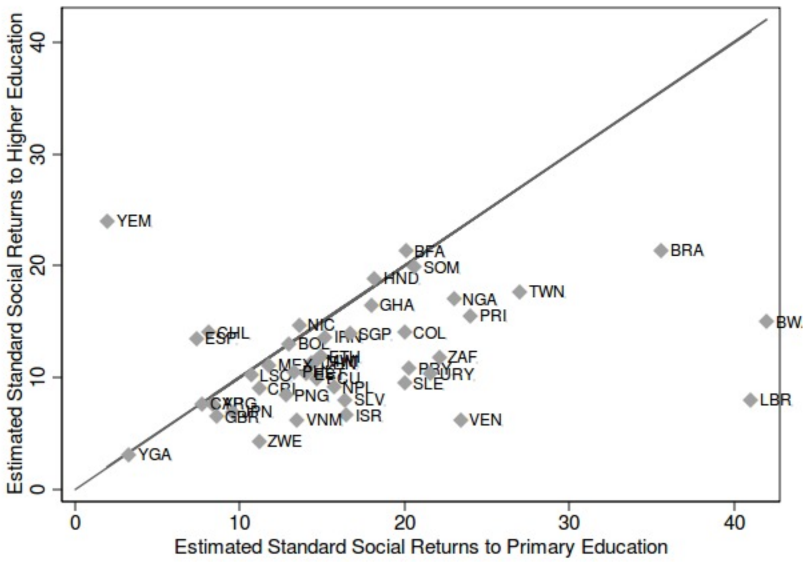
In this paper, I measure externalities to higher education which arise because productivity depends on the proportion of higher educated workers, and higher educated workers are an input in the production of human capital for basic educated workers. The effects of higher educated workers—better teachers, improved basic healthcare delivery, and technological advances—are dynamic, and have spillovers beyond that to the direct consumer. This paper quantifies these effects from aggregate data, and computes their implications for the social ROR to higher education.

I find that when these external effects are taken into account, the true social return to higher education is, on average, two times as large as standard social ROREs (which do not account for any externalities). Contrary to the conclusion of the World Bank education policy paper cited above, standard ROREs cannot be used as a guide for education policy.[2] I also find that, for countries with lower

[1] Standard social ROREs are obtained by adjusting private wage returns to education (from Mincer regressions) for public education subsidies, with no adjustments made for externalities to education (Psacharopoulos and Patrinos, 2007).

[2] For an earlier criticism of formulating policy based on rate of return estimates, see Bennell

Figure 3.1: Standard Estimates of Social Returns



Source: Psacharopoulos and Patrinos (2004)

proportions of higher educated workers, the standard ROREs systematically underestimate social returns to higher education. In fact, larger standard social ROREs to basic education, compared to education at higher levels, is consistent with optimal education policy when these externalities are taken into account.

The paper begins by presenting a macroeconomic model in which the proportion of higher educated workers is an input in the production of basic skills (human capital effect), and the productivity of basic and uneducated workers also depends on the proportion of higher educated workers in the economy (productivity effect). Quantifying the productivity and human capital effects of higher educated workers is challenging, because cross-country wages will differ due to differences in productivity, as well as human capital.

The methodological contribution of this paper is describing how the productivity and human capital effects could be separately identified. The human capital effect of higher educated workers is identified from information on differences in returns to education by country of origin, for immigrants in the U.S. The use of information on returns to education for immigrants in a particular country controls for the productivity effect. As Bratsberg and Terrell (2002) and Schoellman (2012) show, differences in the returns to education for immigrants in the U.S. reflect

(1996) which questions the plausibility of the estimates. There are several reasons why they may not reflect the true private return to education (such as unionization, government job guarantees, urban/rural divisions). The approach here is to assume that the ROREs are accurate reflections of the wage-benefit to education, and show they are still not reliable for education policy.

differences in home country quality of education. To capture the human capital effect, I regress the average rate of return (ROR) to education for an immigrant from a given country, relative to a U.S. native in the year 2000, on relative differences in the 1980 proportion of higher educated workers. The results show that controlling for other determinants of education quality, including teacher salaries, individuals from countries with larger proportions of higher educated workers in 1980 have greater returns to education in the U.S. The parameter estimate from this exercise is used to calculate the size of the human capital effect.

I use estimates of cross-country agricultural productivity gaps (APGs), from Gollin et al. (2011), to quantify the productivity effect. The authors carefully estimate cross-country APGs accounting for quality and quantity of human capital, which controls for human capital effects. The use of within-country sectoral productivity gaps controls for aggregate factors that may influence productivity in all sectors (including investments in education). This strategy captures a productivity externality because it reflects changes in productivity beyond those in the non-agricultural sector, where most higher educated workers are employed. I find that APGs, adjusted for human capital, decrease with the proportion of higher educated workers. The estimate of the elasticity of the APG to the proportion of higher educated workers is used to calculate the size of the productivity effect.

Results from calculations of social RORs reveal that the difference between *true* (accounting for human capital and productivity effects) social returns to higher education and *standard* ROREs are as large as 10-20 percentage points, depending on the country. The model also replicates the finding that standard social ROREs to basic education are greater than those for higher education. However, it does not follow that funds should be reallocated from higher to basic education, because the measured externalities are large. As Figure 3.5 shows, for most of the 33 developing countries in my dataset, the social return to higher education is larger compared to basic education.

Furthermore, I find that education policy which relies on standard ROREs as a guide, encourages greater focus on basic education in countries where the human capital and productivity effects are larger—when optimal education policy will imply greater investments in higher education. This is because the gap between true and standard estimates of social RORs to higher education is decreasing in the proportion of the higher educated, as a result of decreasing human capital and productivity effects.[3] This implies that the difference in standard social ROREs for basic and higher education is larger in countries with lower proportions of higher educated workers (and larger externalities), which is confirmed in the data. Education policy based on standard social ROREs inadvertently leads to systematic underinvestment in higher education.

The conclusion that public focus should be shifted to basic education, based on standard ROREs, is incorrect and could lead to unintended consequences. I show

[3]For more advanced economies such as the U.S., with large proportions of higher educated workers, the productivity and human capital effects are very small (consistent with findings in (Ciccone and Peri, 2006; Acemoglu and Angrist, 1999)).

that these external effects are also important for the profitability of current expansions in basic education. This is because higher educated workers are important for the quality of basic education, as well as the productivity of basic educated workers. A reallocation of funding to basic education to equate standard ROREs in the framework, leads to significant reductions in the quantity of human capital obtained by basic educated workers, and lowers the private return to basic education. The biggest impact, however, is on the wage level of basic and uneducated workers. In some cases, lower productivity means that the wage of basic educated workers falls by over 40%.

There is some evidence that a rapid expansion in basic education, at the expense of higher education, may not have been the best policy for basic educated workers. Association of Universities and Colleges of Canada (2003) report that the rapid expansion of basic education in several developing countries, has led to lower education quality. The low quality of basic education in developing countries, where many students complete basic education with less than basic skills, can be found in Glewwe and Kremer (2006). In a study on the returns to the Universal Primary Education program in Nigeria, Uwaifo-Oyelere (2010) finds the average return to the program to be just 2.8%; which is very low compared to previous estimates of the returns to education in Nigeria. The author attributes the result to stagnant demand for education—the productivity effect.

The primary assumption in this paper is that the productivity and human capital effects are not fully accounted for by the wages of higher educated workers. I focus on these effects, because as I explain below using several examples, they are likely to be important in developing countries with low proportions of higher educated workers.

A positive relationship between returns to basic education and the proportion of higher educated workers can arise because teachers are are an input in the production of basic education. In evaluating the impact of higher teacher quality in the U.S., Hanushek (2011) finds that a teacher one standard deviation above mean effectiveness, in a class size of 20 pupils, generates an annual marginal gain of over $400,000 in present value of future student earnings. It is unlikely these future wage gains from improved teacher quality are completely reflected in teacher wages. This is for reasons related to credit constrained pupils or difficulties in establishing enforceable contracts between teachers and pupils.

Problems with teacher quality are significantly worse in the context of developing countries, suggesting a potential for higher gains in earnings from quality improvements. For example, on average, only about 69 percent of primary school teachers are trained in developing countries, compared to 90% in the OECD. A survey of education systems in developing countries, by Glewwe and Kremer (2006), concludes that many developing countries have too few teachers to accommodate the rapid expansion in primary school enrollment. Developing countries also have the highest pupil-teacher ratios, the lowest measures of teacher effectiveness, and worse student outcomes compared to peers in other countries. This means there are significant gains from training more teachers, and increasing the human capital obtained from a basic education.[4]

Higher educated workers can also affect the return to basic education if they perform other services which enable basic educated workers to get more out of their time in school. For example, Miguel and Kremer (2004) find that deworming improved health and school participation among untreated children at schools in close proximity to those who were treated. They also find that two-thirds of the social effect of deworming comes through reduced rates of transmission, and increased attendance for untreated children. The wages of nurses who deliver deworming and other public health services are unlikely to reflect these positive externalities on schooling outcomes, because a majority of the benefits accrue to untreated students.

Better health leads to greater human capital for future adults, as well increased productivity for current workers. Several studies find that the main economic burden of communicable diseases in developing countries, such as malaria or cholera, come from time spent caring for the ill (see Onwujekwe et al. (2000) for a study in Eastern Nigeria, and Konradsen et al. (1997) for a study in Sri Lanka). A nurse's services in a malaria-prone village not only benefits a sick child, but also allows the child's parents to spend more time at work. If the prevention externalities from deworming exist for other communicable diseases, then the nurse's services also benefit other parents in the community who do not have to take time off work to care for sick children. These external benefits to productivity are unlikely to be fully reflected in the nurse's current wage. This channel is very important in the context of developing countries where there still exists a wide scope for human capital and productivity gains by improving public health services.

Higher educated workers can also affect the productivity of the basic educated workers through other channels unlikely to be fully reflected in current wages. Beyond the role of higher educated workers as factors of production, they are also important for technology adoption and diffusion, as found in several cross-country studies. For example, Acemoglu and Zilibotti (2001) finds that within a given sector, productivity gaps across countries decrease with the proportion of skilled workers. Technical change not only increases the productivity of higher educated workers in a given sector, there is also an increase in the productivity of all other workers in that sector. Ciccone and Papaioannou (2009) also show that a greater share of secondary educated workers is positively related to faster sectoral productivity growth (technological progress) for all workers, especially in human-capital intensive sectors. Caselli and Wilson (2004) finds that the amount of technology embodied in imported machineries is positively related to skill levels. Firm-level studies studies such as Schultz (1975), Doms et al. (1997), and Dunne and Schmitz Jr (1995), find that plants with more skilled workers use more advanced technologies.

Rapid technological progress is linked to increases in returns to education as

[4]Also see a recent study of 351 rural schools in Guinea-Bissau by Boone et al. (2013). In all schools, the authors could not find a single instance where numeracy and literacy were adequate for age, and they also document significant teacher (and quality) shortfalls.

more educated farmers are better equipped to experiment with new technologies (Foster and Rosenzweig, 1996). These activities also have important spillover effects on the productivity of other farmers in an adopter's social network (see Foster and Rosenzweig (1995) for hybrid corn in India, Conley and Udry (2010) for pineapple in Ghana). It is unlikely that these network effects are fully captured in the wage of an adopting farmer, and even less so for wages of higher educated workers partly responsible for technical progress.

This study is important for countries of sub-Saharan Africa and South Asia where education attainment remains low relative to other regions of the world. At the heart of these problems is how to allocate limited education funds. As I discussed earlier, the larger standard social ROREs to basic relative to higher levels of education was taken to imply that relatively more public resources needed to be allocated to basic education (Bennell, 1996). This paper calls attention to the importance of looking beyond standard ROREs in the formulation of education policy, especially in countries with low proportions of higher educated workers. Indeed, what is needed is a balance between the pool of higher and basic educated workers. This would ensure that basic educated workers leave school with sufficient human capital, and are able to employ their human capital in a productive environment. This paper does not speak directly to what the optimal allocation may be, or how it can be achieved. This question is left for future research.

In the next section, a quantifiable model of the interaction between the ROR to basic education and the proportion of higher educated workers is presented. The model also delivers the insight that wage-based estimates of private rates of return are not useful for education policy. The third section explains how the parameters governing the human capital and productivity effects are estimated. Section 4 quantifies the size of the divergence between social and private RORs, and evaluates how changes in the proportion of higher educated workers can impact returns to basic education. The final section concludes.

3.2 Model of Education Funding

3.2.1 General Assumptions

It is assumed that all direct costs of education are publicly financed. This assumption can be justified in the context of the poorer developing countries where over 70% of direct education costs are government financed (Glewwe and Kremer, 2006). Education is financed from a fixed budget G which is allocated to basic education denoted by level *1*, or higher education denoted by level *2*. Since all individuals are assumed to be alike, individuals are randomly selected to attend school.

3.2.2 Production Technology

Output Y is produced using a constant returns to scale production function which depends only on human capital. The production function is given by:

$$Y = A_0(N_0 + N_1h_1) + AN_2h_2.$$

Where N_i represents the number of individuals who have completed level i of education, $i \in \{0,1,2\}$, and $i = 0$ represents those who did not attend school. The terms h_1 and h_2 are the amounts of human capital available to basic and higher educated workers respectively.

The term A represents the total factor productivity (TFP) of individuals in the "modern" sector, which is taken as given. The production function indicates that higher education is needed in order to participate in the modern sector. The TFP of individuals in the "traditional" sector—those who have achieved basic or have no education— depends on the proportion of higher educated workers in the economy:

$$A_0 = Af(\sigma_2). \tag{3.1}$$

Equation (3.1) above reflects the idea that the TFP of workers with a basic education depends on the pool of higher educated workers for reasons already outlined in the introduction. Here, σ_2 is the proportion of higher educated workers, and $f()$ is a function relating the proportion of higher educated to the TFP of basic educated workers. The specification of the production function without complementarities in production ensures that private ROREs from wage regressions reflect the private marginal benefit of education.

Assumption 1: $f(\sigma_2)$ is increasing, concave, twice continuously differentiable with respect to σ_2, $f(0) > 0$, and $f(1) = 1$.

The assumption above implies that the TFP of basic educated workers increases with the proportion of higher educated workers at a decreasing rate, but the productivity of the traditional sector never goes above that of the modern sector.[5] The assumption that $f(0)$ is positive ensures that output in the traditional sector is not zero in the absence of higher educated workers.

3.2.3 Human Capital Production

The human capital of a higher educated worker is taken as exogenous to the proportion of higher educated workers. The focus is on the impact of higher educated workers on the the human capital of the basic educated, and the human capital production of basic educated workers is given by the function:

$$h_1 = \sigma_2^{\beta_1} exp\{\theta s\}. \tag{3.2}$$

[5] This can be justified in the context of developing countries by the observation that productivity in agriculture is consistently lower than that in non-agriculture, and non-agricultural workers are more educated than agricultural workers (Gollin et al., 2011; Restuccia et al., 2008).

Assumption 2: h_1 is increasing and concave with respect to σ_2 (β_1 lies between zero and 1).

The proportion of higher educated workers in the population (σ_2) can be interpreted as a measure of the quality of education. Bils and Klenow (2000) suggest that the formulation for h_1 above is an appropriate way to incorporate Mincerian estimates of the returns to education into a macroeconomic model. The formulation here differs from theirs in that they assume that current human capital depends on the average human capital of the preceding generation.[6] In equation (3.2), s stands for the length of time required to complete a basic education, which ranges from $5 - 9$ years.

From assumption 2, the quantity of human capital is increasing in the proportion of higher educated workers. Notice that if $\beta_1 = 0$, the proportion of higher educated workers does not matter for the human capital obtained through a basic education. In this case, the production function parameter, θ, can be calibrated to match widely available estimates on the returns to schooling. It costs g_1 units of the consumption good to educate a basic educated worker, and g_2 units to educate a higher educated worker who is already basic educated.[7]

3.2.4 The Social Planner Problem

Individuals consume their wages which is earned by inelastically supplying their human capital in the labor market, and as already mentioned are identical with respect to ability and the opportunity cost of going to public school. Individuals who are schooled can either have basic schooling only, or proceed to higher education. Recall that the question of interest is whether it is always profitable to reallocate education resources from higher to basic education based on standard estimates of the returns to education.

Given a fixed education budget G, the social planner problem (SPP) is given by:

$$max_{N_1,N_2} Y = A_0(N_0 + N_1 h_1) + A N_2 h_2$$

$$\text{s.t.} \quad A_0 = A f(\sigma_2)$$

$$h_1 = \sigma_2^{\beta_1} exp\{\theta s\}$$

$$G = g_1 N_1 + (g_1 + g_2) N_2 \tag{3.3}$$

$$N_0 = N - (N_1 + N_2) \tag{3.4}$$

[6]This difference is partly a reflection of different research questions. Their paper interprets the average human capital of the preceding generation as a measure of teacher quality, whereas the interest here is on teacher quality, as well as other services (such as health care) provided by higher educated workers. The average human capital of the preceding generation may be a good measure of teacher quality, but not access to health services for example.

[7]It is important to note that the model presented here is vague on timing. The human capital effect is dynamic, while the productivity effect is contemporaneous and dynamic. This timing is taken seriously in the quantitative exercise which follows, but the static model allows for greater clarity in explaining some of the results.

$$N_i \geq 0 \quad \forall i \in \{0, 1, 2\}.$$

Assumption 3:

i) The quantity of human capital increases with the level of schooling: $h_2 > h_1 > 1$.

ii) The cost of higher education is sufficiently greater than that for basic education: $g_2 > g_1 h_1$ at all levels of σ_2.

The first part of Assumption 3 above ensures that the human capital available to individuals is increasing with their level of education, an assumption which will be disciplined by observed evidence on private returns to education. The problem amounts to picking the number of basic and higher educated workers to maximize output and satisfy the resource constraint, while taking into account the fact that the productivity and human capital of basic educated workers depend on the proportion of higher educated workers.

The first-order conditions reveal that in an interior solution, the optimal proportion of higher educated workers, σ_2^*, equates the net social marginal benefit (SMB) for higher education to the net social marginal benefit for basic education:

$$\frac{h_2 - f^*}{g_2 + g_1} + \frac{f'^*}{g_2 + g_1}[1 + \sigma_1^*(h_1^* - 1) - \sigma_2^*] + \frac{f^*(h_1'^* \sigma_1^*)}{g_2 + g_1} = \frac{f^*(h_1^* - 1)}{g_1}. \tag{3.5}$$

An asterisk (*) above a variable indicates that it is a function of the the optimal proportion of higher educated workers in the population, and a prime ($'$) is the first derivative of the variable with respect to N_2. Let σ_1^* represent the optimal proportion of workers in the economy who only have a basic education, which can be derived by rearranging (3.3):

$$\sigma_1^* = \frac{G}{N g_1} - (1 + g_2/g_1)(\sigma_2^*). \tag{3.6}$$

Expression (3.6) illustrates the trade-off between basic and higher education in the model: If there is no higher education, the term G/Ng_1 denotes the maximum proportion of workers who can be basic educated. The expression tells U.S. that for every basic educated worker who goes on to acquire higher education, there are *potentially* $g_2/g_1 > 1$ workers who have to remain uneducated.

The exercise here can be interpreted as examining whether it is justifiable, at prevailing standard estimates of the social returns to basic and higher education, to have one more higher educated worker over g_2/g_1 basic educated workers. The analysis in Section 4 show that, with reasonable values for $g_2/g_1 > 1$, the human capital and productivity effects are large enough to justify prevailing levels of investment in higher education as optimal.

In general, the outcome of the model depends on the shape of the functions f and h_1, as well as the relative sizes of N, G, g_1 and g_2. As long as the social marginal benefit (left-hand side of (3.5)) to higher education outweighs the net

SMB to basic education when $\sigma_2 = 0$, it will beneficial to have some higher educated workers. For the analysis in the next section, it is assumed that parameters are such that the model yields an interior solution with a mix of higher and basic educated workers which satisfy eqs. (3.5) and (3.6).

3.2.5 Qualitative Results

Rate of Return Analysis Using Wages: Consider the wages which will result from the profit maximization problem of a perfectly competitive firm in this model that takes σ_2^* as given:

$$w_0 = Af(\sigma_2^*) \qquad w_1 = Af(\sigma_2^*)h_1^* \qquad w_2 = Ah_2.$$

Private returns to different levels of education are ideally derived using age-earning profiles to back out internal rates of return. Due to data limitations, an extended Mincer earnings function is commonly used. Years of schooling are converted into dummy variables for each educational level, with controls included for other independent variables.

As Psacharopoulos and Patrinos (2007) show, the extended earnings function method can be approximated by the "shortcut" method, using conditional (on observables) mean wages for different educational levels. For example, the shortcut method estimates the ROR to basic education as: $(w_1 - w_0)/w_0$. This is the conditional mean wage gain for a basic educated worker, divided by foregone earnings.

Applying the shortcut method to wages from the decentralized firm problem, the model counterpart to private ROREs (r^p) to basic and higher education respectively are given by:

$$r_1^p = h_1^* - 1, \qquad \text{and} \qquad r_2^p = \frac{h_2 - f^* h_1^*}{f^* h_1^*}. \tag{3.7}$$

The standard social return to education is estimated by accounting for the resource costs of basic and higher education g_1 and g_2 respectively as part of the opportunity cost. For basic and higher educated workers, the model counterpart to standard estimates of the social return to education are given by:

$$r_1^s = \frac{Af^*(h_1^* - 1)}{Af^* + g_1}, \qquad \text{and} \qquad r_2^s = \frac{A(h_2 - f^* h_1^*)}{Af^* h_1^* + g_2}. \tag{3.8}$$

To be consistent with the pre-existing literature, the expressions in (3.7) will be referred to as *standard* private rate of return estimates (ROREs), and those in (3.8) as the *standard social* (ROREs). Notice that standard social ROREs do not account for any external benefits to basic or higher education, which is important for the analysis that follow.

Remark The first order condition in (3.5) can be written in terms of the marginal wage benefit of basic and higher education weighted by their respective costs. At an interior solution, it must be that:

$$\Gamma^* = \frac{Af(h_1^* - 1)}{g_1} - \frac{A(h_2 - f^* h_1^*)}{g_2} \tag{3.9}$$

Where

$$\Gamma^* \equiv \underbrace{\frac{Af'^*}{g_2}[1 + \sigma_1^*(h_1^* - 1) - \sigma_2^*]}_{\text{Productivity Effect}} + \underbrace{\frac{Af^* h'^* \sigma_1^*}{g_2}}_{\text{Human Capital Effect}}$$

The expression in (3.9) is obtained by rearranging the first order condition in (3.5). The term "Γ^*" is the marginal external benefit of higher educated workers (not reflected in wages of the higher educated) on the traditional sector. It consists of two additive terms: The first is the effect of higher educated workers on the TFP of all workers in the traditional sector (the productivity effect), and the second is the impact on the human capital of basic educated workers (the human capital effect).

Both effects raise the value of a basic educated worker relative to a higher educated, and an uneducated worker. The productivity and human capital effects raise the value of a basic educated worker relative to a higher educated worker, and the human capital effect raises the value of a basic educated worker relative to an uneducated worker.

The condition in (3.9) implies that Γ^* is equal to the difference between the wage benefit of basic and higher education, weighted by their respective costs. This difference in cost-adjusted wage benefits is non-negative since by Assumptions 1 and 2, Γ^* is non-negative. Equation (3.9) is convenient for expressing the relationship between standard social ROREs to basic and higher education. The result below summarizes the relationship between Γ^* and the standard social ROREs:

Result 3 *If Assumptions 1,2, and 3 hold, then:*

1. Γ^* *is an upper bound on the difference between standard estimates of the social return to basic and higher education in* (3.8).

2. *At the optimal level of* σ_2^**, the estimated social returns to higher education is not guaranteed to be as large as that for basic education.*

Proof See appendix A.

The second part of Result 3 implies that as long as Γ^* is positive, the standard social RORE to basic education will be greater than those higher education i.e. $r_1^s \geq r_2^s$. If Assumption 1 and 2 hold (Γ^* is positive), then optimality does not imply that standard social ROREs for basic and higher education should be equal. A significant contribution of this paper is demonstrating that Γ^* is positive and quantitatively large.

The intuition behind the result is simple: estimates of the social return to education which come from individual wages do not account for the fact that higher educated workers have some impact on the productivity and human capital of the basic educated. Standard ROREs underestimate the true social return to higher education. Note that it is not the case that one can justify every situation where $r_1^s \geq r_2^s$ as optimal. Result 3 also shows that the gap between standard ROREs for basic and higher education should be no greater than Γ^*.

Next, I analyze how the value of Γ^* changes with σ_2^*, and conditions under which one can expect the social returns to basic and higher education to diverge:

Result 4 *If Assumptions 1,2, and 3 hold, and the TFP of workers in the traditional sector is not too responsive to changes in the proportion of skilled workers, specifically if $f'/f < (1 + g_2/g_1)/2$, then Γ is decreasing in the proportion of skilled workers. This implies that the gap between standard social ROREs for basic and higher education is decreasing in the optimal proportion of skilled workers, all else equal.*

Proof See appendix A.

To see why this is true, notice that as the proportion of higher educated workers increases, there are opposing forces on the impact of the marginal higher educated workers in the traditional sector. The impact of the marginal higher educated worker, Γ, decreases because the productivity and human capital effects are getting smaller from concavity assumptions. Additionally, the proportion of workers who only have a basic education is getting smaller, which decreases the human capital effect. On the other hand, an increase in the TFP of basic and uneducated workers remaining in the traditional sector will tend to increase the value of Γ. As long as the relative increase in TFP (f'/f) is not large enough to outweigh the reduction in output due to a decrease in basic educated workers (g_2/g_1), Γ will be decreasing.

Is the sufficient condition in Result 4 likely to satisfied? Assume higher education only costs 3 times as much as basic education, which is a very conservative estimate for developing countries (See). The condition says that for a 1 percentage point increase in the proportion of higher educated workers, the TFP of basic and uneducated workers should increase by no more than 2%. Using data from U.S. cities, Moretti (2004) finds that a 1 percentage point increase in the proportion of college graduates raises wages by no more than 2% (this includes any human capital and productivity effects).[8] This is taken as evidence that the condition is likely to be satisfied, and even more so when the cost of higher education relative to that of basic education is a lot larger than 3, as is the case in many developing countries (See Table 3.6 for data from UNESCO (2012), and Table 9 in (Glewwe and Kremer, 2006)).

Result 4 is important because it points out that we should expect to see larger gaps between standard social ROREs for basic education and higher education, in economies where the proportion of skilled workers is relatively low. This is because

[8] Bils and Klenow (2000) also find an elasticity of productivity with respect to the *stock of human capital* of .77 which is consistent with the condition for Result 4.

the impact of higher educated workers on the traditional sector is larger for this group of countries. The result also suggests that the effects being discussed here should be small for countries with large proportions of higher educated workers, which is confirmed by the quantitative exercise.

The set of countries which are being advised to reallocate funding from higher to basic education due to relatively low standard social ROREs to higher education, are the same set of countries where the human capital and productivity effects are larger. Such an education policy which ignores the human capital and productivity effects will be counterproductive.

