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The elasticity of substitution between skilled and unskilled labour in developing countries is about 2

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Abstract

We develop a model of endogenous skill-biased technical change in developing countries. The model reconciles wildly dispersed existing estimates of the elasticity of substitution between more and less educated workers. It also produces an estimating equation for the elasticity, which allow us to produce overdue estimates for developing countries. With four types of data, we find an elasticity of about 2. In a skill-biased technical change framework, this estimate makes sense of what appears to be little or no correlation between relative skill supply and wage inequality.

1 Introduction

By making skilled workers less scarce relative to unskilled workers, education can reduce wage differentials within a country. The size of the impact depends on the degree of substitutability between skilled and unskilled labour, σ . As a result, economists interested in education and wage inequality have sought to estimate σ since around 1970.¹ More generally, σ informs the debate on the relative contributions of endowments and productivity to variations in income across countries;² can be used to reconcile difference between macro and micro returns to education³ and informs the potential for skill-biasing effects of trade.⁴ From a microeconomic perspective, σ is used to calculate the effect of a change in relative factor prices on relative factor demand.⁵

Initial cross-country studies produced widely ranging results, including parameter values which implied inputs are perfect substitutes so that education would not reduce the skill premium. The summary table in Freeman (1986) has a range from 0.6 to 1000. Despite potentially legitimate sources of variation, there is an evident appetite for a single number. Authors have coalesced around a consensus value of about 1.4 attributable to Katz & Murphy (1992). It's from approximately 25 annual observations for the US but is often applied across a range of rich and poor countries. There are some newer estimates, including Ciccone & Peri (2005) and Goldin & Katz (2008) for the United States, but there appear to be none for developing countries.

¹Bowles (1970), Psacharopoulos & Hinchliffe (1972), Tinbergen (1974).

²Hendricks (2002), Papageorgiou & Saam (2008) Dupuy & de Grip (2006), Klenow & Rodriguez-Clare (1997), Caselli (2005).

³Teulins & van Rens (2008)

⁴Acemoglu (2003), Epifani & Gancia (2008), Thoenig & Verdier (2003).

⁵Hamermesh (1993); Cahuc & Zylberberg (2004).

A fresh and reliable estimate of σ for developing countries is overdue. The purpose of this paper is to produce estimates from a number of data sets and to re-examine the relationship between relative skill supply and the wage premium in a cross-country setting. Like the studies cited, we base our estimates on derived relative demand curves producing a relationship between relative wages (the skill premium, in logs) and relative skill quantities (the ratio of skilled to unskilled labour, in logs). Our main innovation is to derive this equation from a model incorporating endogenous skill-biased technical change so that

wage premium =
$$(\sigma - 2)^*$$
 (relative skill supply) (1)

where the coefficient on skill supply is $\sigma - 2$, not $-\frac{1}{\sigma}$ as commonly used. Mechanically, the latter can lead to large variations in elasticity estimates, which tend towards infinity as the correlation approaches zero from below. Furthermore, positive coefficient estimates are outside the feasible set. In contrast, equation (1) permits positive or negative coefficients and produces less variation in elasticity estimates.

The coefficient is $\sigma - 2$ because of endogenous skill-biased technical change (SBTC). New technologies do not automatically favour skilled workers and history provides many examples where they didn't. As modelled in Acemoglu (1998) and Kiley (1999), a rise in the supply of skills increases the market for skill-biased machines, makes it more profitable to produce skill-biased technologies and raises the relative productivity of skilled workers. This "directed technical change" effect counteracts the traditional substitution effect. The size of each effect depends on σ such that $\sigma > 2$ means wage inequality rises while $\sigma < 2$ means it falls. This class of model has been used to explain why, despite a steady rise in the supply of skilled workers in the US and other developed countries, wage inequality increased in the second half of the 20th century.

There is evidence that developing countries, particularly middle income countries, have also experienced technical change that favours skilled workers (Berman & Machin, 2000) and that some have seen rises in wage inequality due to shifts in relative demand for skilled labour (Berman, Bound & Machin, 1998; Goldberg & Pavcnik, 2007). While there is evidence that this is because of technical change in developed countries,⁶ Caselli & Coleman (2006) argue that countries use technologies according to their endowments. The evidence they marshal is a cross-country positive correlation between relative skill supply and the use of skill-biased technologies.

Developing country governments continue to see expanded education access, which reduces the cost of acquiring education, as a tool for raising the relative skill supply. Because this is a strategy to counter the exogenous forces driving up wage inequality, a fresh study of the relationship between relative skill supply and the wage premium is all the more pressing.⁷

Our study takes the following steps. Section 2 builds a formal model of endogenous technical change in developing countries and provides real-life examples of it. The model yields the specification in equation (1). Section 3 shows that, through this new lens, existing empirical estimates are more consistent with each other and less likely to produce nonsensical results. We

⁶Berman, Bound & Machin (1998); Berman & Machin (2000).