Impact of Shifting Education Funding:

Result 5 *If Assumptions 1,2, and 3 hold, and the the economy is at the optimal proportion of higher educated workers with* $\Gamma^* > 0$*, shifting education funding in order to equate standard social ROREs for higher and basic education leads to a lower return to basic education, and also lowers the TFP in the traditional sector.*

Proof If Assumptions 1,2, and 3 hold, from Result 3, we know that at the optimal proportion of higher educated workers, social ROREs for basic education will be greater than those to higher education. Equating social ROREs implies that there must be an increase the proportion of basic educated workers, and a reduction in the number of higher educated workers. The reduction in the proportion of higher educated workers lowers TFP in the traditional sector by Assumption 1, as well as the human capital of basic educated workers by Assumption 2. Consequently, there is an increase the return to a higher education because of the lower productivity and human capital of basic educated workers. There is also a decrease in the return to a basic eduction because of lower human capital.

Result 5 speaks to the potential impact of policies such as UNESCO's Education for All (EFA) initiative which recommend a focus on basic education, often at the expense of higher education. The prominent economic rationale for these policies are larger social ROREs for basic education. Such policies undoubtedly benefit uneducated workers who obtain basic education. For workers who would have obtained a basic education anyway, and those who are now unable to obtain a higher education, the policy makes them worse off.

More important, Result 5 implies that the return to policies such as EFA will be lower than expected if higher educated is neglected. Indeed there is some evidence that expansions in basic education have not been as profitable as one would have hoped in light of the large social ROREs. Uwaifo-Oyelere (2010) for example, using evidence from the Universal Primary Education program in Nigeria, finds that the returns to education are much lower (just 2.8%) than those previously reported in the literature. The result above points out that such low rates of return to a rapid expansion in basic education is to be expected if the quantity of human capital (quality of education) declines due to a decline in the proportion of higher educated workers.

The evidence on decreased returns to education may be a reflection of a decline in marginal ability, or an increase in the supply of skills under conditions of stagnant demand, as opposed to lower quality of education. However, quality declines are also documented in other direct measures documented in UNESCO's EFA global monitoring report (UNESCO, 2004). Other evidence indicating that basic educated workers, in many developing countries, graduate with lower than expected levels of human capital such as poor literacy and numeracy skills, can be found in the survey by Glewwe and Kremer (2006).

The productivity effect impacts the value of basic educated workers relative to higher education workers (it increases the returns to higher education). Lowering the productivity effect, leads to a reduction in the *level* of wages earned by basic educated workers. This may be important in explaining productivity differences across countries in a world with technical change directed towards skilled workers (Acemoglu and Zilibotti, 2001; Ciccone and Papaioannou, 2009). Having a low proportion of skilled workers means that countries are unable to access current technologies, or adopt them for their own uses.

In summary, in a model with human capital and productivity effects, wage-based estimates of social rates of return to basic and higher education are not necessarily equal at the optimal proportion of higher educated workers, unless the proportion of higher educated are sufficiently large. Looking at wage-based social ROREs across countries will present a distorted picture on the optimal allocation of education resources. For countries with a small proportion of higher educated workers, the gap between estimated social returns should be larger because Γ^* is larger, and the gap should decrease as the proportion of higher educated workers increases. Policies aimed at equalizing social ROREs will lead to worse than expected outcomes for basic educated workers. These policies lower the human capital and productivity of basic educated workers. The importance of these predictions however, depends on the size of the human capital and productivity effects, a question which is addressed in the next two sections.

3.3 Estimating Parameters of the Model and Calibration

In this section, I describe how the parameters of the model for the human capital production function, and the relationship between productivity and the proportion of higher educated workers are estimated. All other parameters are chosen so the model matches features of the data on private returns to education, proportion of educated workers in each education category, and GDP per capita. The key object to be quantified is the term Γ:

$$\Gamma \equiv \underbrace{\frac{Af'}{g_2}[1+\sigma_1(h_1-1)-\sigma_2]}_{\text{Productivity Effect}} + \underbrace{\frac{Afh'\sigma_1}{g_2}}_{\text{Human Capital Effect}}.$$

In order to quantify Γ, parameters of the basic human capital production function h_1, as well as the function relating the TFP of basic educated workers to the proportion of higher educated workers, f are required.

3.3.1 Higher Educated Workers and Human Capital Production:

The human capital production function of basic educated workers in (3.2) is given by:

$$h_1 = \sigma_2^{\beta_1} exp\{\theta s\}.$$

The parameter of interest here is β_1 which determines the impact of higher educated workers on the human capital of basic educated workers. From Assumption 2, the null hypothesis is that β_1 is strictly positive, and less than 1(concavity).

Identifying β_1 from wages requires that the productivity effect is held constant as the proportion of higher educated workers changes. This is challenging because a change in the proportion of higher educated workers is reflected in wages through changes in productivity, as well as changes in the quality of human capital. To solve this problem, I exploit observed differences in returns to education, when human capital is employed in a location different from where it was obtained. We can identify β_1 using information on the rate of return to education for immigrants in the U.S., relative to U.S. natives.

Prediction 1 *Consider two basic educated individuals living in the U.S.. These individuals only differ based on the location where education was acquired; one from country i and the other from the U.S., which have different proportions of higher educated workers. Any differences in the gross rate of return to education are related to differences in home-country quality of education:*

$$ln(R_i/R_{U.S.}) = \beta_1(ln\sigma_{2,i} - ln\sigma_{2,U.S.}).$$

The expression above can be obtained by plugging (3.2) into the expression for private return to basic education in (3.7). The model predicts that any differences in wages and rates of return to education, for two individuals who are observably identical except for their country of education, must be due to differences in human capital (proportion of higher educated workers).[9] The proportion of higher educated workers in the model, σ_2, represents the quality of basic education. This strategy identifies the effect of the proportion of higher educated on human capital because it picks up variations in wages that is due to the quality of

[9]A similar result in the context of a different model where individuals choose their years of schooling can be found in Schoellman (2012). The paper uses these estimates of returns to education by country of origin to correct for human capital differences in a growth accounting exercise.

education(proportion of higher educated workers and other home country), while leaving the productivity and other aggregate effects on wages fixed.[10]

To implement the idea, I run the regression below:

$$lnR_{j,2000} = lnR_{U.S.} + \beta ln\sigma_{2\{j,1980\}} + \eta'(\Omega_{j,1980}) + \epsilon_i. \tag{3.10}$$

I use data from Schoellman (2012) for estimates of the average returns to education for immigrants to the U.S. in the 2000, 1990, and 1980 censuses by country of origin. These estimates are especially suited to this application because they control for observables, such as years of schooling, age, licensed/non-licensed occupation, English capability, and year of entry into the U.S.

There are other variables which could influence the quality of education, as suggested by Table 4 in Hanushek and Kimko (2000), and Table 3 in Bratsberg and Terrell (2002). The baseline regression uses returns to education in the U.S. by country of origin in year the 2000. These are regressed on the proportion of higher educated workers, the proportion of basic educated workers, the pupil-teacher ratio, and real government education expenditure per-pupil in 1980, which are contained in Ω.

Data on the proportion of educated workers (aged 25+) at the basic and higher education levels are taken from the updated Barro-Lee dataset (Barro and Lee, 2010). For the regressions, I define higher educated workers as those who have completed a secondary education.[11] All other measures of education quality are taken from the dataset described in Barro and Lee (1996). The year 1980 is chosen to reflect prevailing schooling conditions when immigrants in the 2000 census acquired their basic education.[12] Regional dummies for sub-Saharan Africa, the OECD, Latin America, and East Asia are also included to control for any regional fixed effects. Table 3.8 contains the list of countries used in the estimation, as well as important variable definitions.

Figure 3.2 plots estimates of education quality taken from Hanushek and Kimko (2000) obtained from standardized test scores (PISA and TIMSS) in a variety of countries, against the proportion of higher educated workers in 1980. It provides support for the hypothesis that the proportion of higher educated workers is related to schooling quality. The correlation is .47, but the proportion of primary educated (which includes everybody with primary education and above)

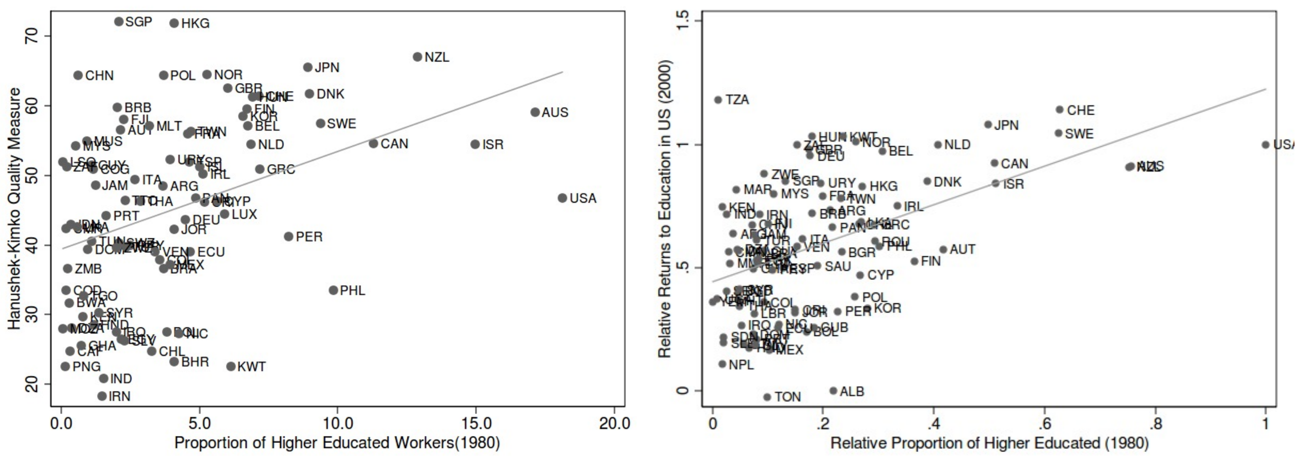
[10] See the aforementioned paper by Schoellman (2012) for more detail on why these returns identify differences in quality of education. The paper demonstrates that after controlling for selection, as well as language effects, these differences still persist. Bratsberg and Terrell (2002) using a smaller sample of countries from the 1980 and 1990 censuses, also show that differences in returns to education by country of origin are strongly related to different measures of education quality, but their measures of quality do not include the proportion of higher educated workers.

[11] I also run the regression using proportion of individuals who have completed tertiary education, or those who have at least attained tertiary education as the definition of higher educated. These change the precision, but not the magnitude of the estimate.

[12] Values from 1975 and 1985 are used to test for the sensitivity of the results to the chosen year of 1980. The results do not change significantly using these alternative measures. Results using the year 1980 are reported here since they also coincide with the 20 year time lags for quality measures used in Bratsberg and Terrell (2002).

is also correlated with schooling quality and proportion of higher educated, with coefficients of .67 and .74 respectively. This indicates that it is important to control for the proportion of primary educated as a measure of education quality in the regression.

Figure 3.2: Quality of Education, Returns to Education, Higher Educated



Education Quality and Higher Ed. Relative Returns and Prop of Higher Ed.

The second part of Figure 3.2 plots estimates of the relationship between average returns to education of an immigrant from a given country relative to a U.S. native (the measure of human capital quality used here), and the 1980 proportion of higher educated workers. These estimates are presented in Table 3.1, and they show that the proportion of higher educated workers is positively related to quality of education, and differences in returns to education for immigrants in the U.S. The second column of Table 3.1 presents the baseline estimate of β_1 at .013. It indicates that a 1% rise in the 1980 proportion of higher educated workers in an immigrant's home country, increases the returns to education of the immigrant relative to a U.S. native by 1.3%.

The third column of Table 3.1 confirms that the proportion of basic educated alone is also strongly correlated with relative returns, but in columns 4-6 which control for the proportion of higher educated workers, this effect disappears. This is taken as evidence that these differences in returns are not a result of basic education per se, but specifically a result of higher educated workers. This is not especially surprising, because as may be seen in Figure 3.3, there is a very weak relationship between the home-country 1980 proportion of basic educated, and returns for immigrants in the U.S. The estimate of β_1—positive and less than one—is also consistent with Assumption 2 which states that the human capital production function is concave and increasing in the proportion of higher educated. Including controls for the pupil-teacher ratio (P-T ratio) and expenditure-per-pupil (Exp), at the primary and secondary levels of education, do not significantly alter the estimate of β_1. The P-T ratio at the primary education level is not significant, and

Table 3.1: Relative Returns to Education and Higher Educated Workers

Dependent Variable is Log-Returns to Education in U.S. for year 2000
T-statistics in parentheses

H-K Quality	0.036***				0.034***		
	(3.30)				(2.73)		
Higher-Educated(1980)		**0.013***		**0.012**	**0.011**	**0.012**	**0.011*
		(3.28)		(2.58)	(2.53)	(2.23)	(1.84)
Basic-Educated(1980)			0.009***	0.001	-0.014	0.006	0.008
			(2.73)	(0.19)	(-1.58)	(0.80)	(1.08)
Pri P-T Ratio(1980)						0.018	0.01
						(1.32)	(0.73)
Sec P-T Ratio(1980)						-0.029**	-0.008
						(-2.60)	(-0.74)
Exp-pri(1980)							-0.009
							(-0.99)
Exp-sec(1980)							0.023***
							(2.83)
EAP						0.002	0.004
						(0.21)	(0.45)
LAC						-0.021**	-0.027***
						(-2.44)	(-3.29)
MENA						0	-0.013
						(-0.01)	(-1.27)
SA						0.003	-0.025*
						(0.19)	(-1.82)
SSA						0.013	-0.016
						(1.03)	(-1.19)
Constant	0.070***	0.087***	0.060***	0.086***	0.096***	0.089***	0.094***
	(24.93)	(12.08)	(19.79)	(8.64)	(11.02)	(9.59)	(9.53)
R^2	0.189	0.159	0.05	0.159	0.304	0.334	0.534
Number of Countries	71	91	92	91	71	82	64

Note: Proportion of higher educated workers refers to all workers who have completed secondary education
***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level

has the wrong sign compared to that in Bratsberg and Terrell (2002). When the same regression is performed without the proportion of higher educated workers, the P-T ratio becomes significant and has the correct negative sign (compare Table 3.1 with Table 3 in Bratsberg-Terrell). I interpret this as evidence that some of the impact of higher educated workers come through teachers, as well as other services such as public health provided to pupils.

Lastly, the effect of higher educated workers remain significant even after controlling for education expenditure. This provides some support for the assumption that teacher salaries alone do not fully capture the effects of differences in education quality. I use $\beta_1 = .013$ in the next section to compute the the human capital effect.

3.3.2 Elasticity of Basic Educated TFP to Higher Educated Workers:

I follow the endogenous growth literature (Romer (1986); Lucas (1988)) and represent the function f as:

$$f(\sigma_2) = \sigma_2^{\alpha}.$$[13]

The traditional and modern sectors in the model are interpreted as the agricultural and non-agricultural sectors respectively. This interpretation is based on a couple of stylized facts on developing countries which are consistent with the structure of the model presented earlier. First, there are important productivity differences between the agricultural and non-agricultural sectors. Within a typical developing country, productivity in agriculture which employs over 70% of the workforce is significantly lower than that in the non-agricultural sector (Restuccia et al. (2008); Gollin et al. (2011)). This implies that the ratio of labor productivity in the non-agricultural to agricultural sector is greater than 1.

Secondly, cross-country differences in agricultural productivity are far greater than differences in aggregate productivity (Restuccia et al., 2008). In a world with high-skill directed technical change where productivity differences decline with a sector's proportion of skilled workers as in Acemoglu and Zilibotti (2001), lower productivity in agriculture relative to the aggregate will imply that it employs a larger proportion of low-skilled workers.

Estimates of human capital differences across sectors confirm that average years of schooling and quality of education are lower in the agricultural sector (Gollin et al., 2011; Vollrath, 2009). Gollin et al. (2011) for example, find that average years of schooling in the non-agricultural sector is about twice as large as that in the agricultural sector, with the ratio rising to 2.8 in the countries of sub-Saharan Africa.

The agricultural productivity gap (APG) is defined as the ratio of effective human capital productivity in the non-agricultural to the agricultural sector. In this model, the APG is given by:

$$\sigma_2^{-\alpha}. \tag{3.11}$$

Assumption 1 will imply that α is strictly positive and less than one, so that the TFP of workers in the traditional sector is an increasing, and concave function of the proportion of higher educated workers. This leads to the conjecture below:

Prediction 2 *Controlling for effective human capital, the agricultural productivity gap across countries is decreasing with the proportion of higher educated workers.*

For data on effective human capital adjusted APGs, I make use of the estimates provided in Gollin et al. (2011). The authors estimate APGs for a set of 97 devel-

[13] One important difference is that most of the literature uses the average stock of human capital instead of the proportion of higher educated workers. The formulation here attempts to capture the effect of human capital on productivity that comes through higher educated workers.

oping countries using value added and employment data from the Food and Agriculture Organization(FAO). The raw APGs are obtained by taking a ratio of value added per worker in the non-agricultural to agricultural sector. They then adjust the raw gaps for hours worked, average years of schooling, and quality of education using information from representative surveys and censuses. Adjustments reduce the average productivity gap by about 50%, but large gaps still remain.

I use these adjusted APGs, which control for factors influencing aggregate productivity in both the modern and traditional sectors, to estimate α. Figure 3.4 plots the raw and adjusted APGs as a function of the proportion of higher educated workers in 1995. I only include countries for which the proportion of higher educated workers are also provided in the Barro-Lee dataset which yields a total of 55 countries (see Table 3.9 for list of countries). The adjusted APGs are negatively correlated with the proportion of higher educated workers, which provides some support for Conjecture 2. The correlation coefficient excluding the outliers, Burkina Faso and Madagascar, is -.32 which is significant at the 1% level. In contrast, the APG is not significantly correlated with the proportion of workers who have completed basic (primary) education, nor the average year of schooling. The correlation coefficients are -.12 and -.11 respectively.

The identifying assumption behind this exercise is that adjusting for differences in human capital, the only reason why the APG differs between countries is due to differences in proportion of higher educated workers (reflected in technological adoption and improved health services for example). All other aggregate factors, such as bad governance or institutions, that may influence productivity and education incentives should leave the current APG unchanged as they affect all sectors. The adoption of technologies, or improved public health services, could also increase productivity in the modern sector. Using the APG deals with this as well because it only captures increases in traditional sector TFP beyond those in the modern sector. This is exactly the productivity effect—increases in TFP due to more higher educated workers reflected in basic and uneducated wages, which are not reflected on the wages of higher educated workers.

The elasticity of traditional sector TFP to higher educated workers is estimated from the equation below:

$$ln(APG_i) = \alpha_0 - \alpha ln\sigma_{2\{i,2000\}} + \psi Controls_{i,2000} + \epsilon_i.$$

The controls are motivated by other determinants the APG dicussed in the literature. Evidence from Caselli and Coleman (2001) and Vollrath (2009) show that agriculture is relatively more physical-capital intensive for countries with a higher proportion of higher educated workers. This calls for controls for physical capital to be included in the regression above, which is taken from estimates of physical capital in agriculture in FAOSTAT (2012). I use the stock of machineries as the measure of capital stock, as it appears to be most relevant to level of education, and also adjust for the number of agricultural workers.

The concern above notwithstanding, if the greater adoption of physical capital in the agricultural sector is due a greater proportion of trained (higher educated)

Figure 3.3: Relative Return in U.S. and Proportion of Basic Educated

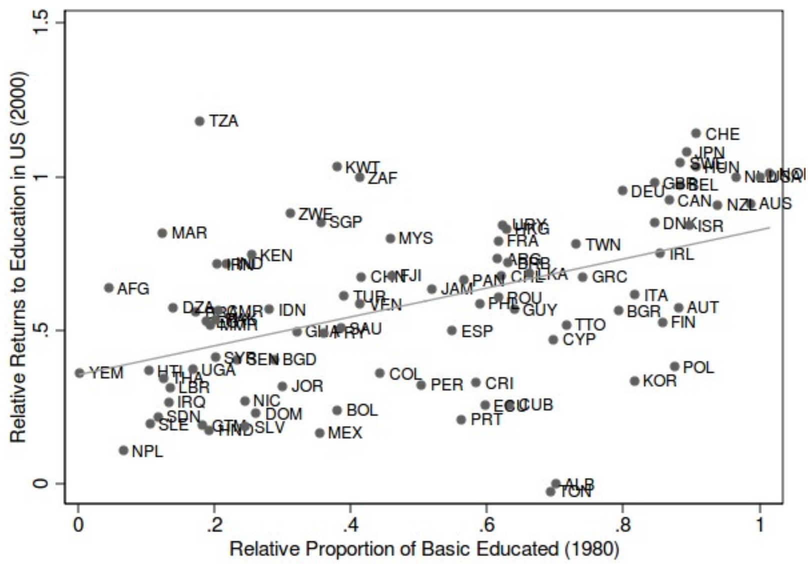
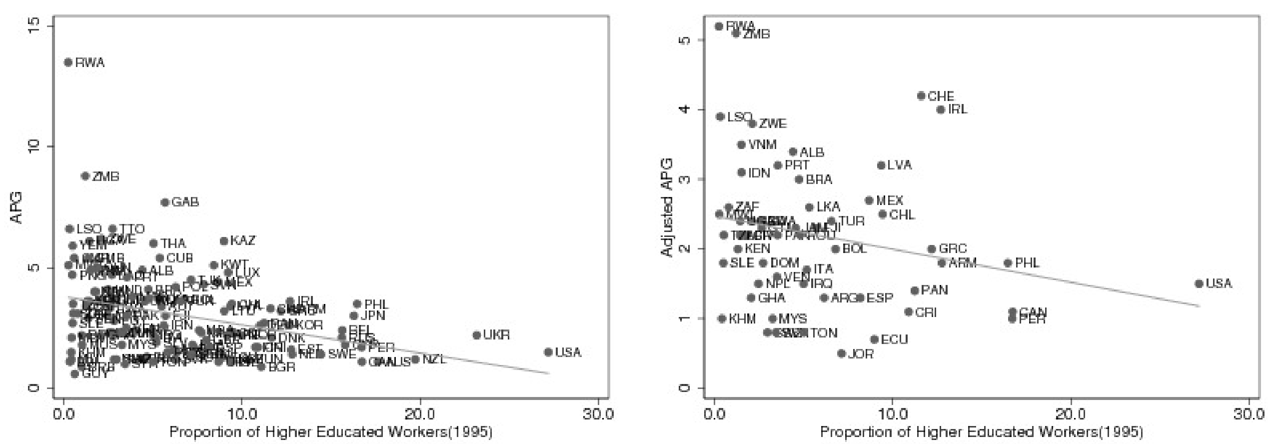


Figure 3.4: Raw and Adjusted APGs, and Proportion of Higher Educated



Raw APG and Prop of Higher Ed. Adjusted APG and Prop of Higher Ed.

workers as technicians for example, controlling for physical capital stocks may underestimate their impact on the agricultural sector. There may also be concerns regarding country fixed effects such as geography or climate which make some countries more productive in agriculture. For this reason, I include regional fixed effects in the regressions. I also control for arable land per capita, and the population growth rate using data from FAO.

Results from the regression are shown in Table 3.2. Column 1 is a regression of the log-adjusted APGs on log of the proportion of higher educated workers in 1995, which yields a baseline estimate of $\alpha = .138$.[14] The regression confirms that the proportion of higher educated workers is negatively related to the APGs, adjusted for effective human capital, as depicted in Figure 3.4.[15] Controlling for the proportion of workers who have at least a basic education does not change the estimate in column 2.

Table 3.2: Adjusted APGs and Proportion of Higher Educated Workers

Dependent Variable is Log-Adjusted APG
T-statistics in parentheses

Higher-Educated(1995)	**-0.138****	**-0.138****	**-0.117**	**-0.132**	**-0.166***
	(-2.20)	(-2.16)	(-1.53)	(-1.34)	(-1.93)
Basic-Educated(1995)		0.017	0.036	-0.053	-0.135
		(0.11)	(0.25)	(-0.40)	(-1.00)
Arable Land Per Worker			0.007	-0.07	-0.234***
			(0.14)	(-1.10)	(-2.93)
Pop. Growth			0.051	0.048	0.051
			(1.13)	(1.19)	(1.48)
Machinery Per Worker					0.172***
					(2.74)
EAP				-0.668**	-0.377
				(-2.58)	(-1.39)
LAC				-0.461**	-0.212
				(-2.67)	(-1.14)
MENA				-1.104***	-0.920**
				(-3.29)	(-2.59)
SA				-0.560*	-0.226
				(-1.99)	(-0.75)
SSA				-0.408	0.004
				(-1.55)	(0.01)
Constant	0.363**	0.381*	0.079	0.407	0.188
	(2.35)	(1.76)	(0.19)	(1.08)	(0.54)
R^2	0.086	0.086	0.11	0.351	0.433
Number of Countries	55	55	55	55	55

***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level
Note: Proportion of higher educated workers refers to all workers who have completed secondary education

Column 5 includes the full set of controls for population growth, machinery, and arable land per capita. The estimates show that a faster population growth

[14] I consider 1995 a suitable year as it reflects prevailing conditions when a majority of these APGs were collected(1995-2005). I also used the proportion of higher educated workers in 1990, 2000, and 2005. But the estimates do not change significantly, the point estimate for α goes from .138 to .13 if I use the year 2000, and .122 if I use the year 2005.

[15] Interestingly, using the APGs which are not adjusted for human capital yields a larger estimate for α. I conjecture that this is because it captures the productivity effect, as well as the effect of higher educated workers on human capital.

increases the APG, and that having more arable land per agricultural worker reduces the APG, as one would expect. Countries with more arable land will be more productive in the agricultural sector regardless of the proportion of higher educated workers. This means that there is a level component in the productivity of the traditional relative to the modern sector which is not explicitly accounted for in the specification for $f(\sigma_2)$, but will be reflected in a higher aggregate TFP (A).

A concern with the identifying assumption here is that the proportion of higher educated workers may be endogenously determined along with the agricultural productivity gap. In the models of Schultz (1975) and Lagakos and Waugh (2011), given low aggregate productivity and a subsistence requirement, individuals who are not particularly good at agriculture may be forced into agricultural work which does not require a higher education. This reduces productivity in agriculture relative to non-agriculture (increasing the APG), and also leads to fewer higher educated workers. So an increase in aggregate productivity will directly reduce the APG by ensuring fewer workers are needed to meet the subsistence requirement, and also increase the proportion of higher educated workers creating a spurious negative correlation.

First, it is not clear that increasing agricultural productivity will immediately result in more education, and more workers leaving the sector. An evaluation of the Millennium Villages Project (MVP) in Kenya found that an increase in agricultural productivity, which enables individuals meet subsistence requirements, actually decreases participation in the non-agricultural sector. Wanjala and Muradian (2011) find that a 70% increase in agricultural productivity for MVP villages decreases participation in profitable non-farm employment, as opposed to moving individuals out of agriculture as subsistence requirements are now being met. There are factors keeping individuals in agriculture, but subsistence requirements do not tell the full story.

Also imagine that in the short term, individuals have acquired human capital specific to the agricultural sector, which discourages movements out of that sector, even with increases in productivity alleviating subsistence needs. An increase in agricultural productivity today will be reflected in more education for the future generation (but not today's farmers). Under the framework described above, and supported by evidence from the MVP in Kenya, there is no endogeneity problem regressing current APGs on current, or past proportion of higher educated workers.

Secondly, it could be that aggregate productivity is low because the proportion of higher educated workers is low as in models of directed technical change and technological adoption (Acemoglu and Zilibotti (2001)). This leads to the correlation between APG, aggregate productivity, and the proportion of higher education as predicted by models, such as the Lagakos-Waugh model of subsistence requirements for example. If this is the case, there is no endogeneity problem and the identification strategy remains valid.

It is probably not the case that all cross-country agricultural productivity differences are due to lack of technological adoption or a shortage of health services provided by higher educated workers. There may be some bias arising out of subsistence requirements. To address these concerns, I also restrict the sample to countries with per-capita incomes above $1000 where subsistence requirements are less likely to be important compared to constraints on technological adoption, and doing so does not change the result.

3.3.3 Calibrating the Other Parameters

Parameters left to be calibrated are: the human capital of basic and higher educated workers, h_1 and h_2, costs of basic and higher education, g_1 and g_2, and aggregate productivity A, which are all country-specific. Given β_1 and α, I choose parameters so the model matches estimates of private returns to education, the proportions of basic and higher educated workers, and GDP per capita. The model is calibrated to data from 1990. When 1990 data is not available, I use the earliest available data in the 10 year window, 1985-1995. The year 1990 is chosen because a majority of the rate of return estimates (ROREs), in Psacharopoulos and Patrinos (2004), were obtained around that time period.

To calibrate the human capital of basic-educated workers, I pick parameters so the model matches the private ROR to basic education. The private return to education in the model is given in (3.7): $r_1^p = h_1 - 1 = [{\sigma_2}^{\beta_1} exp\{\theta s\}] - 1$. Given β_1 from the previous section, as well as σ_2 (the proportion of higher educated workers) in the data, $exp\{\theta s\}$ is chosen so the model matches private ROREs in Psacharopoulos and Patrinos (2004). The human capital of higher educated workers, h_2, is also chosen to match the private ROR to higher education. Given h_1, α, and σ_2, the solution for h_2 solves: $r_2^p = [(h_2/fh_1)] - 1 = [h_2/(\sigma_2^\alpha h_1)] - 1$, for each country.

In order to get ROREs in the model consistent with standard annualized ROREs, I need to take a stand on the length of a basic education. I follow Psacharopoulos and Patrinos (2007), and assume only 3 years of foregone earnings for basic educated workers. So I multiply the ROREs from Psacharopoulos and Patrinos (2004) by a factor of 3, in order to get the private return to basic education.[16] For higher educated workers, I assume 7 years of foregone earning, 3 years for upper secondary school and 4 years for tertiary education.

Given h_1, h_2, and σ_2^α, I set the relative cost of higher to basic education, g_2/g_1, equal to public expenditure on higher relative to basic education, from UNESCO (2012). If data on relative expenditures are not available for 1990, I use the average from 1985 to 1990. If no data is available for those years, then I use the regional average for the country's region, as classified by UNESCO. Then, using data on G/N, aggregate expenditure on education per student from UNESCO (2012), g_1 is chosen to match the proportion of basic educated workers in 1990 from (3.6), and ensures that the the budget constraint holds.

The parameter, A, which is important for computing estimates of social returns

[16] On average, it takes 6 years to complete basic education. But most basic educated pupils are not going to be working at those ages, so assuming 6 years of foregone earnings understates the return to a basic education.

to education from (3.8), is chosen so that output-per-capita in the model matches data on real GDP-per-worker (PPP, constant $) from The World Bank (2012). Table 3.3 summarizes parameter values, for all countries which will be used in the analysis (these are countries for which I have estimates of private returns to basic and higher education from Psacharopoulos and Patrinos (2004), developed countries are excluded.). The full list of parameters are contained in Table 3.6.

Table 3.3: Summary of Parameters

	h_1	h_2	$g2/g1$	g_1	g_2	Af
Mean	1.75	2.92	19.43	1194.56	12125.21	7299.34
Median	1.54	2.47	6.57	633.72	4183.96	6464.29
Min	1.06	1.53	1.11	26.02	874.15	734.46
Max	3.97	9.50	198.50	17763.02	199312.46	20801.07
Standard dev	0.72	1.56	39.35	3017.39	34185.56	5173.30

Number of Countries: 34

$\alpha = .138$ and β_1=.013 for all countries.

Average estimates of the human capital of basic educated workers, h_1, reflect the private returns to basic education for this group of countries, at 75% (25% annualized). Note that these estimates of human capital are only comparable within countries.[17] This is not a problem for my analysis, however, because I only compare returns within countries.

3.4 Results

3.4.1 Productivity Effects, Human Capital Effects, and Social ROREs

In this section, I compute, for all countries in my dataset, the social returns to higher and basic education implied by the model (which I call *the true social ROR*), and *standard* social ROREs which come from wages. In computing social returns, I stick closely to the methodology in Psacharopoulos and Patrinos (2007); benefits divided by social costs (foregone earnings, and the total public cost of education for 7 years).[18] The only difference here is that I also include benefits from the productivity and human capital effects.

[17]For example, a higher educated worker in Botswana has $h_2 = 9.5$, compared to one in Brazil with $h_2 = 4.32$. But this does not mean that a higher educated worker in Botswana has twice as much human capital compared to a Brazilian. Instead, my measure of human capital says that a higher educated worker has 9.5 times as much human capital compared to a basic educated worker, in Botswana.

[18]The conclusion is not very sensitive to the number of years chosen (4-10 years have been tried), because parameters are chosen to match private returns to education. More years of foregone earnings for higher educated workers would be reflected in higher human capital for higher educated workers, h_2.

The true social ROR to higher education is calculated as:

$$r_2^{social} \equiv \overbrace{\underbrace{\frac{Af'[1+\sigma_1(h_1-1)-\sigma_2]}{7(Afh_1+g_2)}}_{\text{Returns from Productivity Effect}} + \underbrace{\frac{Afh'\sigma_1}{7(Afh_1+g_2)}}_{\text{Returns from Human Capital Effect}}}^{\text{External Effects}} + \underbrace{\frac{A(h_2-f^*h_1^*)}{7(Afh_1+g_2)}}_{\text{Standard social ROR}} . \tag{3.12}$$

The social ROR to higher education consists of three parts. The first is the productivity effect, divided by the *social* opportunity cost of one more higher educated worker; the output of a basic educated worker, Afh_1, and the direct cost of higher education, g_2, for seven years of higher education. The second is the human capital effect, also divided by the social opportunity cost of a higher educated worker. The third part is just the standard RORE of social returns to higher education, using information from wages and direct social cost of higher education as in (3.8). Social returns to basic education is calculated using the expression given in (3.8), as it is assumed there are no external returns to basic education.[19]

Social returns to higher and basic education, from the model, are plotted in Figure 3.5 (and are also contained in Table 3.7). It illustrates the basic result of this paper: the productivity and human capital effects are greater than the difference between standard ROREs to basic and higher education. From Figure 3.5 we see that the standard pattern in Figure 3.1 is reversed; for most countries, the social return to higher eduction is now larger than that for basic education.

The median difference between social returns to higher and basic education is about 5.3 percentage points, compared to a difference of -4 percentage points in standard estimates from Psacharopoulos and Patrinos (2004), and -9 percentage points in standard estimates from the model. The median external effect of about 13-percentage points is large enough to more than account for the difference between standard estimates of social returns to higher and basic education.

The calculation assumes there are no externalities to basic education. This is contrary to what has been discussed in the literature on education in developing countries, which emphasizes externalities to basic education, for social and economic reasons (see McMahon (2004) and Mertaugh et al. (2009), for examples). Given the large social externalities to higher education found here, how large do externalities to basic education have to be to overturn the above result?

Evidence on externalities to basic education in developing countries is scarce, but looking at estimates from growth studies, estimates of the external returns to education (at all levels) lie between 14-16% (Mertaugh et al., 2009). These figures are just as large as the external returns to higher education obtained here. To overturn these returns, most the returns to education in growth studies have to be strictly due to basic education. However, we know this is not the case, because there are many countries who have achieved universal education without subsequent significant economic growth.

[19] As the results will show, the social return to basic education would have to be unreasonably large to overturn the results.

Figure 3.5: Social Returns to Basic and Higher Education

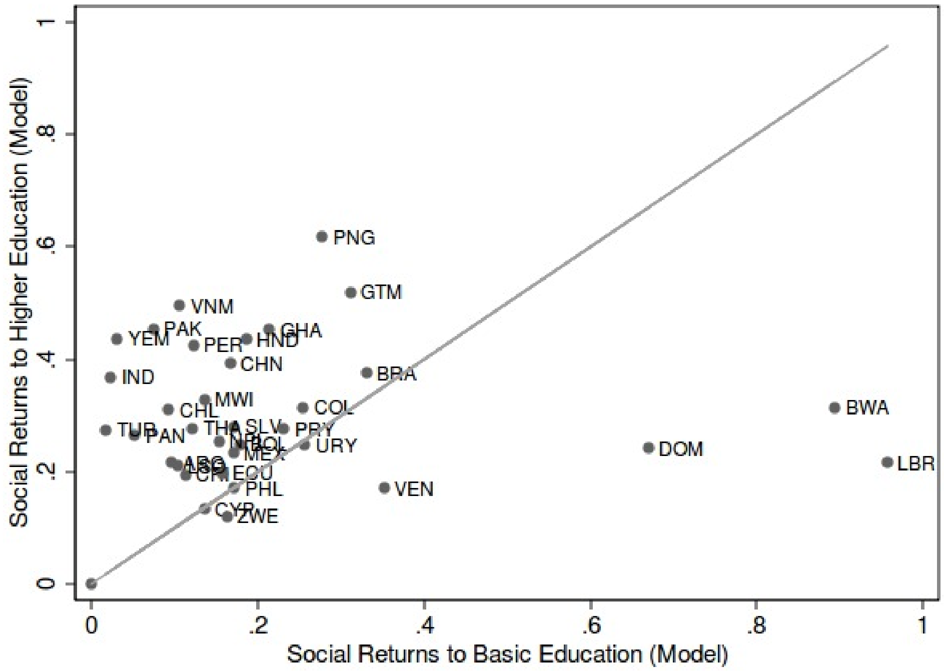


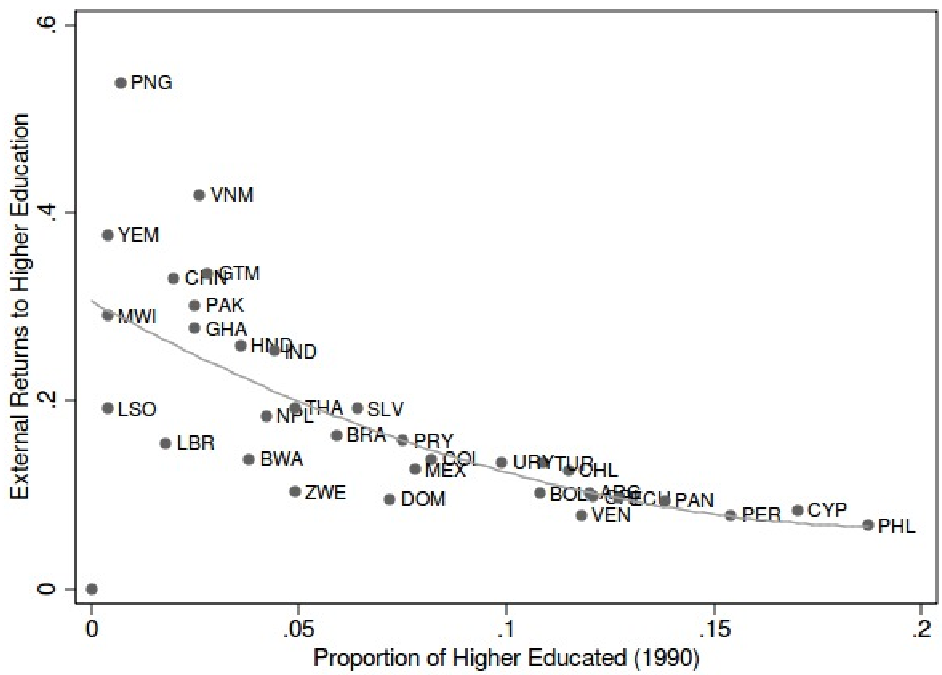
Table 3.7 also shows that returns from the productivity effect predominate. Returns arising from the human capital effect is below 1-percentage point for most countries in the dataset, and do not contribute significantly to the social ROR for higher education. The human capital effect is large for the marginal higher educated worker (it is on average 13% of basic educated wages), but returns are small because this pales in comparison to foregone wages and the costs of higher education. However, this does not mean that the human capital effect is unimportant, it could have important implications for the private return to basic education. Section 4.3 discusses possible impacts of ignoring these external effects, but first I examine how standard ROREs systematically underestimate social ROREs to higher education.

3.4.2 Underestimation of Social Returns to Higher Education

Next, I explore the quantitative significance of Result 4, which predicts that the human capital and productivity effects are decreasing in the proportion of higher educated workers.

The prediction from Result 4 does hold, and the difference between standard and social returns (the external effect) declines with the proportion of higher educated workers, as shown in Figure 3.6. Including all countries, the correlation coefficient is -.81. The result does not hold precisely because "all things are not equal," and the relative cost of higher education (g_2/g_1) tends to decrease with the proportion of higher educated workers. This means that we expect to see larger human capital and productivity effects in countries with smaller proportions of higher educated workers. Indeed, if I calculate the external effects using U.S. proportion of higher educated workers, and costs of education, these effects are quite small, at just 3%.

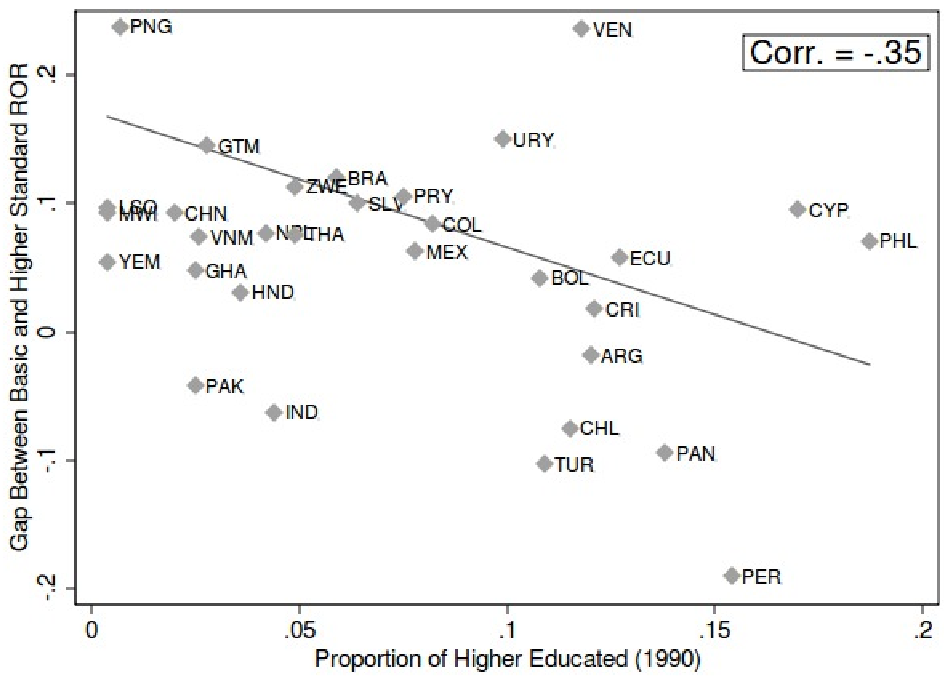
Figure 3.6: External Effects and Proportion of Higher Educated



What does this mean for the gap between standard ROREs for basic and higher education across countries? Figure 3.7 shows how standard estimates of the gap between social returns for basic and higher education are related to the proportion of higher educated workers, and the external effects. A smaller proportion of higher educated workers (larger external effects), imply larger gaps between standard social ROREs to basic and higher education. For example, in Venezuela (VEN), the return due to the external effects is about 23 percentage points, and standard estimates place the social return to basic education 15 percentage points higher than that to higher education. In Argentina (ARG) on the other hand, standard estimates of the gap between social returns to higher education and basic education is close to zero, and the return due to external effects is only 8%.

Thus, standard social ROREs *systematically* overstate the gap between the social return to basic and higher education. In countries where the proportion of higher educated workers are smaller, external effects are larger, and standard estimates of the gap between social returns to basic and higher education are larger. The size of the difference between standard social ROREs is not random, they decrease with the proportion of skilled workers. The conclusion often reached based on standard estimates of social RORs (reallocation of funding from higher to ba-

Figure 3.7: Standard Social ROR Gaps and Proportion of Higher Educated



sic education) is not supported here. Countries where standard social returns to higher education are significantly lower than basic education, who appear to be over-investing in higher education, are those where external effects are larger.

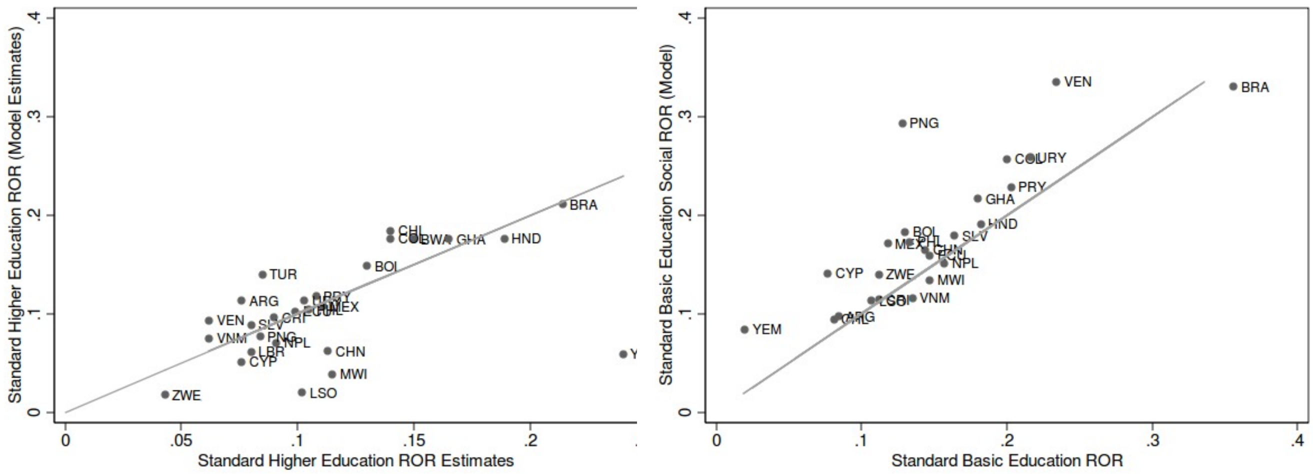
The patterns in Figures 6 and 7 also imply that these external effects and gaps are unimportant for countries with large proportions of higher educated workers. Estimates of social returns to higher and basic education available for a few OECD countries in Psacharopoulos and Patrinos (2004) support this implication. They find standard social ROREs of 8.5% to basic and higher education. External effects, as measured here, are small, indicating that standard social ROREs may serve as a useful tool for education policy in that context. For developing countries with a smaller proportion of higher educated workers, however, these standard ROREs are not reliable.

3.4.3 Model Fit and Optimal Policy

In this section, I show that the simple model presented here provides a good fit to standard social ROREs, and then use it to compute the optimal education policy (proportion of higher educated workers) which is compared to the data.

The difference between social returns to basic and higher education does not disappear because the model systematically overesates *standard* social returns to higher education, or underestimates social returns to basic education. Figure 3.8 and Table 3.4 show the model does a good job of matching standard estimates of social returns to both basic and higher education. Estimates of standard returns

Figure 3.8: Matching Standard Social ROREs



Standard Social Returns to Higher Ed. Social Returns to Basic Education

to education from the model, which do not account for external effects fit well with those from Psacharopoulos and Patrinos (2004). Most of the estimates in Figure 3.8 cluster around the 45-degree line, with a zero mean difference between standard ROREs for higher education in the data and model (see Table 3.4).

If anything, social returns to basic education do tend to be overestimated by the model, but this difference is not statistically significant. As the second part of Figure 3.8 shows, most of the estimates are not significantly different from those estimated from standard data, but outliers such as Papua New Guinea, Venezuela, as well as Botswana, Liberia, and the Dominican Republic noted earlier tend to skew the average. In all, the model matches social returns to education when external effects are not taken into account, and the larger social return for higher education is due to large productivity and human capital effects.

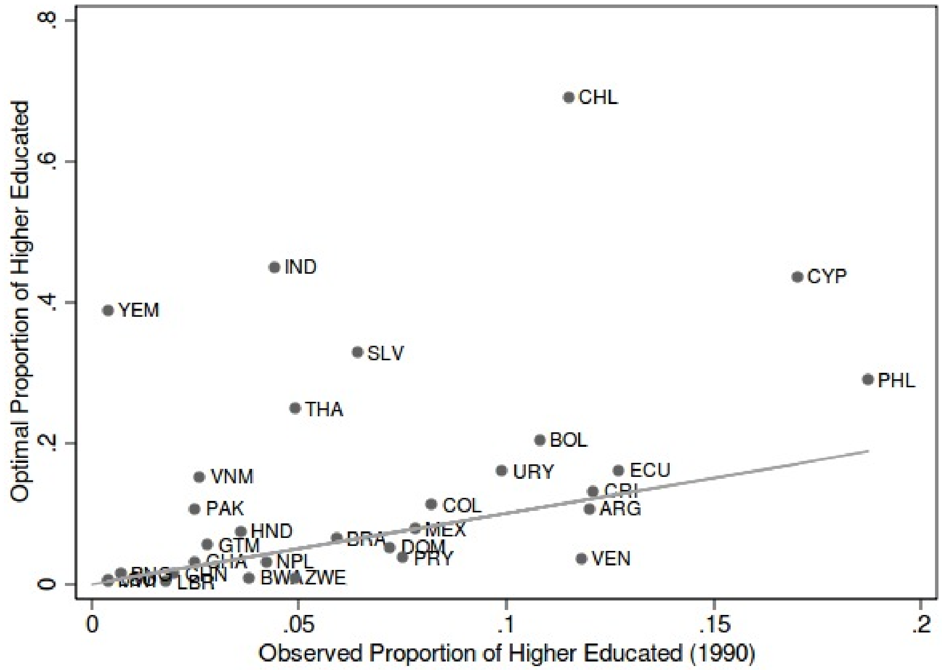
Just as seen in standard estimates, the model also predicts that standard ROREs for basic education will be larger than those for higher education. But based on this pattern alone, we cannot immediately conclude there is an over-investment in higher education. This is because the productivity and human capital effects are large enough to account for the differences in standard ROREs. Ignoring these externalities may lead to a misleading picture of social RORs.

Further, for most countries, the optimal proportion of higher educated workers computed from the model, taking the external effects into account, matches the observed proportion of higher educated workers very well. The computed optimal proportion of higher educated workers is plotted against the observed proportion of higher educated workers in Figure 3.9. Most countries in the picture lie along the 45-degree line, and for these countries, we cannot conclude that there is an over-investment in higher education, even when there are large gaps in standard

Table 3.4: Standard Social ROREs: Model v. Data

Country	**Higher**		**Basic**	
	Model	**Data**	**Model**	**Data**
Argentina	0.113	0.076	0.097	0.084
Bolivia	0.148	0.130	0.179	0.130
Botswana	0.176	0.150	0.894	0.420
Brazil	0.211	0.214	0.331	0.356
Chile	0.184	0.140	0.093	0.081
China	0.062	0.113	0.168	0.144
Colombia	0.176	0.140	0.255	0.200
Costa Rica	0.096	0.090	0.114	0.112
Cyprus	0.051	0.076	0.137	0.077
Dominican Rep.	0.146		0.670	
Ecuador	0.102	0.099	0.158	0.147
El Salvador	0.089	0.080	0.172	0.164
Ghana	0.176	0.165	0.215	0.180
Guatemala	0.183		0.312	
Honduras	0.176	0.189	0.187	0.182
India	0.116		0.024	
Lesotho	0.019	0.102	0.104	0.107
Liberia	0.061	0.080	0.956	0.410
Malawi	0.039	0.115	0.137	0.147
Mexico	0.107	0.111	0.171	0.118
Nepal	0.071	0.091	0.154	0.157
Pakistan	0.151		0.075	
Panama	0.171		0.053	
Papua New Guinea	0.077	0.084	0.278	0.128
Paraguay	0.117	0.108	0.232	0.203
Peru	0.347		0.123	
Philippines	0.104	0.105	0.172	0.133
Thailand	0.084		0.122	
Turkey	0.140	0.085	0.018	
Uruguay	0.113	0.103	0.257	0.216
Venezuela	0.093	0.062	0.352	0.234
Viet Nam	0.075	0.062	0.107	0.135
Yemen	0.059	0.240	0.032	0.020
Zimbabwe	0.017	0.043	0.164	0.112
Mean	0.119	0.113	0.223	0.169
Median	0.110	0.103	0.166	0.146

Figure 3.9: Optimal versus Observed Proportions of Higher Educated (1990)



estimates of the social ROR. This is precisely because the productivity and human capital effects are large enough to rationalize observed choices as optimal.[20]

3.4.4 Impact of Reallocating Funding on Basic Educated

What is the impact of policies which, based on standard ROREs and ignoring any external effects of higher educated workers, call for a shift of resources towards basic education? First, I solve the model for the implied proportion of higher educated workers with, and without accounting for external effects. This involves solving for the optimal proportion of higher educated workers by setting the left-hand side of (3.9) to zero, given the parameters in Table 3.6. I then compute the implied *private* return to basic education (effect of excluding the human capital effect), as well as the wage level of basic educated workers (effect of excluding all effects).

The first two columns of Table 3.5 show the proportion of higher educated workers with, and without, external effects. Education policy which does not account for these external effects potentially misses a significant portion of the social re-

[20]Notice that if anything, a lot of countries, such as Chile, are under-investing in higher education. But this could also be a result of how the relative cost of higher to basic education is computed using public expenditures. It is well known that a majority of the costs of higher education in many countries is privately financed (UNESCO, 2006). So the relative cost of higher education from an individual's perspective may be underestimated, and that could explain the significantly lower observed proportion of higher educated workers observed in Chile, for example.

turn to higher education, and will underfund higher education. For example, in Argentina about 12% of workers have attained higher education, but ignoring external effects, the model predicts that only 1% of workers should have been higher educated, given observed standard returns. The same pattern holds for all countries in the dataset; ignoring external effects leads to a lower optimal proportion of higher educated workers (and a higher proportion of basic educated).