⁷Using a different perspective, de Gregorio & Lee (2002) examine the effects of increasing average schooling across the whole population on wage inequality. Martins & Perreira (2004) argue more able people, who had higher wages anyway, gain more from schooling so that increasing the average actually raises wage inequality.

want to produce an estimate of σ for developing countries which does not rely on data that predates the 1960s, so section 4 discusses the data sets we will use. These include cross-section data used by Bils & Klenow (2000) and Caselli & Coleman (2006), a newer and broader crosscountry data set, a long range world-wide panel, an analogue to the Katz & Murphy (1992) study with Brazilian data and a fuller panel of Latin American data. Section 5 presents the results, which suggest that $\sigma = 2$. Therefore, increasing the skill supply will not reduce wage inequality because the endogenous technical change effect more or less cancels the standard substitution effect. Section 6 discusses candidate objections to this approach. These include the potential endogeneity of quantities to prices, which we argue is less important in our application but would mean σ is a bit lower than estimated. Section 7 presents a concluding discussion.

2 Theory

2.1 The population and labour force

The economy has a constant population L = 1 consisting of portion q skilled workers and 1 - q unskilled workers. Consumer i, skilled or unskilled, has utility function

$$U_{it} = \sum_{h=t}^{\infty} G_{ih} \left(1+r\right)^{-h+t},$$
(2)

where G is output consumed. It is linear and pins down the interest rate at r for all t. Consumers earn wages and the profits from any licences they may hold.

2.2 Production

Total output of final goods is a CES aggregate of two types of intermediate, as described by the linearly homogeneous technology:

$$Y_t = \left[(y_t^s)^{\frac{\epsilon - 1}{\epsilon}} + (y_t^u)^{\frac{\epsilon - 1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon - 1}}$$
(3)

Final output is produced by perfect competitors using two intermediate inputs purchased from intermediates producers. The price of final output is unity. $\epsilon > 0$ is the finite elasticity of substitution between intermediate inputs.⁸ Individual producers take the price of final output and intermediate input prices as given before choosing their optimal quantities of intermediates. For the economy as a whole, a rise in supply of one of the inputs relative to the other would necessitate a relative price adjustment. Each final output producer l chooses its ratio of intermediates such that $\frac{y_{l_t}^s}{y_{l_t}^u} = \left(\frac{p_t^s}{p_t^u}\right)^{-\epsilon}$. For the economy to be in equilibrium, intermediates must have prices p^s and p^u such that:

$$\frac{p_t^s}{p_t^u} = \left(\frac{y_t^s}{y_t^u}\right)^{-\frac{1}{\epsilon}} \tag{4}$$

We employ a variety expansion model (Romer, 1990). Intermediates are produced by *i* perfectly competitive firms, where y^s uses skilled labour and T^s different machines while y^u uses unskilled labour and T^u different machines. Specifically, $y_{it}^s = (L_{it}^s)^{1-\alpha} \sum_{j=1}^{T_t^s} X_{ijt}^{\alpha}$ and $y_{it}^u =$

⁸As $\epsilon \to 1$, the CES function approaches a Cobb Douglas Production Function with the corresponding unit elasticity of substitution.

 $A(L_{it}^{u})^{1-\alpha} \sum_{j=1}^{T_{t}^{u}} Z_{ijt}^{\alpha}$. L_{it}^{s} and L_{it}^{u} are skilled and unskilled labour. X_{ijt} is machine input of type j used by firm i at t. It is the quantity of each of T^{s} machines (capital) that complement skilled labour. Similarly, Z_{ijt} is the quantity of each of T^{u} machines complementing unskilled labour. Capital depreciates fully in each period. A < 1 for unskilled labour makes production a function of effective units of labour, with the coefficient for skilled labour normalised to one. We will refer to T^{s} and T^{u} as the number of skilled machines and unskilled machines.

The price of final output is unity. Firms are profit maximisers and the quantity of each skilled machine demanded by each intermediates producer is such that the marginal product of the machine equals its price. Firm-level demand for each type of skilled machine is $X_{ijt} = \left(\alpha \frac{p_t^s}{p_{jt}^s}\right)^{\frac{1}{1-\alpha}} L_{it}^s$.

The price of each skilled machine, p_{jt}^X , is set by the firm holding the licence for that type of machine. The technology importer must receive ex post profits to persuade them to incur the ex ante licence cost. We describe technology acquisition below but, once the fixed cost of acquiring the licence has been incurred, it costs 1 unit of Y, which has a price of 1, to import each machine. The equation for firm-level demand can be used to show the own-price elasticity of demand is $\frac{1}{1-\alpha}$ for all machines of any type. Therefore each monopolist sets a profit maximizing price of $\frac{1}{\alpha}$ for all j, t. For the economy as a whole, we can condition demand for skilled machines on the quantity of skilled labour. Because final goods are produced using a constant returns to scale technology, we know that, in equilibrium, economy-wide demand for each skill-biased intermediate j must be:

$$X_t = \alpha^{\frac{2}{1-\alpha}} \left(p_t^s \right)^{\frac{1}{1-\alpha}} q_t \tag{5}$$