Table 3.5: Impact of Ignoring External Effects

Country	Proportion of Higher Educated		Private Returns to Basic Edu.		Wage Level	
	No External	External	No External	External	No External	External
Argentina	0.0091	0.12	0.0674	0.1010	12617	16528
Bolivia	0.0047	0.108	0.1557	0.2000	5069	6592
Botswana	0.0001	0.038	0.8531	0.9900	9880	11540
Brazil	0.0005	0.059	0.2900	0.3660	9968	14367
Chile	0.0095	0.115	0.0647	0.0970	12180	15821
China	0.0000	0.02		0.1800	N/A	1753
Colombia	0.0016	0.082	0.2181	0.2770	11261	15423
Costa Rica	0.0075	0.121	0.0852	0.1220	11256	14890
Cyprus	0.0144	0.17	0.1203	0.1540	21970	27031
Dominican Rep.	0.0011	0.072	0.7604	0.8510	7425	7263
Ecuador	0.0070	0.127	0.1310	0.1710	10939	14099
El Salvador	0.0007	0.064	0.1263	0.1890	6062	9680
Ghana	0.0000	0.025		0.2450	N/A	2020
Guatemala	0.0000	0.028		0.3380	N/A	8778
Honduras	0.0001	0.036	0.1256	0.2080	3665	6998
India	0.0107	0.044	0.0087	0.0260	2748	3274
Lesotho	0.0000	0.004		0.1550	N/A	1036
Liberia	0.0000	0.018		0.9900	N/A	1042
Malawi	0.0000	0.004		0.1570	N/A	1311
Mexico	0.0015	0.078	0.1339	0.1890	4912	7049
Nepal	0.0002	0.042	0.0935	0.1660	939	1721
Pakistan	0.0004	0.025	0.0315	0.0840	3326	5520
Panama	0.0247	0.138	0.0354	0.0570	12223	14764
Papua New Guinea	0.0000	0.007		0.3720	N/A	3684
Paraguay	0.0010	0.075	0.1745	0.2370	6018	8982
Peru	0.0244	0.154	0.1072	0.1320	8955	10277
Philippines	0.0218	0.187	0.1529	0.1830	5071	5816
Singapore	0.0000	0.03		0.2220	N/A	43471
Thailand	0.0004	0.049	0.0950	0.1600	3912	6675
Turkey	0.0454	0.109	0.0083	0.0190	19238	21380
Uruguay	0.0022	0.099	0.2209	0.2780	9952	13370
Venezuela	0.0052	0.118	0.3129	0.3630	19974	22830
Viet Nam	0.0001	0.026	0.0365	0.1080	901	1792
Yemen	0.0000	0.004		0.1000	N/A	8705

Formulating education policy based on standard ROREs will lead one to conclude that there is significant over-investment in higher education. For some countries where the gap between standard ROREs to basic and higher education is relatively large, the model without externalities predicts that public resources should not be allocated to higher education (see Ghana, Guatemala, or Lesotho). This is consistent with the conclusion reached by the World Bank (1995) in its education strategy document. As discussed in the introduction, the document concludes that public resources need to be focused on basic education, with higher education moving towards self-financing. Here we see that this conclusion is only valid when external effects are small. As discussed earlier in this section, these external effects are large.

The third and fourth columns of Table 3.5 compute implied private returns to basic education, using the proportion of higher educated workers with, and without. external effects. Since basic and uneducated workers work in the same sector, this only captures the impact of the human capital effect (impact of higher educated workers on the human capital of the basic educated). Ignoring countries for which the predicted proportion of higher educated workers is zero, there is a significant reduction in private returns to basic education in response to an expansion in basic education. In Honduras for example, the private return to basic education falls from 20% to 12% , and in Nepal it falls from 16.6% to 9.4% following an expansion in basic education.[21] Notice that the decline in returns is as a result of a decline in quality, and not a result of an increase in the relative supply of basic educated workers.

This is consistent with the finding in Uwaifo-Oyelere (2010) that the average rate of return to basic education is only 2.8%, following the expansion of Nigeria's universal basic education program; this is a lot lower than the average 11.7% RORE for sub-Saharan Africa countries. The framework here suggests that a decline in returns to basic education, which follows an expansion at the expense of higher education, is partly due to a resultant decline in the quality of basic schooling. Although the human capital effect does not contribute significantly to social ROREs, it still speaks to the impact of higher educated workers on the return and attractiveness of basic education.

The last two columns of Table 3.5 show how the wage level of basic educated workers change with a decline in higher educated workers. There is a decline in the wage level of basic educated (and uneducated) workers in response to the expansion in basic education. Note that this decline is not due to diminishing marginal returns, or increasing abundance of basic educated workers, as the effective marginal product basic educated workers is assumed to be constant. It is caused by a decline in the productivity of the "traditional" sector, as well as a decline in the human capital of basic educated workers.

The size of the decline in wage levels varies based on the size of the external effects. Take Brazil where external effects are large (17 percentage points from Table 3.7), the wage of basic educated workers will be 30% lower than it would have been if education policy (and the proportion of higher educated workers), was set taking external effects into account. In the Philippines where these effects are smaller, the wage of basic educated workers is only about 13% lower if education policy is set based on standard ROREs. Overall, wage levels for basic educated workers are over 15% lower for most countries, as a result of declines in productivity and quality of human capital.

[21] Excluding countries with no higher educated workers is necessary because the human capital production function in (3.2) does not admit zero higher educated workers. This would imply that obtaining a basic education destroys an individual's human capital.

3.5 Conclusion

Standard estimates of the social rate of return (R0R) to education, which are larger for basic compared to higher education, have been used to justify the focus of public resources on basic education, which is often at the expense of higher levels of education. In this paper, I have argued that these standard social ROR estimates are not reliable for education policy. There are quantitatively important externalities to higher levels of education, which are related to their impacts on productivity and future human capital.

I quantify these effects in a cross-section of developing countries. I find that the social ROR to higher education is about 10-40 percentage points larger than standard estimates indicate, as a result of the human capital and productivity effects. Furthermore, for a majority of the countries, the productivity and human capital effects are large enough to rationalize observed proportions of higher educated workers as optimal. I also show that the less educated a country is—lower proportions of higher workers, the larger the external effects of higher education, and the larger the difference between standard estimates of the social ROR to basic and higher education. Lastly, an expansion in basic education at the expense of higher education, based on standard social ROR estimates, potentially leads to some unexpected consequences for basic educated workers. There are lower returns to a basic education, because of a decline in the quality of basic schooling. Furthermore, there is a significant decline in the productivity of basic educated workers. This decline in productivity exceeds 30% of the wage for basic uneducated workers, for most countries in the dataset.

Papua New Guinea (PNG) provides a good case study: We see from Figure 3.7, that for PNG, the difference between standard estimates of the social ROR to basic and higher education is greater than 20 percentage points. Based on this, we may be tempted to conclude that there is significant over-investment in higher education. However, looking at Figure 3.6, we see that external returns from the productivity and human capital effects of higher educated workers in PNG is greater than 50%. Figure 3.9 confirms that the external returns are large enough to rationalize the observed proportion of higher educated workers in PNG as optimal, even with large differences in standard social ROREs.

Standard ROR estimates are therefore unsuitable for education policy because they do not account for the human capital and productivity effects. This study does claim that the social return to higher education is larger than that for basic education; I do not investigate the possibility of externalities to basic education. Basic education is important, but there has to be a balance between basic and higher levels of education. This is because higher educated workers are an input into basic education, and in a world where technical change is increasingly skill-biased, higher educated workers are also important for productivity. What is this balance, and how can it be achieved, especially for countries yet to achieve universal basic education coverage? This question is left for future research.

3.6 Other Tables and Figures

Table 3.6: Calibration Results

Country	h_1	h_2	g_2/g_1	g_1	g_2	A
Argentina	1.30	2.02	10.08	533.99	5382.59	13070.88
Bolivia	1.60	2.79	3.89	557.16	2680.68	4826.40
Botswana	3.97	9.50	42.96	659.05	12298.09	6149.17
Brazil	2.10	4.32	6.57	1046.50	6945.04	9788.02
Chile	1.29	2.39	3.40	574.74	3531.83	12162.24
China	1.54	1.90	30.93	103.88	2491.92	1455.50
Colombia	1.83	3.33	4.93	924.94	5061.40	10787.99
Costa Rica	1.37	1.98	6.64	817.66	5499.61	11649.00
Cyprus	1.46	1.62	1.11	2622.76	6284.69	20801.07
Dominican Rep.	3.55	5.95	4.3	1153.60	4129.09	4279.81
Ecuador	1.51	2.19	4.3	891.85	4183.96	10555.13
El Salvador	1.57	1.83	1.19	799.63	2629.38	8306.11
Ghana	1.74	3.86	13.7	219.53	3247.17	1568.18
Guatemala	2.01	3.23	5.17	595.49	4159.60	7148.32
Honduras	1.62	2.97	6.82	642.85	5775.06	5743.23
India	1.08	1.63	6.55	285.41	3637.18	3061.90
Lesotho	1.47	2.54	52.72	472.18	31559.16	955.72
Liberia	3.97	5.16	198.5	26.02	1729.52	734.46
Malawi	1.47	3.06	108.21	183.14	18424.67	1220.78
Mexico	1.57	2.36	7.06	727.57	4981.89	7048.82
Nepal	1.50	1.83	13.718	118.62	1436.73	1549.14
Pakistan	1.25	2.47	10.65	633.72	9968.06	5026.33
Panama	1.17	2.24	3.68	851.18	5536.47	11674.69
Papua New Guinea	2.12	2.90	12.5	1053.95	20463.84	3125.32
Paraguay	1.71	2.39	12.40	158.80	1369.30	6913.20
Peru	1.40	4.16	2.97	464.88	2320.34	6464.29
Philippines	1.55	2.26	2.70	271.12	874.15	4149.52
Thailand	1.48	1.83	1.92	1847.43	7657.00	5973.34
Turkey	1.06	1.69	3.84	812.15	6581.92	18905.95
Uruguay	1.83	2.57	2.98	763.14	2911.13	9278.22
Venezuela	2.09	2.80	11.96	516.32	3577.53	16440.36
Viet Nam	1.39	1.53	3.12	328.37	3490.32	1556.02
Yemen	1.30	3.12	5.3	17763.02	199312.46	8509.18
Zimbabwe	1.50	1.37	198.5	20.94	1967.43	1428.12

Number of Countries: 34

$\alpha = .138$ and β_1=.013 for all countries.

Calibration is as explained in Section 3.3 of the text.

Table 3.7: Social Returns to Higher and Basic Education(Model)

Country	**Higher Education**				**Basic Education**
	Prod. Effect Ret	**H.C. Effect Ret**	**Total External**	**Social ROR**	**Social ROR**
Argentina	0.096	0.007	0.102	0.216	0.097
Bolivia	0.096	0.005	0.101	0.249	0.179
Botswana	0.129	0.009	0.138	0.314	0.894
Brazil	0.155	0.009	0.164	0.375	0.331
Chile	0.118	0.008	0.126	0.310	0.093
China	0.313	0.018	0.331	0.393	0.168
Colombia	0.130	0.008	0.138	0.314	0.255
Costa Rica	0.092	0.006	0.098	0.195	0.114
Cyprus	0.077	0.006	0.083	0.134	0.137
Dominican Rep.	0.090	0.005	0.095	0.242	0.670
Ecuador	0.090	0.006	0.096	0.198	0.158
El Salvador	0.185	0.006	0.192	0.280	0.172
Ghana	0.263	0.014	0.277	0.452	0.215
Guatemala	0.325	0.011	0.336	0.519	0.312
Honduras	0.249	0.010	0.259	0.435	0.187
India	0.245	0.008	0.253	0.369	0.024
Lesotho	0.187	0.005	0.192	0.211	0.104
Liberia	0.148	0.007	0.155	0.216	0.956
Malawi	0.284	0.007	0.291	0.329	0.137
Mexico	0.120	0.006	0.127	0.234	0.171
Nepal	0.180	0.004	0.184	0.255	0.154
Pakistan	0.295	0.007	0.302	0.453	0.075
Panama	0.089	0.005	0.094	0.265	0.053
Papua New Guinea	0.522	0.018	0.540	0.617	0.278
Paraguay	0.150	0.008	0.158	0.276	0.232
Peru	0.075	0.004	0.078	0.425	0.123
Philippines	0.063	0.004	0.067	0.171	0.172
Thailand	0.188	0.004	0.193	0.277	0.122
Turkey	0.128	0.006	0.134	0.275	0.018
Uruguay	0.126	0.009	0.135	0.248	0.257
Venezuela	0.075	0.003	0.078	0.171	0.352
Viet Nam	0.400	0.020	0.420	0.495	0.107
Yemen	0.376	0.001	0.377	0.436	0.032
Zimbabwe	0.099	0.005	0.103	0.121	0.164

Note: Social returns to higher and basic education calculated as described in (3.12) and (3.8) respectively.

Table 3.8: Countries in Human Capital Regression

Europe and North America	**East Asia and the Pacific**	**Latin America and the Caribbean**	**Sub-Saharan Africa**
AdEc	**EAP**	**LAC**	**SSA**
Netherlands	Myanmar	Brazil	Sierra Leone
Japan	Hong Kong, China	Jamaica	Gabon
Iceland	Philippines	Uruguay	Rwanda
Denmark	Singapore	Costa Rica	Burundi
New Zealand	Fiji	Paraguay	Sudan
Switzerland	Thailand	Trinidad and Tobago	Mauritius
Italy	Papua New Guinea	Dominican Republic	Niger
Portugal	China	Chile	Benin
Sweden	Korea, Rep.	Argentina	Uganda
Belgium	Malaysia	Guyana	Swaziland
Australia	Indonesia	Peru	Mozambique
Ireland	Taiwan	Cuba	Lesotho
United Kingdom	Tonga	Barbados	Central African Republic
Canada		Venezuela, RB	Gambia, The
Greece	**Middle East and North Africa**	Guatemala	Congo, Rep.
Austria	**MENA**	El Salvador	Cameroon
Norway	Egypt, Arab Rep.	Bolivia	Malawi
France	Jordan	Ecuador	Cote d'Ivoire
Luxembourg	Yemen, Rep.	Panama	Kenya
Spain	Malta	Nicaragua	Zambia
Germany	Syrian Arab Republic	Mexico	Congo, Dem. Rep.
Finland	Bahrain	Haiti	Botswana
United States	Morocco	Honduras	Mali
Albania	Algeria	Colombia	South Africa
Hungary	Iraq		Senegal
Bulgaria	Saudi Arabia	**South Asia**	Liberia
Poland	Tunisia	**SAs**	Zimbabwe
Romania	Kuwait	Nepal	Tanzania
Russian Federation	United Arab Emirates	Pakistan	Mauritania
Turkey	Israel	Afghanistan	
	Cyprus	India	
	Iran, Islamic Rep.	Sri Lanka	
		Bangladesh	

Table 3.9: Countries in APG Regression

Europe and North America	**East Asia and the Pacific**	**Latin America and the Caribbean**	**Sub-Saharan Africa**
AdEc	**EAP**	**LAC**	**SSA**
Italy	Vietnam	Ecuador	Ghana
Canada	Tonga	Guatemala	Liberia
Turkey	Fiji	Costa Rica	Sierra Leone
Switzerland	Malaysia	Panama	Cote d'Ivoire
Spain	Philippines	Jamaica	Swaziland
Greece	Cambodia	Peru	Kenya
Portugal	Indonesia	Mexico	Lesotho
Ireland		Venezuela	Zimbabwe
United States	**South Asia**	Dominican Republic	Uganda
Albania	**SAs**	Bolivia	Tanzania
Romania	Bangladesh	Chile	Rwanda
Latvia	Nepal	Argentina	Malawi
Armenia	Pakistan	Brazil	Botswana
	Sri Lanka		Zambia
Middle East and North Africa			South Africa
MENA			Ghana
Syrian Arab Republic			Liberia
Iraq			
Jordan			

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Chapter 4

Appropriate Technology and Income Differences

4.1 Introduction

An important problem in development economics, and economic growth, is understanding how economies use available factors of production. The traditional view is that low-income countries generally use available factors unproductively compared to richer countries. Recent research has found significant productivity differences within low-income countries; some sectors are relatively productive and others very unproductive. Examples include productivity differences between agricultural and non-agricultural sectors (Restuccia et al., 2008; Gollin et al., 2011), differences in productivity by sectoral skill-intensity (Acemoglu and Zilibotti, 2001; Ciccone and Papaioannou, 2009), and sectoral differences in productivity based on tradability of the final good (Herrendorf and Valentinyi, 2012). Thus, compared to high-income countries, low-income countries are not unproductive at everything.

Looking across factors of production, Caselli and Coleman (2006) find that in comparison to high-income countries, low-income countries use unskilled workers relatively more productively than the skilled. In fact, they find that that low-income countries use unskilled workers absolutely more productively than richer countries under their preferred set of parameters. However, the methodology in Caselli and Coleman (2006) cannot distinguish the hypothesis that skilled workers in low-income countries are less productive because they have less embodied human capital, from the hypothesis that skilled workers are less productive because low-income countries adopt technologies that are complementary with unskilled workers.[1]

[1] They acknowledge this possibility and use information on the elasticity of human capital to measures of schooling inputs to argue that human capital quality differences are small, and can only explain a small fraction of the differences in physical productivities. However, recent studies using different data to back out human capital quality, have found considerable cross-country differences in the quality of skilled labour. In many cases, differences in the quality of skilled labour are as large as differences in the quantity of skilled labour (Schoellman, 2012; Erosa et al., 2010;

I first extend the methodology in Caselli and Coleman (2006), and dissect cross-country differences in the productivity of skilled workers (relative to the unskilled) into differences in the amount of human capital embodied in skilled workers, and differences in production techniques or what I call *physical productivities*. For example, are doctors in the U.S. more productive than doctors in Liberia because they are generally better trained (larger embodied human capital), or because they have access to better equipment such as MRI machines (larger physical productivities), or both? This is an important distinction because the source of the higher productivity of skilled workers has different policy implications. If doctors in high-income countries are primarily more productive because they are better trained, this would imply important differences in the quality of doctors across countries. On the other hand, if doctors are more productive in high-income countries because of access to better medical equipment, it would imply significant barriers to technology adoption.

I use estimates of skill premiums for immigrants from different countries living in the U.S. and estimates of skill premiums across countries, to separate differences in embodied human capital from differences in physical productivities. As all skilled workers in the U.S. work with the same technologies, any differences in skill premiums by country of origin must be due to differences in embodied human capital. Then, differences in skill premiums for immigrants in the U.S. and those left behind in their home countries must be due to differences in physical productivities (production techniques).

I find that (compared to richer countries) skilled workers in low-income countries have significantly less embodied human capital. Further, the physical productivity of skilled workers are also higher in high-income countries, implying that they are used more productively relative to unskilled workers. This result holds for various plausible parameterizations of the production function. Compared to the productivity of skilled workers relative to the unskilled in Caselli and Coleman, controlling for embodied human capital implies that differences in the physical productivity of skilled workers are now smaller (differences in production techniques are now smaller). However, large differences in physical productivities still remain because differences in embodied human capital are comparatively not very large. For example, the ratio of embodied human capital in Ghanaian skilled workers relative to their American counterparts is about 3.6, which is small compared to the 50-fold difference in the physical productivity of skilled relative to unskilled workers.

I then go further and ask: are skilled workers relatively unproductive in Ghana, because Ghanaian firms *appropriately* choose technologies which make abundant unskilled workers more productive? I argue that the estimates imply that this is unlikely: In Ghana for example, the estimates imply that skilled workers are 50 times less physically productive compared to unskilled workers, and in Venezuela they are 100 times less productive. However, the data shows that there are just as many skilled and unskilled workers in Ghana and Venezuela. It is

Manuelli and Seshadri, 2005).

unlikely that unskilled workers being 50 times as physically productive as skilled workers is appropriate, given that skilled workers are just as numerous, possess more human capital, and are substitutable with unskilled workers. In fact, Ghana could increase GDP per capita by a factor of 2.5 simply by using the mix of skilled-unskilled physical productivities used by Ecuador or Greece, for example, leaving all else the same.

To formally investigate, I compare the estimated relative physical productivity of skilled workers to what they would be if technologies were chosen by profit-maximizing firms in each country, following models of appropriate technology. I assume a specific form for the technology frontier and check to see if estimated choices of technology are consistent with appropriate technologies chosen by firms facing that frontier. The shape of the technology frontier is assumed to be the same across countries, but the height of the frontier, or number of available technologies, is allowed to vary by country.[2]

For most of the 49 countries in the dataset, the estimated physical productivities of skilled workers are significantly lower than what is optimal. This is true under various definitions of skilled-unskilled labour, and values of the skilled-unskilled labour elasticity of substitution. Furthermore, the distance between estimated and optimal physical productivity of skilled workers is decreasing with GDP-per-capita. For richer countries such as South Korea, Japan, Israel, the Netherlands, and Australia, we cannot reject that they use skilled and unskilled workers appropriately. For other countries, such as Thailand, China, India, Venezuela, Ghana, and Kenya, the estimated physical productivity of skilled workers is four times less that what is appropriate.

This finding differs from regular notions of appropriate technology which argue that poor countries use technologies that are appropriate for a high skilled workforce, but inappropriate for their relatively unskilled workforce. The result here is in fact the opposite; controlling for the human capital embodied in skilled workers, low-income countries tend to use technologies which make skilled workers very unproductive, and unskilled workers too productive. This suggests significant income gains by adopting more technologies that make skilled workers more productive, *and unskilled workers less productive*.

To get a sense of potential income gains from using more appropriate and skill-complementary technologies, I compare income-per-capita with estimated physical productivities to income per-capita under the optimal physical productivity of skilled workers. Note that in this exercise, all factors of production are held constant, and only the relative productivity of skilled and unskilled workers are changing. Under the preferred set of parameters, the average country in the data

[2]Caselli and Coleman (2006) estimate the technology frontier assuming that firms in every country choose technologies appropriately. Note that the finding that the estimated mix of skilled-unskilled physical productivities are inappropriate is independent of the exact shape of the world technology frontier. This is because a lot of countries could increase output by using the estimated mix of skilled-unskilled physical productivity of other countries in the data. This implies that there is a possible mix of technologies which would increase income in many low-income countries, by making skilled workers more productive relative to the unskilled.

increases its income-per-capita by a factor of 2 from using its appropriate technology, and increasing the relative physical productivity of skilled workers.

There is some variation in income gains from adopting appropriate technologies, depending on a country's income relative to the U.S. Countries in the lowest income quartile experience a seven-fold increase in income, because they are farthest away from their optimal mix of skilled-unskilled physical productivities. More than 50% of all countries in the dataset could increase incomes by a factor of 4 from adopting the appropriate mix of skilled-unskilled worker complementary technologies. Countries in the top income quartile only experience a 23% increase in income by adopting their appropriate technologies, and most of the gains are driven by France and Greece. This is in contrast to Caselli and Coleman (2006) who find large income losses in low-income countries from the adoption of production techniques used by richer countries.

These results could be interpreted as the result of significant barriers to technology adoption, in a world in which new technologies are complementary with skilled workers.[3] As traditional technologies are complementary with unskilled workers, the adoption of newer skilled-complementary technologies are readily blocked by vested interests, rendering skilled workers relatively less productive than they could be.[4] A report by McKinsey (2001) documents the prevalent non-adoption of more productive technologies in many Indian sectors. A recent example is the resistance to Walmart's entry into the Indian retail market by small-scale retailers (see the Bloomberg news report by Pradhan and MacAskill (2011)).

Other plausible interpretations are that these are a result of government policies leading to the misallocation of skilled workers to unproductive sectors. Examples include government job guarantees (Assaad, 1997), or policies which encourage skilled workers to remain on small-scale farms (Adamopoulos and Restuccia, 2013). The inefficient use of skilled workers could also be a result of financial frictions which prevent a firm from investing in newer technologies (Buera and Shin, 2010; Banerjee and Duflo, 2004). Furthermore, the lack of a supporting infrastructure could deter the adoption of the latest technologies. For example, given that most skill-complementary technologies are energy intensive, the inadequate energy production in low-income countries may be a deterrent to importing more skill-complementary technologies.[5]

This paper is closely related to other studies of the implications of appropriate technology for productivity differences. Acemoglu and Zilibotti (2001) assume that all countries use technologies appropriate for high-income countries, and find that the use of these advanced technologies that are inappropriate for the relatively less-skilled workforce in developing countries, could account for cross-country differences in aggregate productivity. On the other hand, Caselli and Coleman (2006)

[3]See Acemoglu (2002), Berman et al. (1998), and Ciccone and Papaioannou (2009), for evidence that recent technologies have been skilled biased.

[4]For examples of how vested interests can block the adoption of new technologies, see Bridgman et al. (2007) and Bellettini and Ottaviano (2005).

[5]The United States produces about 13,000 kWh per person, while Ghana barely produces 300 kWh per person (The World Bank, 2012).

assume that all countries are choosing technologies appropriately, and back out the world technology frontier. They find significant income losses if low-skilled countries are forced to use technologies which are appropriate for the U.S. Also, since countries are choosing technologies appropriately, the only significant productivity gains come from accessing the world technology frontier, or increasing the height of the frontier. Here, I find that leaving the height of the frontier fixed, there are significant income gains from increasing the productivity of skilled workers relative to the unskilled.[6]

This ties the results directly into the literature on barriers to technology adoption, as in Parente and Prescott (1994, 1999), and its implications for productivity differences in a world with skill-biased technical change (see summary in Violante (2008)). It is also related to the literature on the misallocation of factors across different sectors of the economy, summarized in Banerjee and Duflo (2005). Skilled workers may be used relatively unproductively because they are stuck in sectors where their skills are not being utilized. Finally, the results also have some implications for the question of why increases in years of schooling have not translated to growth in GDP (see Hanushek and Woessmann (2008)). Most studies in this area emphasize the role of low and declining schooling quality. While schooling quality is indeed important, this study also suggests a role for increasing the relative physical productivity of skilled workers.

In the next section, I present the model which is used to estimate the relative productivities of skilled and unskilled workers, and explain why it is important to control for the human capital embodied in skilled workers. Section 3 outlines the quantitative framework, and construction of data. Section 4 presents the results, followed by a discussion of the results and assumptions in Section 5. Section 6 concludes.

4.2 Model

4.2.1 Exogenous Technology

Consider an economy, j, with a representative firm which produces output, y_j, according to the constant returns to scale production function:

$$y_j = k_j^{\alpha}[(A_j^s h_j L_j^s)^{\eta} + (A_j^u L_j^u)^{\eta}]^{\frac{1-\alpha}{\eta}}. \tag{4.1}$$

The per-capita stock of physical capital is given by k_j, and the capital share of output is given by α. The variable L_j^s is the stock of skilled labour in n-years of schooling equivalents, where n is the number of years it takes to become skilled, and it is taken to be the same across countries. However, the quantity of human capital embodied in a skilled worker who has completed n-years of schooling is

[6] In fact, using the U.S. mix of technologies would increase incomes for most low-income countries compared to their estimated physical productivities. However, assuming all countries use the U.S. mix of technologies would imply unrealistically high returns to education in developing countries.

given by h_j, and is allowed to vary across countries. Thus, h_j would capture differences in the quality of schooling across countries. The variable L_j^u is the stock of unskilled labour in no-schooling equivalents, and it is assumed that individuals with no schooling are the same across countries with embodied human capital normalized to 1.

The parameters A_j^u, A_j^s and h_j, all determine labour productivity, but they do so in different ways. The parameters A_j^u and A_j^s are defined as the *physical productivities* of unskilled and skilled workers respectively. These parameters depend on the production technology and are not embodied in workers. For example, consider a skilled teacher who has to grade multiple-choice grade exams, which could be done manually or using scanning technology. Having the exams scanned and graded by a machine would increase the productivity of the skilled teacher grading the exams, which would imply a higher A_j^s. For the same teacher, with the same skill level and embodied human capital h_j, grading the exams manually would make her less productive and this lowers the value of A_j^s. However, suppose the teacher is unskilled and is unable to use the scanning technology, then grading the exams manually would increase his productivity, A_j^u, relative to scanning the exams.

From the example above, we can see that physical productivities of skilled and unskilled workers are endogenously chosen by firms. Suppose the exam grading firm has a lot of unskilled teachers, it might be optimal to have less scanning machines, A_j^s, relative to pencils for the manual grading of exams, A_j^u.[7] Thus, the optimal ratio of A_j^s relative to A_j^u would depend on the proportion of skilled and unskilled workers available to the firm, as in models of induced innovation and appropriate technology (Kennedy, 1964; Acemoglu, 2002; Caselli and Coleman, 2006).

The quantity of human capital embodied in a skilled worker, $h_j \geq 1$, also increases his relative productivity. While it could be endogenous to a firm through firm training programs, it is taken to be exogenous and mostly determined by schooling quality. The crucial difference between skilled worker physical productivity, A_j^s and, embodied human capital, h_j, is that h_j moves with the worker. Thus, if a skilled worker in the U.S. is more productive compared to one in Ghana because he has obtained more human capital for the same years of schooling (a higher h_j), then relative to the Ghanaian, the American skilled worker would be more productive regardless of location. As already mentioned, the human capital embodied in an unskilled worker is normalized to 1 and is assumed to be the same across countries.

Further, note from the production function that all workers within a given skill category are perfect substitutes, but could have different efficiency units depending on years of schooling. The elasticity of substitution between skilled and un-

[7] This example suggests that the production technology is embodied in physical capital, and while this intuition is maintained throughout the paper, it strictly does not have to be the case. Production technology may respond to different legal institutions, and problems with contract enforcement may induce firms to adopt different production techniques which could have implications for worker productivity (see Nunn (2007) for example).

skilled workers is given by $1/(1-\eta)$. When $\eta < 0$, skilled and unskilled workers are *complements*, and when $0 < \eta \leq 1$, they are *substitutes*. The production function is Cobb-Douglas when $\eta = 0$, with degree of substitution between skilled and unskilled labour equal to 1.

Taking prices as given, and fixing the firm's choice of technologies A_j^u and A_j^s , the firm chooses efficiency units of skilled and unskilled labour $L_j^s h_j$ and L_j^u, and capital, k_j, in order to maximize profits. From the firm's first order conditions, we find that the ratio of prices for skilled and unskilled labour is given by:

$$\frac{w_j^s}{w_j^u} = \left[\frac{A_j^s}{A_j^u}\right]^{\eta} \left[\frac{L_j^s h_j}{L_j^u}\right]^{\eta-1}. \tag{4.2}$$

Caselli and Coleman (2006) describe a methodology for backing out A_j^s/A_j^u, from a variant of (4.2) when $h_j = 1$, using estimates of the skill premium and the proportion of skilled and unskilled workers. However, with the more general specification given here, A_j^s/A_j^u cannot be separately identified from $h_j > 1$ using the methodology described in Caselli and Coleman (2006). This is because we do not observe the skill prices w_j^s/w_j^u above, instead we observe :

$$\omega_j \equiv \frac{w_j^s h_j}{w_j^u} = \left[\frac{A_j^s}{A_j^u}\right]^{\eta} \left[h_j\right]^{\eta} \left[\frac{L_j^s}{L_j^u}\right]^{\eta-1}. \tag{4.3}$$

Where ω_j is the ratio of wages for a skilled worker relative to an observationally equivalent unskilled worker. The skill premium contains information on skill prices, w_j^s/w_j^u, as well as embodied human capital, h_j . From (4.3), we see that differences in the skill premium across countries could be due to differences in the physical productivity of skilled relative to unskilled workers ($\left[\frac{A_j^s}{A_j^u}\right]$), differences in human capital embodied in skilled workers (h_j), and differences in the endowment of skilled labour (L_j^s/L_j^u). Using only information on skill endowments and the skill premium, differences in relative physical productivity cannot be separated from differences in the quality of skilled labour.

In their paper, Caselli and Coleman (2006) find that the cross-country productivity of skilled workers relative to unskilled workers, $A_j^s h_j/A_j^u$, increases with income. They interpret this result as implying that high-income countries adopt relatively more skill-complementary technologies. However, from (4.3), one could also conclude that physical productivities are the same across countries, but skilled workers in high-income countries have more embodied human capital, because of a better schooling quality in rich countries (Hanushek and Kimko, 2000; Erosa et al., 2010; Schoellman, 2012). For example, Bowlus and Robinson (2012) examine changes in the U.S. college-wage premium across time, and find that the increase in the wage premium is driven by changes in the quality of skilled labour, with very little changes in relative skill price (physical productivity) of a college educated worker. Thus, differences in the human capital embodied in skilled workers across countries could account for some of the differences in the relative productivity of skilled labour found by Caselli and Coleman (2006).

In this paper, I present a methodology for studying differences in relative physical productivities and embodied human capital across countries. In addition to (4.3), which expresses the skill premium for a native of country j in country j, we can also express the skill premium for immigrants from country j, living in country i as:

$$\omega_i^j \equiv \frac{w_i^{j,s} h_j}{w_i^{j,u}} = \left[\frac{A_i^s}{A_i^u}\right]^\eta \left[h_j\right]^\eta \left[\frac{L_i^s}{L_i^u}\right]^{\eta-1}. \tag{4.4}$$

The key difference between (4.3) and (4.4) is that the skill premium would differ, depending on the immigrant's country of origin, as a result of differences in embodied human capital, h_j. Bratsberg and Terrell (2002) and Schoellman (2012) show that returns to schooling for immigrants in the U.S. differ based on country origin, and that these differences are due to differences in quality of schooling in the immigrant's home country. The framework presented here further illustrates why differences in the skill premium (returns to schooling) for immigrants contain information on embodied human capital. Since the relative physical productivity, and supply, of skilled workers is the same for all individuals, any differences in the skilled wage premium, by country of origin, must be due to differences in embodied human capital, h_i. An estimate of the human capital embodied in an immigrant from country j, relative to a native of country i, can be obtained from ω_i^j/ω_i^i.

Then we can infer the size of differences in physical productivities, from (4.3) which gives the skill premium for natives of country j, who live in country j. From (4.4) to (4.3), we see that using data on skilled worker endowments, estimates of the skill premium for immigrants from country j living in country i, and the skill premium for natives of country j living in country j, we can solve for relative physical productivities: $\frac{A_j^s}{A_j^u}/\frac{A_i^s}{A_i^u}$.

We can obtain estimates of the physical productivity of skilled relative to unskilled workers and embodied human capital, all relative to a base country, using the methodology described above. However, for development accounting purposes, I also need to derive the absolute levels of relative physical productivities and embodied human capital. I derive these by endogenizing the choices of physical productivity of skilled and unskilled labour chosen by firms. This puts more structure on the model above and allows me to explicitly solve for A_j^s/A_j^u and h_j.

4.2.2 Endogenous Technology

In this section, I endogenize the physical productivities of skilled and unskilled workers. This is motivated by the literature on induced technical change, which mostly aims to explain why technical change has been skill-biased in the U.S. and other developed nations. The key evidence for the skill-bias of technical change is a non-decreasing skill-premium despite rapid increases in the number of skilled workers.[8] The main theoretical result from this literature is that under fairly general conditions, which I elaborate upon below, innovation would be biased towards

[8] See Acemoglu (2002); Berman et al. (1998) for prominent examples.

the more abundant factor. Thus, in the absence of free labour flows, technologies should be biased towards skilled labour in skill-abundant countries, and vice versa in skill-scarce countries.

There is ample empirical evidence that firms change production techniques in response to changes in factor endowments. In a study of U.S. manufacturing plants, Lewis (2011) finds that plants in areas with higher rates of (less-skilled) immigration adopted significantly less machines per unit output, despite all firms having similar initial adoption plans. Blum (2010) studies a sample of 27 developing and developed countries, and finds that countries absorb changes in factor endowments by changing production techniques, but not the mix of products. The more abundant factor simply gets used more intensively in all sectors of the economy.[9] Caselli and Wilson (2004) find significant differences in the composition of imported machines across countries. Importantly, they find that these differences are strongly related to differences in the availability of other complementary factors within the country. For example, skill-abundant countries import machines that have greater R&D content, and are complementary with skilled labour.

At this point, it is useful to reparameterize (4.1), and rewrite it as:

$$y_j = A_j^{1-\alpha} k_j^{\alpha} [(\mu_j L_j^s h_j)^{\eta} + ((1-\mu_j) L_j^u)^{\eta}]^{\frac{1-\alpha}{\eta}}. \tag{4.5}$$

Where, in comparison to (4.1), $A_j^s = A_j \mu_j$, $A_j^u = A_j(1-\mu_j)$, and $A_j^s/A_j^u = \mu_j/(1-\mu_j)$. The form of the production function in (4.5) emphasizes our interest in the physical productivity of skilled workers relative to unskilled workers, $A_j^s/A_j^u = \mu_j/(1-\mu_j)$, and not the levels of A_j^s and A_j^u. Following the result in Caselli and Wilson (2004) discussed above, one can think of μ_j in (4.5) as the fraction of machines which are complementary with skilled workers. All else the same, the greater availability of machines complementary with skilled workers relative to unskilled workers (higher μ_j) means a relatively more productive skilled workforce. The model which I present below studies the problem of firms choosing the proportion of machines to allocate to skilled and unskilled labour, which would have implications for relative physical productivities.

The Firms' Problem

I follow Caselli and Coleman (2006) and study an economy with many perfectly competitive firms, each producing output using the production function in (4.5):

$$y_j = A_j^{1-\alpha} k_j^{\alpha} [(\mu_j L_j^s h_j)^{\eta} + ((1-\mu_j) L_j^u)^{\eta}]^{\frac{1-\alpha}{\eta}}.$$

[9]This also shows that unlike what some trade models with specialization might suggest, differences in sectoral composition across countries are not important determinants of skilled-unskilled worker productivity differences. For example, Acemoglu and Zilibotti (2001) using cross-country data from UNIDO, show that skilled-unskilled worker productivity differences are large, even within narrowly defined sectors. Further, using census data, Hendricks (2010) shows that the large cross-country differences in the employment of skilled workers are primarily driven by within-sector variations in skilled employment, as opposed to the variation in sectors, across countries.

In addition to hiring efficiency units of labour, and renting capital, firms also choose the relative physical productivity of skilled labour (proportion of machines devoted to skilled labour), μ_j, to maximize profits. As μ_j is the proportion of machines complementary with skilled labour, it is restricted to be between 0 and 1. The firm faces a tradeoff between the physical productivity of skilled workers and that of unskilled workers. Increasing μ_j increases the physical productivity (and relative wage) of skilled workers, but simultaneously decreases the physical productivity of unskilled workers. The problem above abstracts from how A, which is the absolute number of machines used by skilled and unskilled labour (the height of the technology frontier), is determined.

For concreteness, one can think of a firm involved in filing documents. It could store these documents electronically, on a computer, or print and store them in physical folders. Skilled workers are able to store files using both media, but are relatively more productive using computers because unskilled workers are not computer literate. In choosing its production technology, the firm faces a tradeoff between the physical productivities of its skilled and unskilled workers, and the optimal ratio of physical and electronic storage systems the firm would employ depends on the relative supply of skilled and unskilled workers. The firm might find it optimal to store most of the files physically if it has relatively more unskilled workers, because using computers would render its unskilled workers unproductive. On the other hand, it might store most files electronically if it has access to relatively more skilled workers. As we would see below, the relative supply (and wage) of skilled workers, and the elasticity of substitution between skilled and unskilled workers, would play a role in determining μ_j.

As is well known, it is not important whether technical change arises out of improvements in the quality of machines, or expanding the variety of machines and products, so I abstract from the exact form of technical change (see page 5 in Acemoglu (2002), and the citations therein). There remains the question of how the number of machines for skilled and unskilled labour are produced and financed. The framework above abstracts from these considerations. Acemoglu (2002) presents a more detailed framework in which firms demand machines which are supplied by technology monopolists. In the analysis below, I outline conditions under which the result regarding the determinants of the relative physical productivities of (number of machines complementary with) skilled and unskilled workers are the same as in that more detailed model.

Finally, I assume that factors of production are inelastically supplied. This is consistent with my goal of understanding the relative physical productivities of skilled and unskilled workers, and general features of the production function across countries, at a particular point in time. The problem of how relative physical productivities and the supply of skilled and unskilled workers evolve is left for future research.

The economy is at an equilibrium if all firms maximize profit and the markets for skilled labour, unskilled labour and capital, clear. Caselli and Coleman (2006) show that if $1 > \frac{\eta}{1-\eta}$, an equilibrium always exists with the following features: The equilibrium is symmetric, in the sense that all firms choose the same proportion of machines complementary to skilled workers (same relative physical productivity of skilled workers), μ_j, and the same factor ratios, $L_j^s h_j/k_j$ and L_j^u/k_j. Otherwise, the equilibrium is asymmetric, with some firms using only skilled labour with $\mu_j = 1$, and others using only unskilled labour with $\mu_j = 0$.[10]

A formal proof of the statement above is omitted because it is a specific form of Proposition 1 in Caselli and Coleman (2006), specialized to the model presented here in which firms face a linear technology frontier. The equilibrium has the features described above because in general, the production function could exhibit increasing returns to scale since firms choose the technology and inputs.

When $1 > \frac{\eta}{1-\eta}$, the equilibrium is symmetric because it ensures that firms' production functions do not exhibit increasing returns. Thus, all firms use some quantities of skilled and unskilled labour in equilibrium. Intuitively, η governs the elasticity of substitution between skilled and unskilled labour, which is given by $\frac{1}{1-\eta}$. Hence, the condition for a symmetric equilibrium, $1 > \frac{\eta}{1-\eta}$, says that if the elasticity of substitution is not too large, each firm would want to use a mix of skilled and unskilled labour— so the equilibrium must be symmetric since all firms are identical.[11]

The symmetric equilibrium with all firms employing a mix of skilled and unskilled labour is the empirically relevant case. The condition for a symmetric equilibrium is always satisfied when the elasticity of substitution is less than 2, or $\eta < 1/2$.[12] Available evidence shows that the elasticity of substitution for skilled and unskilled labour lies between 1 and 2, which places η between 0 and $1/2$. Ciccone and Peri (2005) use exogenous changes in child labour and compulsory schooling laws across U.S. states, between 1950-1990, as instruments for changes in the supply of skilled labour. They find that the elasticity of substitution lies between 1.2 and 2, with a preferred estimate of 1.5. Autor et al. (1998) also argue that the elasticity of substitution is unlikely to lie outside of the $[1, 2]$ range.

Choice of Appropriate Technology

The rest of the analyses focus on a symmetric equilibrium, with $\eta < 1/2$ or elasticity of substitution less than 2. From the first order condition for firms in country j, and differentiating with respect to μ_j, we find that the choice of relative physical productivities and appropriate technology is determined by the relative supply of skilled and unskilled workers:

[10]Note that the condition $1 > \frac{\eta}{1-\eta}$ is the same as $\eta < 1/2$, and is the same as requiring that the elasticity of substitution between skilled and unskilled labour is less than 2.

[11]This can be seen more clearly when $\eta < 0$, skilled and unskilled labour are complements, and the condition that $1 > \frac{\eta}{1-\eta}$ is always satisfied. In this case, a firm must use a combination of skilled and unskilled labour, and the equilibrium has to be symmetric.

[12]This condition shows up again below in the context of the slope of the relative (inverse) demand for skilled labour.

$$\frac{\mu_j}{1-\mu_j} = \left[\frac{L_j^s h_j}{L_j^u}\right]^{\eta/1-\eta}. \tag{4.6}$$

For convenience, I also reproduce (4.3) which gives the skilled wage premium in country j that comes from the first order conditions for skilled and unskilled labour:

$$\omega_j \equiv \frac{w_j^s h_j}{w_j^u} = \left[\frac{\mu_j}{1-\mu_j}\right]^{\eta}\left[h_j\right]^{\eta}\left[\frac{L_j^s}{L_j^u}\right]^{\eta-1}. \tag{4.3}$$

Equation (4.6) characterizes the appropriate choice of technologies, and optimal physical productivity of skilled workers relative to unskilled workers. When the factors are substitutes ($\eta > 0$), choice of technologies will make the more abundant factor more productive. In the earlier example using skilled and unskilled teachers, (4.6) implies that if skilled and unskilled teachers are substitutes in grading exams, then the more skilled teachers we have, the more firms use scanned exams which make skilled teachers more productive. The reverse would be the case when both types of labour are complements.

The intuition for the result above is similar to that in models of directed technical change and induced innovation (Acemoglu, 2002). To see this, I combine (4.3) and (4.6) to get:

$$\frac{\mu_j}{1-\mu_j} = \frac{w_j^s L_j^s h_j}{w_u L_j^u}. \tag{4.7}$$

Equation (4.7), which is also the income share of skilled workers relative to unskilled workers, shows that that the fraction of machines complementary with skilled workers is higher when the relative price of skilled workers rises, or their relative supply rises.[13] The ratio, $\frac{w_j}{w_u}$ is the "price effect," which increases the supply of machines complementary to the relatively more expensive factor. The second ratio, $\frac{L_j^s h_j}{L_j^u}$, is the "market-size effect," which increases the supply of machines for the relatively more abundant factor. From (4.3), we know that an increase in the relative supply of skilled workers decreases the relative price of skilled workers; so the price and market-size effects work in opposite directions.

In (4.6), the market-size effect dominates the price effect when skilled and unskilled workers are substitutes, because a greater availability of skilled workers means that the firm is able to economize on the more expensive unskilled workers by increasing the productivity (and employment) of skilled workers. When the factors are complements, the choice of technologies will lead to more machines complementary with the less abundant factor. This is because the firm cannot easily substitute towards the relatively more abundant factor, and has to increase the productivity of the more expensive (and scarce) factor.

The expression for the choice of appropriate technology in (4.6) is not particular to the model presented here. It is equivalent to those in the induced innovation

[13]Also see Kennedy (1964), who argues that innovations will be induced towards the factor with the higher share of total costs.

models of Acemoglu and Zilibotti (2001) and Acemoglu (2002), when a dollar spent on R&D for unskilled labour complementary machines produces the same number of machines as a dollar of R&D spent on skilled complementary machines.[14] The model presented here also assumes there is limited state dependence so that the cost of R&D in skilled complementary machines does not vary with previous discoveries of such machines. The evidence on this issue is scant; on one hand, it could be that as a result of externalities, the greater the number of researchers working on producing skilled complementary machines, the greater the probability of success. On the other hand, others may argue that with a lot of skilled complementary machines, it becomes increasingly more difficult to produce an additional variety. In the absence of strong evidence on either side, the approach here effectively assumes that the marginal cost of producing both types of machines are equal.

Next, consider the general effect of the relative supply of skilled labour on the skilled wage premium, which is obtained by substituting (4.6) into (4.3):

$$\omega_j \equiv \frac{w_j^s h_j}{w_j^u} = \left[h_j\right]^{\frac{\eta}{1-\eta}} \left[\frac{L_j^s}{L_j^u}\right]^{\frac{2\eta-1}{1-\eta}}. \tag{4.8}$$

From (4.8), we see that as long as $\eta < 1/2$, and holding the quality of human capital fixed, the relative demand for skilled labour is downward sloping. Recall that this is the same condition which guarantees the existence of a symmetric equilibrium. Even with firms choosing inputs and production techniques, the model is consistent with cross-country estimates showing the skill premium decreases with the proportion of skilled workers.

Next, I explain how equations (4.3) and (4.4), combined with (4.6), can be used to solve for embodied human capital, and the relative physical productivity of skilled workers across countries.

4.3 Quantitative Framework

Using equations (4.3) and (4.4), combined with (4.6), I can solve for the physical productivity of skilled relative to unskilled workers for all countries for which there are estimates of returns to education, and estimates of returns to education for its immigrants in the U.S. The U.S. is used as the base country because of available estimates of the returns to education for immigrants to the U.S.

From the expression for the wage premium in (4.8), the average quality of skilled workers in the U.S., $\bar{h}_{U.S.}$ (the average for natives and immigrants), can be derived using the average skilled premium, and the proportion of skilled and unskilled workers:[15]

[14] See to equation (21) in Acemoglu (2002). The reader may also compare the expression for the wage premium to that in equation (22) of the aforementioned paper.

[15] In practice, the estimate of the average human capital in the U.S. is not different from the average human capital of an American native. This is because estimates of the average skill premium in the U.S. are not significantly different from estimates of the skill premium for American born

$$\bar{\omega}_{U.S.} \equiv \frac{w^s_{U.S.}\bar{h}_{U.S.}}{w^u_{U.S.}} = \left[\bar{h}_{U.S.}\right]^{\frac{\eta}{1-\eta}} \left[\frac{L^s_{U.S.}}{L^u_{U.S.}}\right]^{\frac{2\eta-1}{1-\eta}}. \tag{4.9}$$

Next, I assume that firms in the U.S. choose their mix of physical productivities according to (4.6):

$$\frac{\mu_{U.S.}}{1-\mu_{U.S.}} = \left[\frac{L^s_{U.S.}\bar{h}_{U.S.}}{L^u_{U.S.}}\right]^{\eta/1-\eta}. \tag{4.10}$$

Thus, firms in the U.S. choose technologies, appropriately, to match the proportion of skilled workers, where $\bar{h}_{U.S.}$ is the average quality of skilled workers in the U.S. (natives and immigrants combined). There are three primary reasons why it is plausible that the U.S. chooses its technologies appropriately. The status of the U.S. as the richest large country makes it plausible that firms in the U.S. choose technologies appropriately. If technological choices were inappropriate in the U.S., the country should not have been as successful as it has been.[16] Further, the traditional role of the U.S. as the world's technology leader suggests that new technologies are being developed to match the needs of American firms as the primary market for these technologies. Lastly, in the absence of any models, one would intuitively assume that close to 100% of the technologies in the U.S. are complementary to skilled workers because the U.S. has very few unskilled workers. The estimate of $\mu_{U.S.}$ I find using (4.10) is .99 which matches this simple intuition.

In comparison to related studies, Acemoglu and Zilibotti (2001) assume that firms in the U.S. choose technologies optimally, and all other countries are forced to use the technology appropriate for the U.S. They motivate this assumption by appealing to property rights and patent enforcement problems which deter the development and adoption of technologies appropriate for low-income developing countries, but not not high-income countries.[17]

Caselli and Coleman (2006) explain their finding that the relative productivity of skilled workers is higher in rich countries, by appealing to the idea that (all) countries choose their technologies appropriately. The authors then use a general form of (4.6) to estimate the world technology frontier. The framework here assumes that the technological choice of the U.S. is appropriate without placing a restriction on the choice for other countries.

Given the physical productivity of skilled to unskilled workers in the U.S. from (4.10) above, I can solve for the human capital embodied in skilled workers for all other countries. These can be obtained from (4.4), which gives the expression for the skill premium of foreign-born and foreign-educated workers in the U.S.[18] The

individuals; probably a result of the fact that immigrants only constituted about 1 in 10 of the U.S. labour force in 1990.

[16] I am grateful to a member of the audience at a talk I gave on this paper for pointing this out.

[17] As a preview to the results, it is worth noting that the estimates show that there are other high-income countries choosing technologies appropriately (Canada, Australia and Japan, for example).

[18] The estimate of embodied human capital would be upward biased if only the most able skilled workers get to emigrate. In Section 4.5.3, I show that such selection patterns do not affect the main results of the paper.

physical productivities of skilled relative to unskilled workers (choice of technologies) can be obtained from (4.3), which is the skill premium for individuals from country j living in their countries of birth.

The strategy boils down to assuming that the U.S. is choosing its technology appropriately, according to the model of appropriate technology described earlier. I then solve for embodied human capital and physical productivity of skilled workers for all other countries. These estimates are constructed to be consistent with the skill premium for immigrants in the U.S. and natives in their home countries.

Data Construction

In order to solve for the relative physical productivity and human capital embodied in skilled workers (μ_j and h_j) using the steps described above, I need estimates of the skill premium in the U.S., skill premiums for immigrants in the U.S., the skill premium in country j, and the proportion of skilled and unskilled workers. For ease of comparison, I try to be consistent with Caselli and Coleman (2006) when constructing all variables.

The skill premium for a country with estimated annual return to education, β, and years of schooling required to become skilled, n, is given by: $exp(\beta n)$. Estimates of β used in constructing skill premiums for immigrants in the U.S. are taken from estimates of the returns to schooling, by country of origin, published in Schoellman (2012). The skill premium for all other countries are constructed using estimates of the returns to schooling published in Psacharopoulos and Patrinos (2004). I use estimates of the returns to schooling for immigrants from the 1990 U.S. census in order to match the time period for the estimates in Psacharopoulos and Patrinos (2004)

A skilled worker is defined as an individual who has completed primary education for the baseline analysis. The number of years it takes to complete primary education is $n = 4$, which is the minimum for the countries in the dataset. Besides ease of comparison with the previous literature, defining unskilled workers as workers who are uneducated makes the measure of the human capital embodied in skilled workers comparable across countries. Defining unskilled workers as individuals who have not completed primary education makes it plausible that they are the same across countries, with "raw labour power" the only human capital they posses. Thus, if $h_j > h_i$ for countries i and j, not only can we say that skilled workers in country j are of better quality than skilled workers in country i, we can also say that skilled workers in country j have h_j as much human capital as unskilled workers in both countries i and j. Basically, the quality of workers who have not completed primary schooling should not vary significantly across countries, so the reference point for embodied human capital (the denominator) is comparable.

Completing primary education is also preferable as the definition of skilled, because as Caselli and Coleman (2006) argue, there are qualitative differences between a primary educated and an uneducated worker which makes them imperfect substitutes. The completion of (a good) primary education endows an individual with the literate and numerical foundations needed for further education; a skill not possessed by an uneducated individual. It could be argued that post-primary education is just adding unto the foundations established by basic schooling. So primary educated workers may be perfectly substitutable with secondary educated workers. However, there are several tasks in which no number of illiterate (uneducated) workers can replace one who is literate and has completed primary schooling. Notwithstanding the above considerations, for sensitivity, the analysis is also performed with a secondary-completed definition of skilled.

I construct the proportion of skilled and unskilled workers following Caselli and Coleman (2006), using an approach which would get the income share of skilled relative to unskilled workers right. I sum up the proportion of workers who belong to a given skill category, and weight additional years of education by relative wages. For example, under the primary definition of skilled, everyone who has not completed primary schooling is counted as unskilled; but those who have ever been to primary school (but have not completed) will have more "efficiency units" of human capital compared to those who have never been. The proportion of unskilled workers will be the proportion of individuals who have never been to primary school, plus the proportion of workers who have some primary education (but not completed) multiplied by their relative wage, $exp(\beta 2)$, where 2 years is half of a primary education.[19] Unskilled workers are the same across countries since the base group is defined as those who have never been to school.

Similarly, for skilled workers, primary completed workers are the base group, and individuals who have attained but not completed secondary education will have more efficiency units of human capital than the base group. Their efficiency units over the base group is the skill premium consistent with half the number of years it takes to complete secondary schooling. Secondary educated workers will have efficiency units over the base group equal to the skill premium consistent with the number of years it takes to complete secondary education, and so on for higher levels of education. Due to the fact that the number of years it takes to to compete primary education varies across countries, the proportion of skilled workers is multiplied by $exp(\beta(n_j - 4))$. Where n_j is the length of time it takes to complete primary education in country j, and the adjustment converts all measures of the proportion of skilled into 4-year equivalents. So the base group for skilled workers are individuals who have completed 4 years of schooling.

Data for the proportion of workers (25+) in each education category, for the year 1985, is taken from the latest release of the Barro-Lee dataset published in Barro and Lee (2010). Data on the length of time it takes to complete primary and secondary schooling is taken from Barro and Lee (1996), and for college education, I use data from UNESCO (2012). Data for output per capita, y, and the capital stock per capita, k, are taken from the Penn World Tables (Heston et al., 2012).

[19]The number 2 in the expression is half the number of years it takes to complete a basic education. Workers who have attained, but have not completed, a given level of education are assumed to have half the number of years required to complete that level of education. I also experimented with lumping these workers into the lower education category, but the results do not vary significantly.

Lastly, I take values of the elasticity of substitution between skilled and unskilled workers, η, from estimates provided by Ciccone and Peri (2005). As I mentioned earlier, they find the elasticity of substitution for skilled and unskilled labour to lie between 1.2 and 2. I use an elasticity of substitution equal to 1.4 for the analysis below, and explore the implication of elasticities of substitution equal to $1.2, 1.6, 1.8,$ and 2.[20] I set the capital share of output equal to $1/3$, which is consistent with Gollin (2002), who finds that the capital-output share does not vary with income.

4.4 Results

4.4.1 Physical Productivity and Human Capital Relative to U.S.

I focus on results for a degree of substitution between skilled and unskilled labour equal to 1.4 as in Caselli and Coleman (2006), unless stated otherwise. The results show significant cross-country variation in relative physical productivities (technology choice) and human capital embodied in skilled workers. Table 4.1 summarizes the physical productivity and human capital embodied in skilled workers for the countries in the data relative to the U.S., under various definitions of skilled labour. For these results, I do not assume that the U.S. is choosing its physical productivities appropriately. I use skill premiums for immigrants relative to U.S. natives to solve for embodied human capital relative to U.S natives. I then use this ratio, and the skill premiums for immigrants relative to natives of their home countries, to compute physical productivities relative to the U.S.

Table 4.1: Physical Productivity and Embodied Human Capital

Skilled Definition	**Obs**	**Mean**	**Std. Dev.**	**C.o.V.**	$Corr_y$
	Embodied Human Capital Relative to U.S.				
Primary	49	.86	.09	.11	.46
Secondary	49	.71	.18	.25	.46
College	49	.61	.23	.38	.47
	Physical Productivities Relative to U.S.				
Primary	49	.03	.15	4.30	.32
Secondary	49	.03	.14	4.76	.24
College	49	.18	.46	2.52	-.022

The average human capital embodied in skilled workers, for all countries in the data, is about 86% of the U.S. level under the primary-educated definition of

[20] Most studies use the high school-college as measures of skilled-unskilled labour, but in this paper, I use the uneducated-primary completed distinction. It is reasonable to believe that the elasticity of substitution between an illiterate and educated worker is even less than that between a high school and college educated worker, and lower values in the $[1.2, 2]$ range are more plausible.

skilled. There is significant variation in the human capital embodied in skilled workers, even among high-income countries. Skilled workers in Portugal embody about about 70% of the human capital embodied in an American worker, and skilled workers in France embody about 105% of the U.S. level.

The variation in embodied human capital (labour quality) also increases with the secondary and college-competed definitions of skilled; the coefficient of variation jumps from .11 for the primary-educated definition of skilled, to .38 for the college-educated definition. The last column of Table 4.1 show that, relative to the U.S. level, the human capital embodied in skilled workers strongly increases with GDP irrespective of the definition of skilled labour. The correlation coefficient is .46. This is consistent with other studies which find the quality of skilled labour increases with output (Hanushek and Kimko, 2000; Erosa et al., 2010; Manuelli and Seshadri, 2005).

A summary of the ratio of skilled-unskilled worker physical productivity, relative to the U.S, is shown in the second part of Table 4.1. An interesting finding is that the relative physical productivity of skilled workers is higher for the college educated definition of skilled. This could be explained by the finding that cross-country productivity gaps are larger in agriculture, compared to non-agriculture, where most college educated workers are employed (Gollin et al., 2011). Thus, the skilled workers that are relatively less productive in low-income countries are not the most-educated, but those with intermediate levels of education.

It could also be true that cross-country productivity gaps are larger in sectors employing relatively more unskilled workers in developing countries, as Acemoglu and Zilibotti (2001) find. Acemoglu and Zilibotti interpret this as evidence that low-income countries adopt technologies, from high-income countries, which are complementary with highly skilled workers. Further evidence that technologies are more uniform (do not vary with income), at the college-educated level, can be seen from the last column of Table 4.1 which shows that college-educated physical productivity is uncorrelated with output across countries.

However, at the primary and secondary-completed definitions of skilled, there is significant variation in the physical productivity of skilled workers relative to the U.S.. High-income countries tend to use skilled workers more productively relative to unskilled workers, even after controlling for the human capital embodied in skilled workers. Thus, the analyses from here on will focus on the primary and secondary completed definitions of skilled, with greater emphasis on the primary-completed definition.

Also note that most of the cross-country differences in skill premiums are a result of differences in physical productivities. Under the primary educated definition of skilled for example, the human capital embodied in skilled workers is, on average, about 86% of the U.S.level. Compare this to the average ratio of the physical productivity of skilled to unskilled workers being only about 3% of the U.S. level. Table 4.1 suggests that cross-country differences in embodied human capital are not very large in comparison to differences in physical productivities, and this is confirmed in the next part of the analysis.

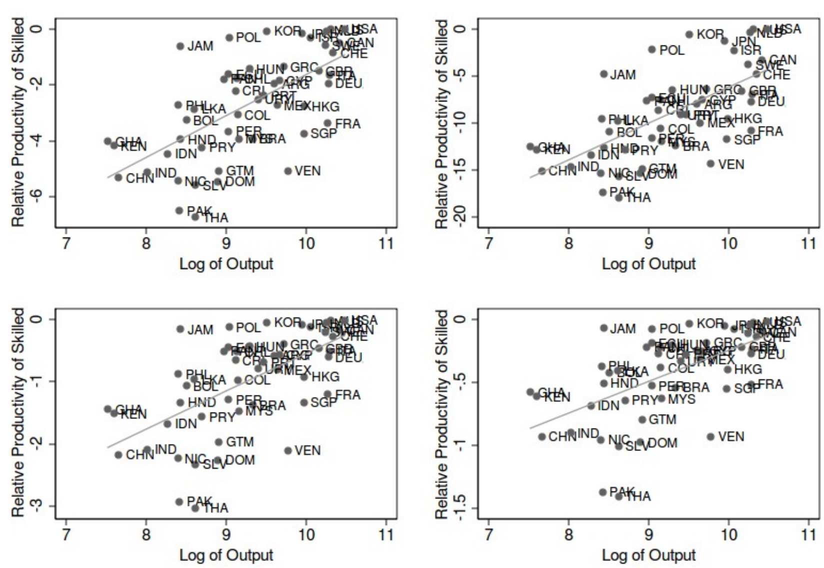
Next, I present results using insights from the model of appropriate technology to solve for the physical productivity of skilled workers in the U.S., and then physical productivities for all other countries.

4.4.2 Physical Productivity and Embodied Human Capital

Assuming the U.S. chooses the physical productivity of skilled labour relative to unskilled labour, as in (4.6), I can compute levels of the physical productivity and quality of skilled labour for all other countries. The U.S. level of physical productivity, $\mu_{U.S.}$, equals .99. This is interpreted as saying that 99% of all machines in the U.S. are complementary with skilled workers. The result makes intuitive sense because we expect that almost all machines in the U.S. have to be complementary with skilled workers since almost all workers in the U.S. are skilled under the primary-completed definition. This is especially true since the U.S. is considered the world technology leader.

I find that the physical productivity and human capital embodied in skilled workers increases with per-capita income. Furthermore, the basic finding that skilled workers are relatively more productive in high income countries in Caselli and Coleman (2006) remains true after accounting for differences in embodied human capital. However, the gap in physical productivities across countries is now smaller, because some of the differences in the relative productivity of skilled workers is now accounted for by differences in embodied human capital.

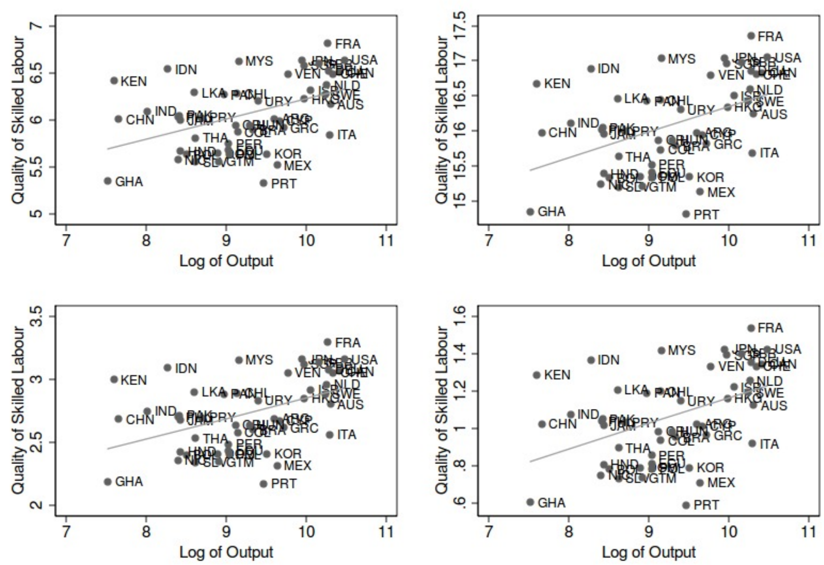
Figure 4.1: Physical Productivity of Skilled Workers and Output (Primary)



Clockwise: Elasticity of Substitution = 1.4, 1.2, 1.6, 1.8

Figure 4.1 plots the physical productivity of skilled workers, μ_j, against output in logarithmic scale, for various values of the elasticity of substitution for skilled and unskilled workers (1.4, 1.2, 1.6, 1.8). It is clear that for all plausible values of the elasticity of substitution, the physical productivity of skilled workers, relative to unskilled workers increases with output. High-income countries tend to adopt proportionally more machines which are complementary with skilled workers, and low-income countries adopt proportionally more machines complementary with unskilled labour. This result goes against the common idea that low-income countries may be unproductive because they adopt machines complementary with skilled workers, but not the unskilled workers who are abundant in these countries. All countries do not adopt the same production techniques, and Caselli and Wilson (2004) provide evidence that types of machines imported in different countries varies with skill level.

Figure 4.2: Embodied Human Capital and Output (Primary)



Clockwise: Elasticity of Substitution = 1.4, 1.2, 1.6, 1.8

The estimates also show that the human capital embodied in skilled workers is higher in high-income countries. Figure 4.2 plots (the log of) embodied human capital against the log of output. Again, for all plausible values of the elasticity of substitution, embodied human capital is increasing in output. Thus high-income countries have better skilled labour quality, and use production techniques which make skilled workers relatively more productive.

Estimates of physical productivity and embodied human capital increase with income, because if physical productivities and embodied human capital are assumed to be the same across countries, (4.3) predicts very low skill premiums in high-income countries. To match observed skill premiums, the model implies that skill-abundant (high-income) countries must have more embodied human capital, or be relatively more physically productive with skilled workers. Recall that for any given country, the human capital embodied in its skilled workers is chosen to match the estimate of the skill premium of its natives who are living in the U.S. Then the physical productivity of its skilled workers is chosen to the match the average skill-premium in that country, given embodied human capital.

In order to match higher skill premiums for immigrants from high-income countries, it must be that they have more embodied human capital. However, the higher human capital embodied in skilled workers from high-income countries does not completely explain why observed skill premiums in high-income (skill-abundant) countries are high. Hence, to match the average skill premium in these countries, it must be that the relative physical productivity of skilled workers is also higher. This explains why the data implies that the physical productivity and human capital embodied in skilled workers must be increasing with output. Figures 4.11 and 4.12 show the same results for the secondary-completed definition of skilled.

It is interesting that rich countries have higher proportions of skilled workers, use skilled workers more physically productively relative to unskilled workers, and also have a higher quality of skilled workers. One might expect that the quality and quantity of skilled workers may be substitutes, or that the relative physical productivity of skilled workers may be substitutable with worker quality. These results call for a framework for understanding why the quantity, quality, and physical productivity of skilled workers are all complementary and increase with income.

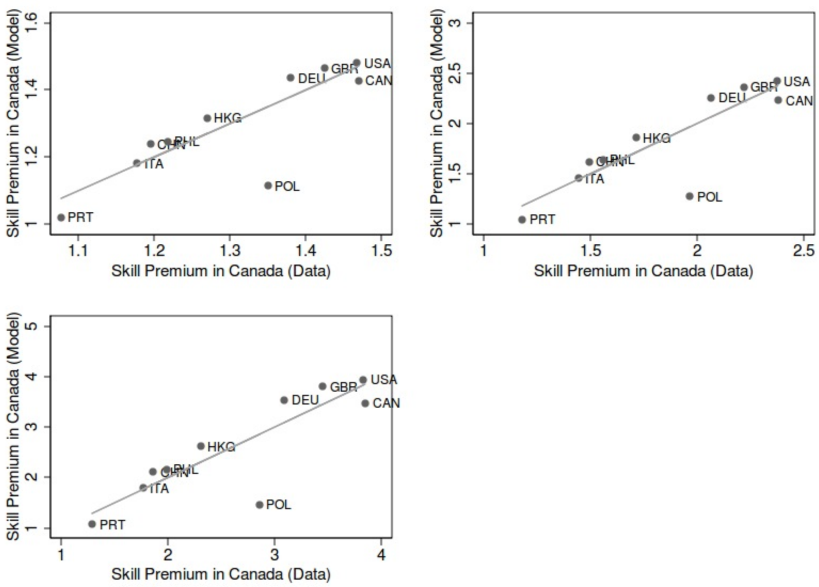
At this stage, one might wonder whether the estimates of embodied human capital and physical productivities are consistent with other data. In order to test the validity of the model in terms of skill premiums, I investigate how the results match observed skill premiums for immigrants from different countries in Canada. I compute predicted skill premiums for natives of different countries living in Canada using estimates of the relative physical productivity of skilled workers and the observed skilled-unskilled labour ratio in Canada, combined with estimates of the human capital embodied in skilled workers for natives of different countries. The predicted skill premiums are then compared to those estimated from the data taken from Schoellman (2012).

The results are displayed in Figure 4.3 for all 3 definitions of skilled labour. The Figure plots predicted skill premiums against those estimated from the data, using an elasticity of substitution equal to 1.4. For all countries for which there are estimates of the skill premium in both Canada and the U.S., the model does a very good job of matching observed skill premiums in Canada, with Poland being an exception.[21] The correlation coefficient is around .85 for all 3 definitions of skilled labour, and does not vary greatly using different elasticities of substitution. I believe this speaks to the validity of using (4.3) as a model of skill premiums across countries, and also the validity of using returns to education for natives of

[21]The skill premium does not exactly match observed returns for native-born Canadians in Canada, because the physical productivity of skilled workers was chosen to match average returns in Canada.

different countries residing in a given country in order to understand differences in skilled labour quality.

Figure 4.3: Predicted Skill Premiums in Canada



Clockwise: Primary, Secondary, College

4.4.3 Appropriateness of Observed Relative Productivities

In summary, rich countries use skilled labour more efficiently relative to unskilled labour. Caselli and Coleman (2006) interpret this finding as indicating that countries choose technologies which are appropriate for the composition of their workforce. Next, I examine the estimates more closely and ask whether the estimated physical productivities of skilled and unskilled workers are appropriate.

Looking at the estimates for physical productivities across countries, it is unlikely all countries are choosing the appropriate mix of skilled-unskilled labour complementary technologies. For example, the estimate for the physical productivity of skilled workers in Ghana, μ_j, is equal to .02. This could be interpreted as saying that in 1990 Ghana, only 2% of all machines are complementary with skilled workers, or that unskilled workers are more physically productive than the skilled by a factor of 50. This situation is unlikely to be appropriate since Ghana has roughly the same number of skilled and unskilled workers over the same time period; the skilled-unskilled worker ratio is 1.07 (see Table 4.4). Venezuela is another example: in 1990, only 1% of machines are relatively complementary with skilled workers, and unskilled workers are more physically productive by a factor of 100. Just as in Ghana, Venezuela also has an equal share of skilled to unskilled workers, so it is unlikely that one factor being 100 times more physically productive is appropriate.

The situation in Ghana and Venezuela is prevalent in many low-income countries in the data, and suggests that because skilled workers embody more human capital and are substitutable with unskilled workers, Ghana and Venezuela could increase output by increasing the physical productivity of skilled workers relative to the unskilled (leaving aggregate productivity A the same). To formally investigate the appropriateness of technology choices, I compute the physical productivity of skilled workers for all countries, assuming they choose the proportion of machines complementary with (physical productivities of) each labour type according to equation (4.6).

The exercise here is to fix the technology frontier available to each country (A), and search for a different point on the frontier (μ) which would increase output. The exercise is not trivial since increasing the physical productivity of one factor also decreases the physical productivity of the other. I assume that the frontier is linear, so that countries are able to choose any fraction of skilled-unskilled workers complementary machines. So a firm can have 98 workers storing files electronically, and 2 storing files manually if need be. In contrast, Caselli and Coleman (2006) assume that countries choose technologies appropriately, and then use the equilibrium equations to estimate what their technology frontiers must be. As I have argued using examples from Ghana and Venezuela, and coupled with what we know regarding barriers to technology adoption in some countries, it is unlikely that the estimated physical productivities are appropriate.[22]

I primarily report results for the preferred definition of skilled, which is primary-educated workers, and elasticity of substitution equal to 1.4. I also explore the implications of other values of the elasticity of substitution.[23] The main result is that just as in Ghana and Venezuela, several countries use skilled workers relatively unproductively; more than 75% of all countries are far away from their optimal mix of skilled-unskilled productivities as computed from (4.6).

Figure 4.4 plots the (log of) optimal relative physical productivity of skilled workers against output. As might be expected, high-income countries are supposed to be using technologies which are relatively complementary to skilled workers, who are more abundant in those countries. High income and skill-abundant

[22]The exact form of the technology frontier is not crucial for the results that follow. While the true form of the frontier is important for finding the appropriate production technique, the message here is that current production techniques in many countries are inappropriate. Inappropriate in the sense that regardless of the form of the technology frontier, Ghana could increase income per capita by using the ratio of skilled-unskilled worker complementary technologies used in Ecuador or Greece, leaving the total number of machines the same. In fact, the poorest countries in the data would increase output by using the mix of skilled-unskilled worker technologies in use by Greece, and increasing the physical productivity of skilled workers relative to the unskilled. The fact that these techniques are being used in other countries means that it is *possible*, so the question is why are they not being used in Ghana, Kenya and other low-income countries?

[23]These results also hold for the secondary-educated definition of skilled, so for the sake of brevity, these results are omitted.

countries such as the U.S., Australia (AUS), Canada (CAN), United Kingdom (GBR) should be using similar production techniques. On the other hand, countries such as Bolivia (BOL), Colombia (COL), and Peru (PER) should also be using similar production techniques, consistent with their level of economic development and skill endowment.

Figure 4.4: Optimal Physical Productivity and Output

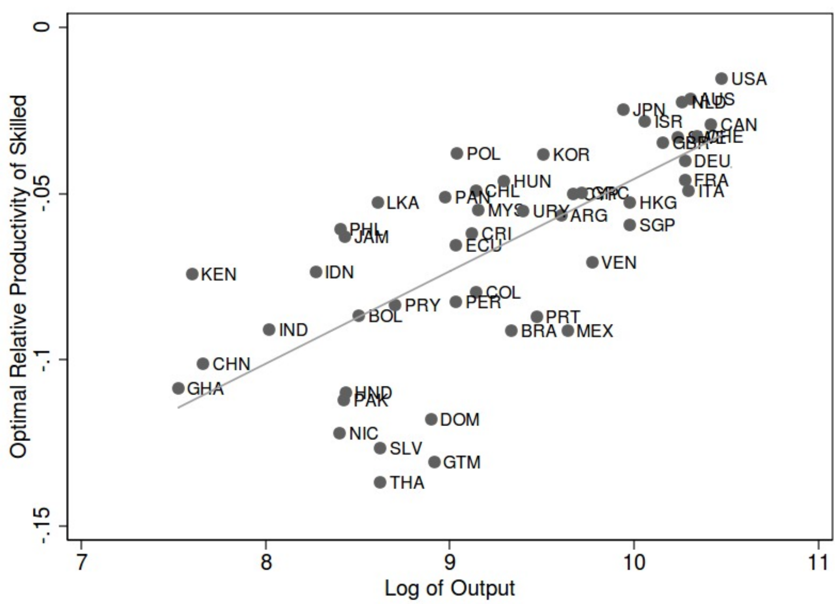
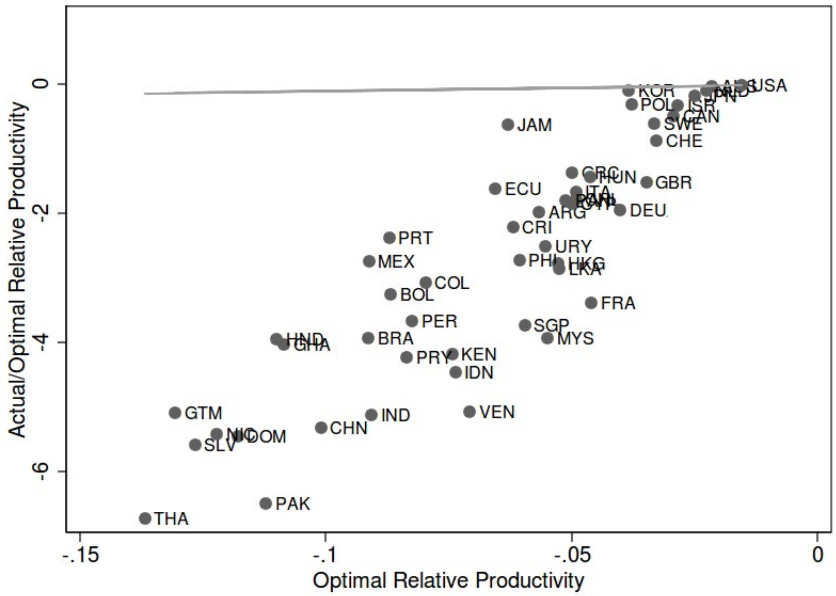


Figure 4.5 plots the estimated physical productivity of skilled workers against optimal physical productivities. It shows that the estimated physical productivity of skilled workers increases with optimal productivity. However, the figure reveals substantial differences in optimal-estimated physical productivities. If all countries were using their skilled workers optimally, estimated physical productivities would lie on the ($45°$) line, which is clearly not the case as most countries lie below the line. Thus a lot of countries use inappropriate technologies which make skilled workers too unproductive, and unskilled workers too productive. For more than half of the 49 countries in the dataset, the physical productivity of skilled workers is less than twice what it should be if chosen by profit maximizing firms.

For example, given the proportion of skilled workers in Thailand, profit-maximizing firms would allocate 87% of all machines to skilled workers. But the estimated physical productivity of skilled workers that is consistent with the skill premium in Thailand and individuals from Thailand living in the U.S., is just .01. Thailand would increase its output (and aggregate productivity) by using skilled workers more productively, and reducing the physical productivity of the unskilled.

The degree of the inappropriateness of estimated technologies can also be seen

Figure 4.5: Optimal versus Estimated Physical Productivity



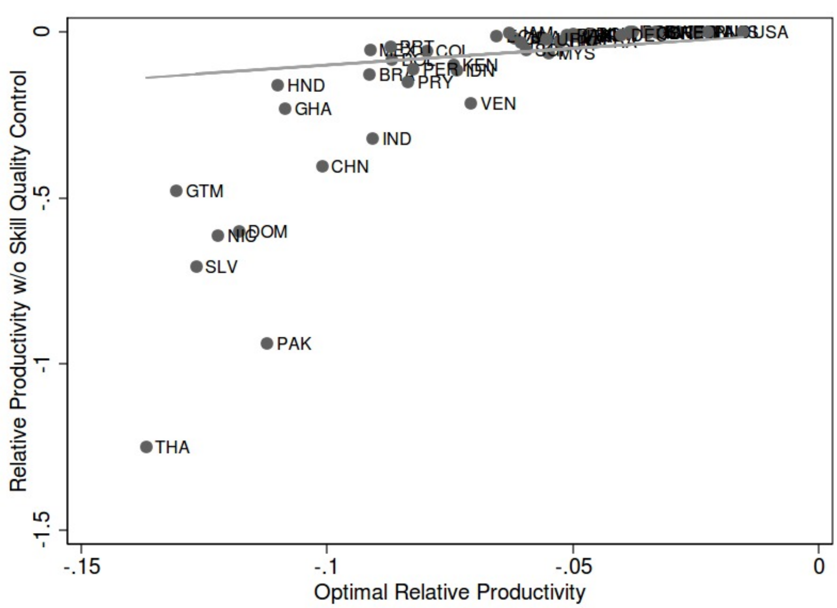
Note: The line above the data points is a 45° line, the x-axis has been truncated.

by comparing the ranges of the optimal and estimated physical productivity of skilled workers in Figure 4.5. Estimated physical productivities range from -7 to -.01 in log-scale (μ ranges from .01 to .99), while optimal relative productivities only range from -.15 to -.01 (optimal μ ranges from .86 to .99). Countries are very similar in the optimal physical productivity of skilled workers, which is not surprising since the cross-country variation in the proportion of primary educated workers is not large. The cross-country variance in optimal physical productivities is consistent with the variance in the the cross-country proportion of primary-educated workers, but the variance in estimated physical productivities is comparatively too large.

Regular notions of inappropriate technology, as it relates to factor intensities, argue that some countries adopt technologies from high skilled countries which are complementary with skilled workers, but not the vast number of unskilled workers in these countries (see Acemoglu and Zilibotti (2001), and Basu and Weil (1998), for examples). In the framework here, under the regular notion of inappropriateness, one would argue that low-skilled countries use technologies which are appropriate for the U.S labour force, for example. Such a choice of technology is also inappropriate, as it would use skilled workers too productively, and the large numbers of unskilled workers unproductively. The result here is the opposite of the regular story of inappropriate technology; after controlling for the human capital embodied in skilled workers, several countries use too many technologies which are complementary with unskilled workers, and skilled workers are used relatively unproductively. Under the preferred calibration, in no case do I find a country using skilled workers too productively. Uncovering this result does depend on controlling for the human capital embodied in skilled workers.

Figure 4.6 shows the optimal-estimated physical productivity relationship without controlling for cross-country differences in the human capital embodied in skilled workers. One would conclude from the picture that most countries are using appropriate technologies, because most countries are in, or around, the $45°$ line. The approach here disentangles embodied human capital from physical productivity, which leads to the finding of inappropriate technology. Evidence from estimates of immigrant returns to education and studies using test scores do show significant variation in the quality of skilled workers, and provides justification for the approach.

Figure 4.6: Optimal versus Estimated (No Embodied Human Capital Control)



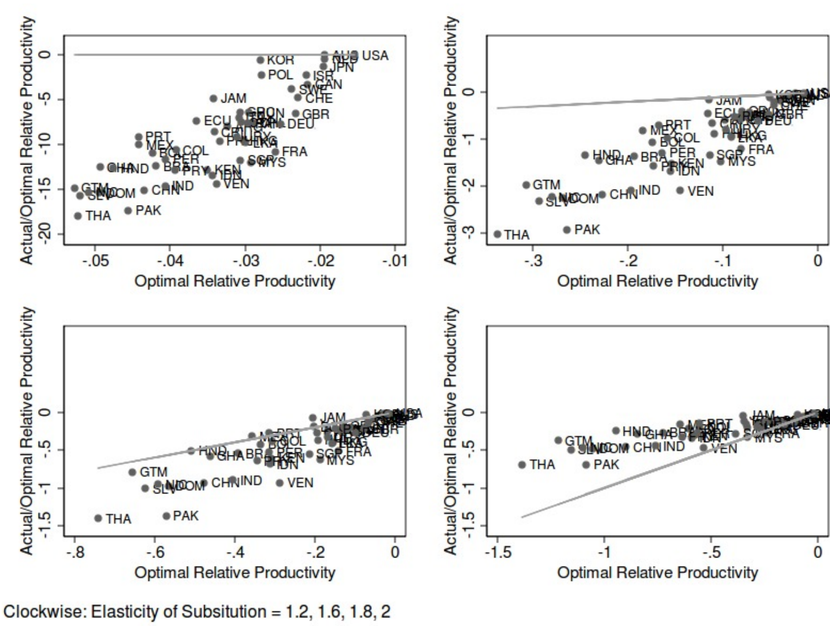
Note: The line above the data points is a $45°$ line, the x-axis has been truncated.

Furthermore, note that the U.S. is not the only country using its appropriate technology as was assumed from the outset. As may be seen from Figure 4.5, a simple t-test cannot reject that countries such as South Korea (KOR), Japan (JPN), Australia (AUS) and the Netherlands (NLD), are using appropriate technologies. Thus, we would obtain the same results if we assumed, instead, that any one of the above countries are choosing the physical productivity of skilled workers appropriately. There does not appear to be anything particularly special about the assumption that the U.S. is using its skilled and unskilled workers optimally.

A simple t-test would also reject the hypothesis that all countries are using appropriate technologies. Further, given the significant differences in optimal and estimated relative productivities, assuming appropriateness would overstate the skill premium for individuals living in their home countries. Take Thailand for example, if we assumed skilled workers were used appropriately, the skill premium for natives living in Thailand would be more than 5, whereas it is only 1.6 in the data. Using a combination of the skill premium for emigrants and natives disciplines estimates of the human capital capital embodied in skilled workers, and physical productivities.

Figure 4.7 compares the optimal and estimated physical productivities of skilled workers under different skilled-unskilled labour elasticities of substitution. With the exception of very high elasticities of substitution, when the elasticity of substitution is greater than or equal to 2 or $\eta \geq 1/2$, the result that most countries use skilled workers relatively unproductively holds. As already explained earlier, such high elasticities are implausible, but it is worth exploring why the result is overturned in those cases.

Figure 4.7: Optimal versus Estimated (Other Elasticities)



Note: The line above the data points is a $45°$ line, the x-axis has been truncated.

With very high elasticities of substitution, differences in skilled-unskilled worker ratios do not matter for the skill premium. So the higher skill premium in developing countries is not due to the scarcity of skilled workers, but a result of relatively more productive skilled workers. With high elasticities and increasing returns to scale, firms would like to use only one type of labour. Therefore, to rationalize the high skill-premiums and presence of skilled workers in skill-scarce countries, it must be that skilled workers there are relatively very productive.

However, very high elasticities of substitution are not consistent with evidence on the behaviour of the skill premium in response to changes in skilled labour endowments.[24] They are inconsistent with the observation that the skill premium declines with the skilled-unskilled labour ratio.

4.4.4 Patterns of Technology Adoption and Income Differences

I interpret the patterns uncovered above as patterns of technology adoption. Skill-abundant countries adopt technologies which increase the relative productivity of abundant skilled labour, and skill-scarce countries adopt technologies which increase the relative productivity of unskilled workers. In addition, I also find that several countries are using skilled workers inefficiently. In this section, I investigate how patterns of technology adoption, that is differences between estimated and optimal relative productivities of skilled workers, are related to GDP per capita.

Figure 4.8 plots output (GDP per capita) in 1990 against the difference between optimal and estimated physical productivity of skilled workers (in logs). We see that poorer countries tend to be further away from their optimal mix of physical productivities. The correlation coefficient is high at about -.64. The inefficient use of skilled workers, but not unskilled workers, in low income countries can account for some of the variation in cross-country aggregate productivity.

Figure 4.9 shows the relationship between output, and the difference between optimal and estimated physical productivity of skilled workers under different values of the elasticity of substitution. The relationship remains strongly negative until we get to higher elasticity values. Now, we find that poorer countries use skilled labour too well and use unskilled workers too poorly. Again, even though these high values of the elasticity of substitution are inconsistent with other data, they still indicate that poorer countries systematically use inappropriate technologies. The implication is that in several countries, an increase in the physical productivity of skilled workers relative to unskilled workers, without any change in inputs, could lead to significant gains in income per capita.

Using the production function in (4.5), I compute GDP-per-capita for all countries using the estimated relative productivity of skilled workers obtained in Section 4.2, and the optimal relative productivity of skilled workers computed from (4.6). In all cases, I compute the increase in income relative to the U.S. when the country uses skilled and unskilled workers optimally. Note that in this calculation, the aggregate TFP term, A, and all inputs, are held constant. Only the value of the physical productivity of skilled relative to unskilled workers, μ_j, changes.

Figure 4.10 plots the income gain from the adoption of appropriate technologies against GDP-per-capita in 1990 relative the U.S., under different values of the elasticity of substitution. There are three striking findings: income gains from the

[24] See Blum (2010) for cross-country evidence, and Acemoglu (2002), and Ciccone and Peri (2005) for time-series evidence from the U.S.

Figure 4.8: Output and Estimated-Optimal Skilled Productivity Gap

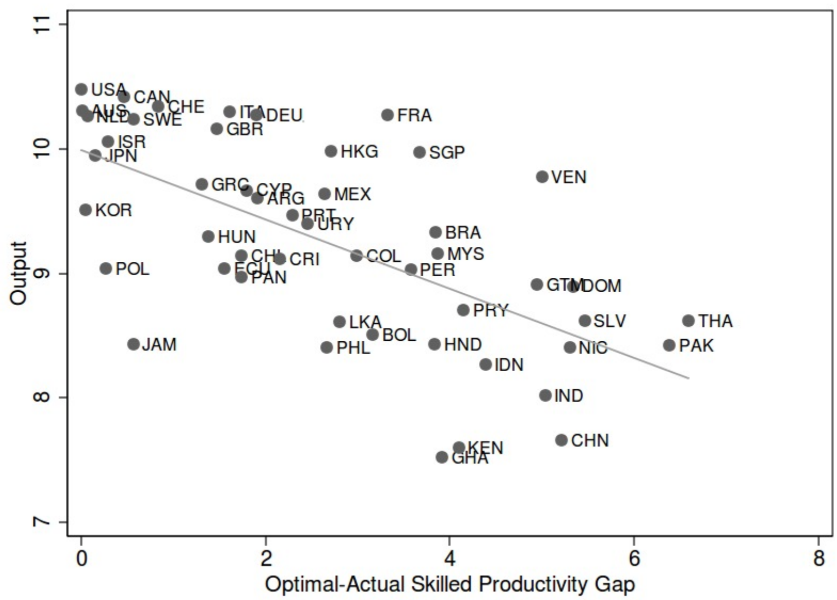
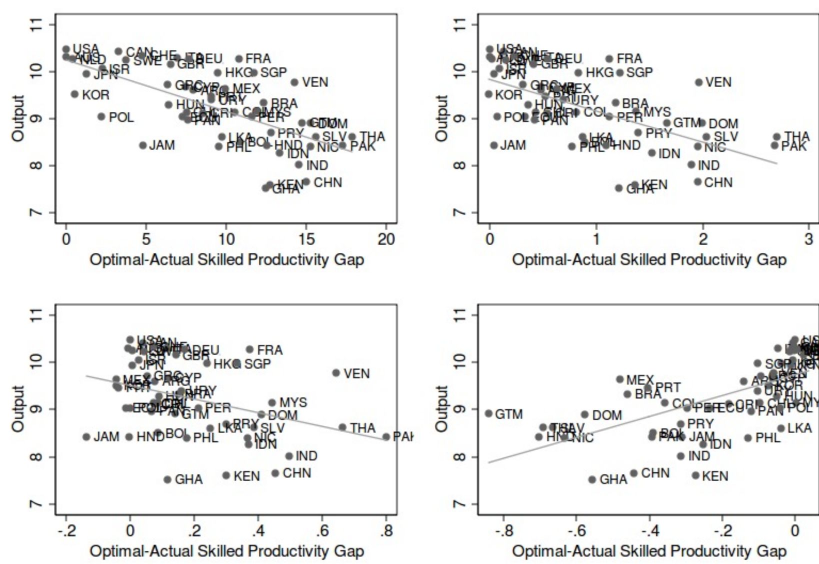
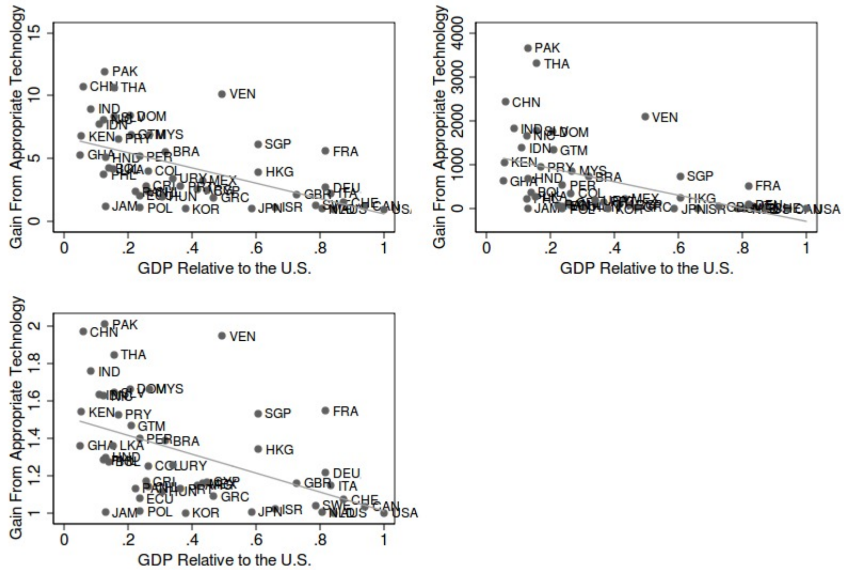


Figure 4.9: Output and Estimated-Optimal Gap (Other Elasticities)



Clockwise: Elasticity of Substitution = 1.2, 1.6, 1.8, 2 adoption of appropriate technologies are large, the gains decline with GDP relative to the U.S., and the gains decline with the elasticity of substitution.

Figure 4.10: Income Gains From Using Appropriate Technology



Clockwise: Elasticity of Substitution = 1.4, 1.2, 1.6

Under the preferred calibration, many countries can increase per capita incomes by a factor of 4, from their 1990 levels, simply by using skilled workers relatively more efficiently. These countries include Thailand, China, Kenya, Ghana, Pakistan, and Brazil, amongst several others. These are large and significant gains to income given that there are no changes to inputs and the technology frontier.

Table 4.2 breaks down the gains from appropriate technologies by income quartile. Under the primary completed definition of skilled, the average country in the dataset could increase its per capita income by a factor of 2, by increasing the efficiency of skilled labour relative to unskilled labour. More than half of all countries in the dataset could increase per-capita incomes by an average factor of 4.

There is significant variation across income groups. Countries in the lowest income quartile increase income by a factor of 7 by using appropriate technologies. Gains decline monotonically across income groups, with countries in the top income quartile, only experiencing a 23% increase in income by adopting appropriate technologies, and this mostly driven by the significant gains accruing to France.

Gains from adopting appropriate technologies decline with per-capita income because the difference between optimal and estimated physical productivity of skilled workers decreases with per-capita income, and poorer countries have a large proportion of workers who have completed primary education. High-income countries have a large proportion of skilled workers, but since they are estimated

Table 4.2: Gains to Using Appropriate Technology

Quartile/Elasticity	**1.4**	**1.2**	**1.6**
	Primary Educated		
1	7.64	89.54	1.38
2	4.81	33.74	1.24
3	2.82	5.72	1.19
4	1.23	3.18	1.12
Average Country	1.88	4.67	1.18
	Secondary Educated		
1	1.71	12.52	1.13
2	1.75	29.29	1.02
3	1.94	13.48	1.10
4	1.34	2.58	1.15
Average Country	1.53	4.28	1.11

to be relatively close to their optimal choice of technologies, the gains to improving the relative productivity of skilled workers are smaller.

Gains from using appropriate technologies decrease with the elasticity of substitution. With lower elasticities, skilled and unskilled workers are not very substitutable, so output losses are greater if skilled workers are not being used efficiently. Therefore, gains to moving to the optimal level of technology will be larger (see Table 4.2 and Figure 4.10). On the other hand, with larger elasticities, skilled and unskilled workers are more substitutable, and the fact that skilled workers are not being used as efficiently as they could be, does not translate to large losses in per-capita income. A similar picture emerges under the secondary-completed definition of skilled workers, as shown in Table 4.2. More than three-quarters of all countries can increase per-capita income by a factor of 2 by adopting appropriate technologies. However, in this case, the gains do not decline with initial per-capita income. Even though low-income countries are further behind their optimal technological choices, income gains are not larger compared to higher income countries because in 1990 they do not have a very large proportion of secondary-educated workers. High-income countries on the other hand, while being closer to their optimal choice of technologies, have a relatively larger proportion of secondary educated workers, which translates into income gains similar to lower-income countries.

To summarize, low income countries tend to be farther away from their appropriate choice of technology. Hence, there are large income gains if they use skilled workers relatively more productively; gains as large as seven-fold increases in income per capita for countries in the lowest income quartile. Next, I discuss some possible interpretations for the patterns of technology adoption uncovered here, and how they may be related to other findings in the growth and development literature.

4.5 Discussion

In this section, I briefly provide some interpretations for the above findings and related them to other evidence on the development and growth experience of low-income countries. I also discuss how the results change with estimates of the returns to education, which are used in computing the skill premium.

4.5.1 Interpretation of Findings

Barriers to Adoption

The most straightforward interpretation of the finding of "inappropriately backward" technologies, in most low-income countries, is that it is evidence of significant barriers to technology adoption in the spirit of Parente and Prescott (1994, 1999). This barrier specifically affects skilled workers. This could be the case in a world in which "traditional" technologies tend to be complementary with unskilled workers, and recent technologies that are primarily developed in richer economies are complementary with skilled workers. Then barriers to the adoption of new technologies would adversely affect the physical productivity of skilled workers relative to the unskilled.

A report on the Indian economy, by McKinsey (2001), documents the inefficient use of factors of production in several industries. The authors find that it would be profitable for most firms to adopt the latest technologies, but many firms do not do this and operate significantly below optimal scale. They conclude that most firms use inappropriate technologies, consistent with the findings in this paper. Evidence that non-adoption of the latest techniques primarily affects skilled workers lies in their finding that in the apparel industry (one of many such industries), most of the non-adopting firms are unskilled "mom-and-pop" shops.

How are these barriers sustained? Evidence points to a combination of government protection and regulation in an environment where groups of unskilled workers are better able to organize themselves, and block the adoption of superior technologies which would make them relatively more unproductive (Bridgman et al., 2007; Bellettini and Ottaviano, 2005). In the context of India, small-scale tailor shops could organize and block the establishment of large-scale garment shops, which are noted as adopters of best technological practices in the McKinsey study. Recent protests, backed by small-scale firms, against Walmart's entry into the Indian retail market provides more evidence of a group of workers blocking the adoption of more efficient technologies (Pradhan and MacAskill, 2011).

The lack of supporting infrastructure could also pose a barrier to the adoption of the latest production techniques. The energy intensity of the several production techniques may prevent low-income countries, who do not produce enough energy, from adopting these technologies. For example, in 1990, energy consumption per person was just about 250 kWh in Ghana and 125 kWh in Kenya. These numbers are very small compared to per-capita energy consumption of 12,000 kWh in the U.S, and 9,000 kWh in Australia (The World Bank, 2012). The United States produces over 40 times as much energy per person compared to Ghana, a number which is strikingly similar to the physical productivity of skilled workers in the United States relative to Ghana (see Table 4.4). The cost of adopting more skilled worker complementary, but energy intensive, production techniques in Ghana could pose a significant barrier to adoption. Other barriers include the presence of financial frictions that prevent firms from achieving optimal scale (Banerjee and Duflo, 2004; Buera and Shin, 2010).

Misallocation

An interrelated interpretation of the finding is that it reflects the misallocation of resources in developing countries. Evidence of severe misallocation of resources are documented in Banerjee and Duflo (2005). For example, it is well known that productivity in agriculture, which employs a significant portion of the labour force in many countries, is significantly lower than productivity in non-agriculture (Gollin et al., 2011; Restuccia et al., 2008). A variety of government land policies, documented in Adamopoulos and Restuccia (2013), could also keep some skilled workers in agriculture where they are relatively unproductive. Vollrath (2009) finds that a reallocation of workers from agriculture to non-agriculture could lead to significant gains in income.

Misallocation of skilled workers could also arise from government policies targeting skilled workers. Assaad (1997) documents the effects of a government policy in Egypt guaranteeing employment to every college-educated worker. Due to the relatively large size of the public sector, this leads to a long queue for skilled workers waiting for their chance at a government job. This could mean the employment of a large number of skilled workers in a sector in which they are not as productive as they could otherwise be.

Education Externality

The result that rich countries have a higher proportion of skilled workers, higher labour quality and use skilled workers more productively, could be taken as evidence of externalities to education as in the endogenous growth models of Lucas (1988) and Romer (1986). Thus, a skilled worker would be more productive in the presence of other skilled workers. While there are likely externalities to education, the available evidence does not point to them being very large.

For example, to explain the 10-fold difference between the physical productivity of a skilled worker in the U.S. compared to one in Thailand, externalities would have to be more than 10 times the private return to education. The evidence on externalities to education show that externalities are not that large. Rauch (1993) finds externalities of about 3% to 5% for skilled workers, which is inferred from differences in the proportion of skilled across U.S. cities. Acemoglu and Angrist (1999) study the cross-state variation in U.S. compulsory schooling laws, and find externalities to education of less than 1%.

Over-investment in Education

A related concern is that governments in developing countries have over-invested in education, relative to available technology. Thus, it is not that there are barriers to education, but that the growth in the proportion of skilled workers has outpaced the capacity of firms to adopt appropriate technologies. In the exercise of Section 4.3, there would also be an increase in income for many countries from an increase in the supply of unskilled workers, relative to the skilled. The decline in schooling quality associated with the rapid schooling expansion in several developing countries is often cited as evidence of over-expansion in schooling (Glewwe and Kremer, 2006).

However, there are no large high-income economies with low proportions of skilled workers. This points to schooling and the adoption of appropriate technologies as being prerequisites to achieving higher incomes. Hence, the relevant question should be why the increase in the quantity of skilled workers in several low-income countries has not translated into higher incomes? The results in this paper point to the relatively unproductive use of skilled workers as an answer.

4.5.2 Relative wages and Relative Productivities

Differences in cross-country labour market institutions may sever the relationship between relative wages and relative productivities. For example, the skill premium may be smaller in countries with more egalitarian labour markets even when relative productivities are not. Strictly speaking, nothing can be said about relative physical productivities across countries if wages do not reflect productivity. In this section, I discuss what deviations from competitive labour markets, if any, imply for my estimates of cross-country skilled-worker physical productivities. I find that while there are significant differences in labour market institutions across countries, they do not necessarily imply a break in the link between productivity and wages. Further, the key patterns in the estimates of physical productivities between low and high income countries cannot be explained by differences in labour market institutions.

I begin with a discussion of how differences in labour market institutions between low and high-income countries may affect the patterns of relative physical productivities estimated from information on relative wages. Keep in mind that the focus of the study is on differences between low and high-income countries.

Low-Income and High-Income Country Labour Markets Recall that the estimates imply that relative to unskilled workers, skilled workers are less physically productive in low-income countries. This is because in low-income countries, the skill premium is too small compared to what it should be from (4.3), given the proportion of skilled workers and the human capital embodied in those workers. The validity of this result would be suspect if observed skill premiums are too small in low-income countries, because relative to high-income countries, wages are more compressed due to unionization or government policies.

As Caselli and Coleman (2006) point out, it is well known that forces to reduce income inequality are greater in high-income countries. To verify this claim, I present data on wage compression ratios taken from The World Bank (2011) in Table 4.3. The wage compression ratio is defined as the ratio of public sector wages in the 90th percentile of the pay scale to those in the 10th percentile. The data reveal that if there is wage compression in skill premiums, it is probably in high-income (OECD) countries. The United States, as might be expected given its more competitive labour market, has the highest compression ratio of any OECD country at 3.3. This ratio is small compared to the average compression ratio of 10 for all the other low-income country groups. Given the cross-country pattern in wage compression and the estimated higher returns to schooling in low-income countries in Psacharopoulos and Patrinos (2004), I conclude that wage compression in low income countries cannot explain the low estimated physical productivity of skilled workers for these countries.[25]

High-Income Country Labour Markets I briefly examine OECD labour markets to investigate whether differences in labour market institutions systematically affect relative wages, and estimates of physical productivities. First, Lazear and Shaw (2009) compare wage structures across OECD countries using matched employer-employee datasets and conclude that even with different labour market institutions, "countries are remarkably similar in their structures of wage levels."

Secondly, I classify countries into different labour market institutions based on trade union densities (TUD) and collective bargaining coverage (CBC) rates, with more egalitarian labour markets having higher TUD and CBC measures. I summarize the results here, while the details are contained in appendix B.

The first finding is that in line with Lazear and Shaw (2009), the returns to schooling, from which skill premiums are computed, are similar across labour market types and OECD countries. Thus estimates of the returns to schooling do not vary systematically by labour market institutions. Secondly, assuming that the return to schooling is the same (at 10%) across every OECD country does not alter the results in the paper.[26] Lastly, if we assume that all countries use the same technologies, this would imply very high returns to schooling in OECD countries, in comparison to estimates from the U.S. and even low-income countries.

Having a more egalitarian pay policy in any given country does not necessarily break the link between marginal productivities and relative wages for a number of reasons. First, a key response of of firms to inflexible labour markets is to outsource low-skilled jobs which, combined with generous unemployment benefits, is a leading cause of the high unemployment rate in many Southern European countries (OECD, 2004). Furthermore, as Acemoglu (2003) points out, if the skill

[25]The wage compression ratios come from wages in the public service. But if the government has no strong incentives to compress wages as a result of inequality concerns, it is unlikely that firms in the private sector will have more compressed wages.

[26]Assuming that the return to schooling is the same in OECD and low-income countries would imply even lower physical productivity of skilled workers in low-income countries, because low-income countries generally have larger estimated returns to schooling.

Table 4.3: Wage Compression Ratios

Region	**Country**	**Ratio**
Africa	Togo	13
	Nigeria	7
	Niger	10
	Mozambique	9
	Malawi	32
	Ghana	13
	Cote D'Ivoire	9
	Burkina Faso	8
	Benin	13
East Asia and Pacific	Thailand	14.4
	Philippines	9.5
	Mongolia	3.4
	Indonesia	2
	Cambodia	5.5
Europe and Central Asia	Serbia	9
	Montenegro	4.95
	Moldova	2.5
	Kosovo	2.5
	Albania	3
Latin America and Caribbean	Uruguay	3.4
	Suriname	2.6
	Jamaica	15
	Dominican Republic	33
	Colombia	4
	Brazil	22
	Belize	9.8
	Barbados	5.5
OECD	United States	3.3
	United Kingdom	1.5
	New Zealand	2.4
	Netherlands	2.3
	Luxembourg	3.1
	Finland	2.3
	Australia	2.8

Note: Estimates of wage compression ratios are taken from The World Bank (2011). The wage compression ratio is defined as the ratio of average wages for public servants in the 90th percentile to those in the bottom 10th.

premium is artificially low in jobs that cannot be outsourced, it encourages firms to adopt technologies complementary with low-skilled workers. Thus if the skill premium is initially too low as a result of policies external to firms, firms maintain the link between productivity and pay by increasing the relative productivity of unskilled workers. These endogenous responses to different labour market institutions could explain the low estimated physical productivity of skilled workers in France, Greece, and Italy, without recourse to a break in the link between relative pay and relative productivities.

4.5.3 Selective Migration and Estimated Physical Productivities

The returns to schooling for Italian emigrants living in the U.S. may overestimate the human capital embodied in Italian skilled workers, and underestimate the physical productivity of skilled workers in Italy. This would be the case if only the best skilled Italians leave Italy, for example.

To assess the potential role of selective migration on these estimates, I give all OECD countries in Table B.1 the lowest estimated embodied human capital for the countries in the full dataset. This places an upper-bound on the ability of selective migration to explain differences in the estimated relative physical productivity of skilled workers. To get an idea of the magnitude of this reduction in embodied human capital, the lowest estimated embodied human capital is about a quarter of the human capital embodied in American skilled workers. In France for example, we are assuming that emigrants embody four times as much human capital as non-migrants.

The final column of Table B.1 gives the results from assuming that embodied human capital is as low as it could plausibly be. Compared to column 4 of the same table, selective migration could account for a lot of the differences in estimated physical productivities for OECD countries. The estimated physical productivity of skilled labour jumps from .14 to .36 in Germany, .22 to .5 in the U.K, .03 to .13 in France, and .42 to .7 in Switzerland. Nevertheless, large differences still remain across this group of countries even with drastic reductions in estimated embodied human capital. Skilled workers in OECD countries are estimated to have the largest embodied human capital, which implies estimated relative physical productivities would rise the most. For low-income countries, the increase in estimated physical productivities of skilled workers would be smaller because estimates of embodied human capital are already small, and further reductions would not increase estimated physical productivities significantly.

4.5.4 Estimates of Returns to Schooling

While the estimates of returns used here to compute skill premiums across countries are standard in the literature, there is some concern regarding the reliability of some of the estimates, especially for a group of African countries. A major concern is that these estimates overstate the returns to schooling in many countries, and that returns are the same, at about 10% in most countries (see Banerjee and Duflo (2005)).

First, most of the troublesome estimates from African countries are excluded from the dataset. The only African countries included in the analysis are Kenya and Ghana, for which there are recent and reliable estimates of the returns to schooling. Secondly, if the returns to schooling are actually lower than the standard estimates reported by Psacharopoulos and Patrinos (2004), it would only strengthen the result that many countries use skilled workers relatively unproductively. Recall that the returns to schooling shows up in two places: in computing the skill premium in a particular country, and the proportion of skilled workers. With lower estimates of the returns to schooling, the skill premium is lower, and the proportion of skilled workers is also lower (lower efficiency units for every year of schooling). Estimates of the human capital embodied in skilled workers do not change, because it is computed from estimates of the returns to schooling for immigrants in the U.S. A lower proportion of skilled workers in (4.3), would imply an even higher skill premium in low-skilled countries. To match the now even lower observed skill premium, it must be that skilled workers are used even more unproductively relative to the unskilled.

4.6 Conclusion

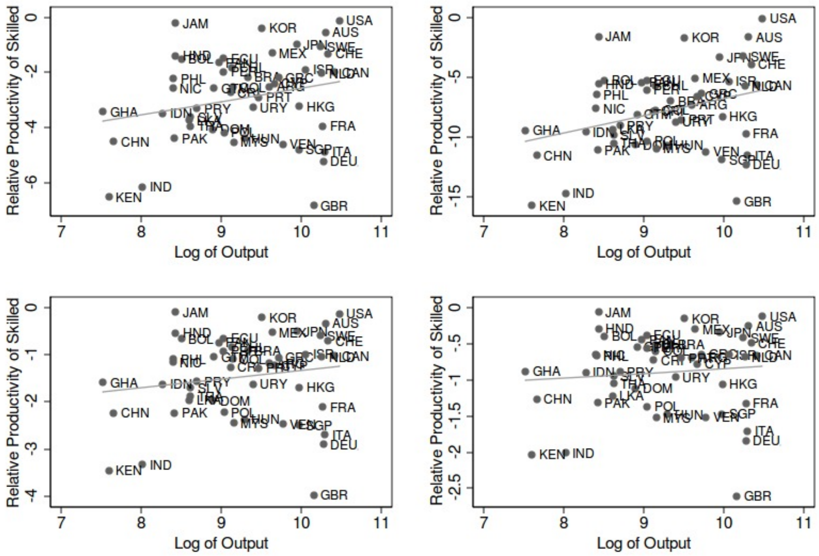
I have broken down the cross-country productivity of skilled workers relative to unskilled workers into components due to embodied human capital, and physical productivities that reflect differences in choice of production techniques. My estimates show that skilled workers form high-income countries tend to have more embodied human capital, and are also more physically productive relative to the unskilled. I interpret these findings as indicating that skilled workers from high-income countries are of better quality, and firms in high-income countries adopt more technologies that are skilled-complementary. Compared to Caselli and Coleman (2006), cross-country differences in relative productivities are smaller, but they remain large because differences in embodied human capital cannot account for all of the differences in skilled-unskilled worker productivity.

I also find that estimated physical productivities are inappropriate in most low-income countries. Several countries could increase output by increasing the physical productivity of skilled workers relative to the unskilled, and adopting more skilled worker complementary technologies. The finding that very low physical productivities of skilled workers, relative to the unskilled, are inappropriate is driven by three factors: skilled and unskilled workers are substitutes, skilled workers embody significantly more human capital, and under the primary definition of skilled, skilled workers are just as abundant as the unskilled in most countries. This result is in contrast to regular notions of appropriate technology, arguing that low-income countries adopt too many skilled-complementary technologies relative to the skilled composition of their workforce. For countries in the bottom half of the income distribution, output could increase by an average factor of 4 from using appropriate technologies; increasing the physical productivity of skilled workers relative to the unskilled.

There is abundant evidence of cross-country differences in the human capital embodied in workers (see Schoellman (2012); Erosa et al. (2010); Hanushek and Kimko (2000)), and some more on the skill-complementarity of technologies across countries. To name a few, Caselli and Wilson (2004) document a positive relationship between the R&D content of imported machines by country skill composition. Berman et al. (1998) provide evidence of increasingly skilled complementary technologies in developed countries, and Berman and Machin (2000) find that the rise in skilled complementary technologies is not prominent in low-income countries. While these are all consistent with my findings, more firm-level evidence is needed on whether the different production techniques used in different countries are indeed appropriate to the workforce. Income differences across countries does suggest production techniques must be inappropriate in low-income countries, but more evidence is needed on whether this is indeed related to the low productivity of skilled relative to unskilled workers.

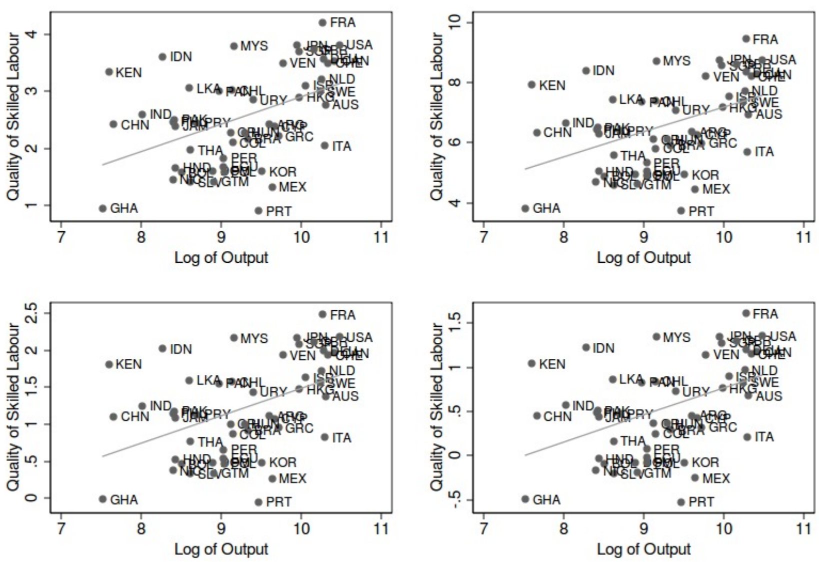
4.7 Other Tables and Figures

Figure 4.11: Physical Productivity of Skilled and Output (Secondary)



Clockwise: Elasticity of Substitution: 1.4, 1.2, 1.6, 1.8

Figure 4.12: Embodied Human Capital and Output (Secondary)



Clockwise: Elasticity of Substitution = 1.4, 1.2, 1.6, 1.8

Table 4.4: Data and Baseline Estimates

Country	**WBcode**	**y**	**k**	$\frac{w^s}{w^u}_j$	$\frac{w^s}{w^u}_j^{U.S.}$	L^u	L^s	μ_{base}	μ_{opti}	y_{gain}
Argentina	ARG	14805.00	33151.00	1.51	1.24	43.03	129.21	0.14	0.95	2.57
Australia	AUS	29858.00	88076.00	1.38	1.29	6.16	188.11	0.97	0.98	1.00
Bolivia	BOL	4953.00	9076.00	1.53	1.11	64.54	93.34	0.04	0.92	4.24
Brazil	BRA	11297.00	21227.00	1.80	1.20	80.70	78.34	0.02	0.91	5.58
Canada	CAN	33337.00	82443.00	1.43	1.43	17.00	166.78	0.61	0.97	1.24
Chile	CHL	9323.00	22452.00	1.62	1.34	43.43	143.21	0.17	0.95	2.39
China	CHN	2124.00	4156.00	1.63	1.24	60.17	86.27	0.00	0.90	10.75
Colombia	COL	9360.00	15434.00	1.75	1.19	66.58	94.86	0.05	0.92	4.03
Costa	CRI	9118.00	16695.00	1.55	1.22	45.14	114.34	0.11	0.94	2.85
Cyprus	CYP	15805.00	37046.00	1.23	1.23	25.30	106.19	0.16	0.95	2.47
Dom. Rep.	DOM	7314.00	12232.00	1.46	1.12	83.91	53.63	0.00	0.89	8.40
Ecuador	ECU	8388.00	21190.00	1.60	1.13	43.22	123.59	0.20	0.94	2.07
El Salvador	SLV	5548.00	5617.00	1.47	1.09	83.55	48.28	0.00	0.88	8.32
France	FRA	28972.00	84929.00	1.49	1.56	46.62	106.75	0.03	0.96	5.62
Ghana	GHA	1854.00	1218.00	1.40	1.03	62.65	66.73	0.02	0.90	5.31
Greece	GRC	16607.00	42802.00	1.36	1.21	25.45	115.96	0.26	0.95	1.89
Guatemala	GTM	7431.00	7773.00	1.81	1.09	93.44	49.39	0.01	0.88	6.92
Honduras	HND	4597.00	6175.00	2.02	1.12	100.98	75.64	0.02	0.90	5.11
Hong Kong	HKG	21532.00	29128.00	1.28	1.32	34.01	98.97	0.06	0.95	3.95
Hungary	HUN	10869.00	33857.00	1.19	1.22	20.30	108.44	0.24	0.95	1.99
India	IND	3046.00	3775.00	1.53	1.27	75.90	61.89	0.01	0.91	8.94
Indonesia	IDN	3914.00	8084.00	1.97	1.44	85.20	76.06	0.01	0.93	7.73
Israel	ISR	23362.00	51768.00	1.29	1.35	11.75	151.68	0.73	0.97	1.13
Italy	ITA	29552.00	82318.00	1.10	1.18	17.72	90.23	0.19	0.95	2.24
Jamaica	JAM	4596.00	12831.00	3.16	1.23	74.02	171.67	0.53	0.94	1.25
Japan	JPN	20807.00	64181.00	1.70	1.48	17.24	225.28	0.84	0.98	1.06
Kenya	KEN	1998.00	2748.00	1.93	1.39	77.59	76.59	0.02	0.93	6.81
Malaysia	MYS	9472.00	23543.00	1.46	1.48	51.70	90.62	0.02	0.95	6.93
Mexico	MEX	15330.00	28449.00	1.76	1.08	72.94	103.61	0.06	0.91	3.29
Netherlands	NLD	28550.00	79069.00	1.34	1.37	6.97	151.13	0.91	0.98	1.02
Nicaragua	NIC	4453.00	8762.00	1.47	1.10	83.49	51.82	0.00	0.89	8.11
Pakistan	PAK	4552.00	3793.00	1.47	1.25	77.54	37.75	0.00	0.89	11.91
Panama	PAN	7898.00	19794.00	1.73	1.33	50.14	150.37	0.17	0.95	2.38
Paraguay	PRY	6015.00	9689.00	1.58	1.24	76.18	82.53	0.01	0.92	6.59
Peru	PER	8387.00	18075.00	1.38	1.15	58.04	85.89	0.03	0.92	5.19
Philippines	PHL	4473.00	8042.00	1.38	1.25	42.72	105.17	0.07	0.94	3.72
Poland	POL	8439.00	33949.00	1.12	1.11	8.97	109.38	0.74	0.96	1.11
Portugal	PRT	12960.00	29437.00	1.49	1.02	41.15	79.67	0.09	0.92	2.82
S. Korea	KOR	13483.00	24651.00	1.72	1.12	17.05	200.41	0.92	0.96	1.01
Singapore	SGP	21470.00	56218.00	1.71	1.46	64.22	95.59	0.02	0.94	6.14
Sri Lanka	LKA	5476.00	5919.00	1.32	1.34	33.94	92.83	0.06	0.95	4.15
Sweden	SWE	27886.00	72777.00	1.31	1.33	15.36	139.41	0.55	0.97	1.31
Switzerland	CHE	30965.00	107870.00	1.37	1.42	18.82	142.07	0.42	0.97	1.52
Thailand	THA	5558.00	7477.00	1.58	1.17	116.90	42.62	0.00	0.87	10.64
UK	GBR	25775.00	50409.00	1.31	1.46	21.36	123.97	0.22	0.97	2.17
Uruguay	URY	12036.00	23398.00	1.47	1.31	43.23	113.70	0.08	0.95	3.42
USA	USA	35439.00	87330.00	1.49	1.48	5.42	236.04	0.99	0.98	1.00
Venezuela	VEN	17529.00	42713.00	1.46	1.42	70.22	73.40	0.01	0.93	10.16
W. Germany	DEU	28992.00	89368.00	1.36	1.43	31.00	133.97	0.14	0.96	2.70

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Chapter 5

Conclusion

So why is GDP per person in the U.S. 20 times as large as it is in Ghana? This thesis has made several key contributions to answering this question. Chapter 4 shows that while the difference in the proportion of skilled workers between the U.S. and Ghana is large, the inappropriate use of skilled workers (relative to the unskilled) in Ghana is of primary importance. From Table 4.4, we know that Ghana could increase GDP per person by a factor of 5 if firms use the relatively few available skilled workers appropriately. This points to significant barriers to the adoption of production techniques which would increase the productivity of skilled workers.

These barriers include political and economic factors that deter appropriate investments. For example, energy production in Ghana is only 300 kWh per person compared to over 13,000 kWh person in the U.S. As various skill-complementary technologies (used in developed countries) are energy intensive, the lack of adequate energy infrastructure in Ghana lead firms to adopt less energy intensive production techniques which are more complementary with unskilled workers. Other economic factors include the lack of well developed credit markets that constrain the ability of firms to invest in appropriate technologies. Political factors may also play a role in realigning investment incentives. Government job guarantees in many countries may lead to skilled workers working for the government in sectors where they are not very productive. Political instability which translates to economic policy uncertainty possibly leads firms to stick with traditional technologies.

Chapter 3 also shows how bad government policy in the education sector influences productivity. There, I find that the focus on basic education at the expense of education at higher levels has led to declines in basic education quality, and has also constrained increases in productivity. The chapter also shows that the social returns to higher levels of education could be just as large as the social returns to basic education if account for externalities to higher levels of education. The results suggest that good education policy would balance investments in basic and higher levels of education. While basic education is undoubtedly important, higher educated workers are also needed to enhance the value of a basic education.

The primacy of increases in productivity is also evident from Chapter 2, which assesses the effects of the high emigration of skilled workers (brain drain) in developing countries. Table 2.10 shows that the brain drain is of secondary concern. Shutting down skilled emigration in Ghana, which has the highest rate of skilled emigration at 33%, only increases the proportion of skilled workers from .009 to .011. This increase is not enough to make a significant difference to GDP per person in Ghana, and certainly does not increase GDP per person by a factor of 5 (as using skilled workers appropriately would). In the chapter, I also find that increasing brain drain does not encourage further investments in schooling, because brain drain does not help to lower the high cost of schooling (relative to GDP) in developing countries. Increasing skilled worker productivity would encourage more skilled workers to stay in their home countries, and would also relax the borrowing constraints faced by many households which could increase schooling investments.

In summary, increasing the productivity of workers, especially that of skilled workers, is the primary key to increasing incomes in Ghana and many other developing countries. As has been widely addressed in the economic development literature, productivity could be increased through improvements in schooling years and quality. This thesis points to significant gains in productivity by having firms use production techniques which are complementary with skilled workers, a topic that has not been widely addressed. It leads me into a broader research agenda that studies the reasons why firms in developing countries use skilled workers inappropriately even when more appropriate technologies exist, and the relationship between the appropriate use of skilled workers and household schooling investments. This would improve our understanding of how firms work in these countries, and hopefully help in developing a framework for improving firm productivity. While there is no single panacea to economic underdevelopment, I believe a study of the production techniques used by firms would further our understanding of economic development.

Appendix A

Appendix to Chapter 3

Description of Data and Sources:

- Data on proportion of educated for individuals aged 25+ is taken from Barro and Lee (2010).
- Data on education systems; parent-teacher ratios and expenditure per pupil at the primary and secondary levels of education are taken from Barro and Lee (1996), and supplemented with data from UNESCO (2012).
- Data on returns to education for immigrants from different countries in the U.S. is taken from Schoellman (2012).
- Data on human capital quality adjusted agricultural productiviy gap is taken from Gollin et al. (2011).
- Controls for agricultural physical capital, arable land per agricultural worker, and population growth are taken from FAOSTAT (2012).

Proof of Results in Chapter 3:

Result 3: Result 3 states that at the optimal proportion of higher educated(σ_2^*), Γ^* which is positive(see text) is an upper bound on the gap between standard estimates of the social ROR to basic and higher education.

From (3.8), the difference between standard estimates of the social ROR to basic and higher education is given by:

$$\frac{Af^*(h_1^*-1)}{Af^*+g_1} - \frac{A(h_2-f^*h_1^*)}{Af^*h_1^*+g_2} \qquad (1).$$

From (3.9), we also know that at σ_2^*, Γ^* is given by:

$$\frac{Af^*(h_1^*-1)}{g_1} - \frac{A(h_2-f^*h_1^*)}{g_2} \qquad (2).$$

Subtracting (1) from (2), we find that result 1 will be true if and only if:

$$\frac{f^*(h_1^* - 1)}{g_1}\left[\frac{Af^*}{Af^* + g_1}\right] > \frac{(h_2 - f^* h_1^*)}{g_2}\left[\frac{Af^* h_1^*}{(Af^* h_1^* + g_2)}\right] \quad (3)$$

From Assumptions 1 through 3, we know that all terms in the expression above are positive. Since $(f^*(h_1^* - 1))/(g_1) > (h_2 - f^* h_1^*)/(g_2)$ (because $\Gamma^* > 0$). Result 1 holds if $(Af^*)/(Af^* + g_1) > (Af^* h_1^*)/(Af^* h_1^* + g_2)$, or restated a different way:

$$Af^* h_1^* + g_2 > Af^* h_1^* + g_1 h_1^*.$$

The expression above is true by the second part of Assumption 3, which requires that $(g_2/g_1) > h_1$, if the cost of higher education relative to basic education is sufficiently large.

The second part of the result says that because (2) is positive, (1) cannot be expected to be equal to zero, since $Af^* h_1^* > Af^*$. However, if (2) is approximately zero and we know that $(g_2/g_1) > h_1$, then (1) should also be close to zero. ∎

Result 4: Plugging in the expression for σ_1 in (3.6), the first derivative of Γ as described in (3.9) with respect to σ_2 is given by:

$$\frac{h_1'' f}{f'}[\bar{\sigma_1} - (1 + g_2/g_1)\sigma_2] + \frac{f''}{f'}[1 + [\bar{\sigma_1} - (1 + g_2/g_1)\sigma_2](h_1 - 1) - \sigma_2] - [(1 + g_2/g_1)(h_1 - 1) + 1]$$
$$- \frac{h_1' f}{f'}(1 + g_2/g_1) + 2h_1'(\bar{\sigma_1} - (1 + g_2/g_1)\sigma_2)$$

Where $''$ denotes second derivatives, and $\bar{\sigma_1} = G/Ng_1$. From assumptions 1 and 2, we know that the first 2 parts of the first derivative are negative (h_1 and f are increasing, and concave), and the fact that $\bar{\sigma_1} - (1 + g_2/g_1)\sigma_2$ is positive, since σ_1 cannot be negative. The fact that $h_1 > 1$ from Assumption 3 guarantees that the third part is also negative.

Examining the last two terms, we find that because $\bar{\sigma_1} = \sigma_1 + (1 + g_2/g_1)\sigma_2 < 1 + (1 + g_2/g_1)$, since σ_2 and σ_1 cannot be greater than one. Simply put, 1 is an upper bound for $\bar{\sigma_1} - (1 + g_2/g_1)\sigma_2$. The sum of the two expressions will be negative if:

$$f'/f < (1 + g_2/g_1)/2.$$

Given that the condition above holds, the derivative of Γ with respect to σ_2 is negative which concludes the proof. ∎

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Appendix B

Appendix to Chapter 4

Labour Market Institutions and Relative Wages: I examine the link between country-specific labour market institutions, the skill premium, and estimates of the relative physical productivity of skilled workers by looking at differences within high-income countries. Examining the estimates for France, Greece, and Italy for example, it may appear that the estimated relative physical productivity of skilled workers is low because of inflexible labour markets that imply skill premiums may not reflect actual productivity.[1]

Lazear and Shaw (2009) compare wage structures across countries from matched employer-employee datasets and conclude that even with different labour market institutions, "countries are remarkably similar in their structures of wage levels." The average coefficient of variation in wages is about .25 (the standard deviation of wages is about 25% of the mean wage), which is similar across the countries they study. Nevertheless, there is some variation across countries; from their estimates, the coefficient of variation in Sweden and France is .3, which is lower than the coefficient of variation of about .7 in the U.S.[2] However, even with similarly egalitarian labour markets in France and Sweden, their estimated physical productivities of skilled workers are very different (.03 versus .55 in the third column of Table B.1), with Sweden looking more like the U.S in this regard even though it has a labour force that looks like that of France.

I further place countries into "labour market groups," based on trade union density (TUD) and collective bargaining coverage (CBC), as defined by the OECD in 1990.[3] I then ask what the skill premium (returns to education) in the more egalitarian labour markets would have to be in order to explain the estimated differences in relative physical productivities. A country is defined as being egalitarian if its TUD or CBC is higher than or equal to the OECD average.

[1]Note that if inflexible labour markets lower the productivity of skilled workers because they are less motivated, then the results still hold. Inflexible labour markets become a problem if high-ability individuals receive less than their marginal products in wages in order to have a more egalitarian society, for example.

[2]See Figure 1.7 in Lazear and Shaw (2009).

[3]Trade union density is the percentage of workers who belong to a trade union, and collective bargaining coverage is defined as the percentage of workers covered by a collective bargaining agreement.

Table B.1 classifies the labour market in different countries as egalitarian or non-egalitarian depending on TUD or CBC. The table reflects the well known fact that the Anglo-countries (Canada, US, UK) have less egalitarian labour market institutions compared to the Southern European (Italy, France, Greece, Portugal) and Scandinavian (Sweden) countries. The first two columns of the table, after the country names, give the CBC and TUD measures for each country. There is a lot of variation in CBC ratios, from a high of 92% in France, to a low of 18.3% in the U.S. Collective bargaining coverage rates are well above 70% for the countries with egalitarian labour markets, and less than 50% for those with non-egalitarian labour markets.

Table B.1: Estimates and Labour Market Institutions

	CBC	TUD	Skilled Prod	Returns to Schooling		Skilled Productivity	
				Data	If same Tech	If same Returns	If Low h
Egalitarian							
Australia	80.0	39.6	0.97	0.08	0.13	0.98	0.99
France	92.0	9.9	0.03	0.10	0.64	0.03	0.13
Germany	72.0	31.2	0.14	0.08	0.50	0.19	0.36
Greece	70.0	34.1	0.26	0.08	0.45	0.33	0.38
Hungary		49.1	0.24	0.04	0.43	0.41	0.37
Italy	83.0	38.8	0.19	0.02	0.43	0.41	0.28
Netherlands	82.0	24.3	0.91	0.07	0.21	0.94	0.97
Portugal	79.0	28	0.09	0.10	0.56	0.09	0.09
Sweden	89.0	80	0.55	0.07	0.35	0.66	0.75
Non-Egalitarian							
Canada	38	34	0.61	0.09	0.36	0.65	0.84
Chile		18.2	0.17	0.12	0.54	0.13	0.34
Japan	23.0	25.4	0.84	0.13	0.31	0.77	0.95
Poland		30.4	0.74	0.03	0.26	0.88	0.79
S. Korea		17.2	0.92	0.14	0.26	0.87	0.94
Switzerland	48.0	22.7	0.42	0.08	0.40	0.49	0.70
UK	54	38.2	0.22	0.07	0.46	0.31	0.50
USA	18.3	15.5	0.99	0.10	0.10	0.99	1.00
OECD	**70.3**	**40.1**					

Note: Data for collective bargaining coverage rates (CBC) and trade union densities (TUD) are taken from OECD (2004). Data on regular returns to schooling are taken from Psacharopoulos and Patrinos (2004). Refer to the text for the calculation of all other variables.

The third column reproduces the physical productivity of skilled workers estimated in section 4.1. The estimated physical productivity of skilled workers (μ) tends to be higher in the non-egalitarian countries compared to the egalitarian markets, .39 versus .57 respectively. However, it is worth pointing out that this difference is small compared to the difference between low and high income countries as a group, a difference greater than .4 on average. There is also significant variation within country-groups, Australia is an egalitarian labour market with physical productivity of skilled workers equal to .97, compared to France at .03, or Italy at .19. Sweden with its highly egalitarian labour market has an estimated physical productivity of skilled workers equal to .55, which is greater than that of the non-egalitarian UK and Switzerland at .22 and .42 respectively. From this simple classification, it is clear that link between labour market institutions and the estimated physical productivity of skilled labour is not straightforward.

One might wonder if all OECD countries use the same technologies, but the variation in estimated physical productivities arise from skilled workers in some countries being paid well below their marginal products? To assess the plausibility of this claim, the fourth and fifth columns of Table B.1 contain the returns to schooling for each country, and what the returns would be if all countries use the U.S. technology respectively. If we believed all OECD countries use the U.S. technology, the returns in the column 5of Table B.1 tell us what the returns to education must be if not for differences in labour market institutions.

The results show it is unlikely that all of these countries have the same physical productivity of skilled workers, because the implied returns to schooling would be too high.[4] For example, if we believed that France has the same skilled worker physical productivity as the U.S., but this is not reflected in wages due to an egalitarian labour market, then the true return to schooling in France is .64, which is more than 6 times as large as the estimate of .10 (which is also the estimated returns to schooling in the US). Also, in countries such as Italy and Hungary, the estimatd returns to schooling would have to be compressed by factors of 20 and 10 respectively if they use th same technologies as the U.S. Ultimately, the similarity of returns to schooling across the different country groups is evidence skill premiums reflect relative productivities.[5] With the exception of Poland, Italy, and Hungary, most of the estimates lie between .07 and .1.

The sixth column of Table B.1 computes the physical productivity of skilled labour (μ) if all OECD countries had the same returns to education, equal to that of the U.S.. Assuming that differences in returns to education are due to differences in labour market institutions, it gives us what the physical productivity of the skilled would be if all countries had the U.S. return. The big changes here (compared to the estimates in Table 4) are in the estimated physical productivities of skilled workers in Hungary, Italy, the UK, and Greece as a result of their relatively lower estimated returns to schooling. In general, significant differences in the physical productivity of skilled workers remain between OECD countries even when returns to schooling are forced to be equal. As already pointed out in the previous paragraph, one has to assume very high and unrealistic returns to schooling if physical productivities are equal across these countries.

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[4] The highest returns to schooling estimated by Psacharopoulos and Patrinos (2004) is .29 for Jamaica. Any returns to schooling larger than this for a high-income country is implausible, because returns to schooling generally declines with aggregate income.

[5] This is in addition to the finding by Lazear and Shaw (2009) that even with different labour market institutions, pay structures are remarkably similar across countries.

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