Similarly, economy-wide demand for each unskilled machine is:

$$Z_t = A\alpha^{\frac{2}{1-\alpha}} \left(p_t^u\right)^{\frac{1}{1-\alpha}} \left(1-q_t\right) \tag{6}$$

Economy-wide output of skilled and unskilled intermediates is:

$$y_t^s = T_t^s q_t^{1-\alpha} X_t^\alpha \tag{7a}$$

$$y_t^u = T_t^u A^{1-\alpha} (1-q_t)^{1-\alpha} Z_t^{\alpha}$$
 (7b)

In intermediates production, rises in X and/or Z (a rise in the quantity of every machine used) will encounter diminishing returns. However, the fact that T^s and T^u enter additively ensures constant returns to increases in the variety of inputs. As long as T^s or T^u rise, y^s or y^u will rise. This is the basis for endogenous growth. The model literally considers T^s and T^u as the number of different types of machines a firm can use, but can also be thought of as the technical complexity of the firms' production processes (Barro & Sala-i-Martin, 2004). This latter interpretation is why, as described by the production technology, new machine types will always be employed.

However, increases in T^s relative to T^u or a rise in the proportion of skilled workers (q) will induce price adjustments.

2.3 Prices and wages

An exogenous change in the relative skill supply would lead to a rise in the relative quantity of

 y^s produced. By (4), this would necessitate a relative price adjustment. If the ratio of T^s to T^u were to change, this too would necessitate a relative price adjustment. After substituting from (5) and (6), combining (7) and (4), we can write

$$p \equiv \left(\frac{p^s}{p^u}\right)^{\frac{1}{1-\alpha}} = \left(\frac{T^s q}{T^u A(1-q)}\right)^{\frac{-1}{\sigma}} \equiv (TQ)^{\frac{-1}{\sigma}},\tag{8}$$

where $T \equiv \frac{T^s}{T^u}$, $Q \equiv \frac{q}{A(1-q)}$ and $\sigma = \epsilon + \alpha - \epsilon \alpha$ is the elasticity of substitution between skilled and unskilled labour. In (8), we see a negative relationship between the relative price of the skill intensive good on the one hand and the relative number of skilled technologies on the other.⁹ Producers of intermediate goods hire labour such that wage equals marginal revenue product. For equilibrium in the economy, relative wages are given by:

$$W \equiv \frac{W^s}{W^u} = Tp = T^{\frac{\sigma-1}{\sigma}}Q^{\frac{-1}{\sigma}}$$
(9)

Equation (9) mirrors the findings of Acemoglu (2002a). The far right of the equation shows relative wages are affected by two things. First, the standard substitution effect, where a rise in the relative quantity of skilled labour reduces the relative skilled wage, ceteris paribus. This effect operates through p: a relative rise in skill supply leads to a relative rise in skilled intermediates, which leads to a fall in p and hence a fall in the relative marginal revenue product of skilled labour.

Second, relative technologies, the effect of which can be positive or negative. A rise in T raises the relative physical productivity of skilled labour. However, a higher T leads to lower p and hence lower W. The net effect depends on σ , as will be discussed. Equation (9) describes the important direct relationship between wages and the skill supply. It also describes the relationship between wages and technology. The next section describes how technology adoption is determined by the skill supply.

2.4 Technology adoption

2.4.1 Empirical background

Before proceeding with the model, we present the relevant facts on technical change. Most countries do not develop their own technologies but acquire them from abroad (Eaton & Kortum, 2001). Calculations based on data from the OECD patents database for 2003 show the top five sources of patents account for 84% of those world-wide in the database (and 86% of OECD patents). The sixteen developing countries for which data are available account for only 3%. Savvides & Zachariadis (2005) find empirically that developing countries undertake no own R&D but rely on foreign technology transfer. According to Eaton & Kortum (2001), those countries engaged in designing the machines tend to produce and export them. Caselli & Wilson (2004) argue that equipment imports are a good proxy for investment in technology. For developing countries, it is therefore especially pertinent to model technology acquisition as a purchase from abroad rather than as a result of R&D and home production.

However, countries do not absorb any new methods automatically, but consider domestic factor market conditions before choosing appropriate technologies. For example, Knight (1979)

⁹We can show that $\epsilon = 1 \Leftrightarrow \sigma = 1$ and that $d\sigma/d\epsilon > 0$. Also, $\epsilon \to \infty \Leftrightarrow \sigma \to \infty$. Therefore, as $\epsilon \to \infty$, changes in relative labour quantities or relative numbers of machine varieties would have no effect on p.

notes that capital can replace skilled or unskilled labour and describes how the introduction of the colour bar restricted the supply of skills in South Africa and may have led to capital substituting for skilled workers. Tellingly, when the colour bar was relaxed, a large degree of substitution of machines for *unskilled* labour took place.¹⁰ Acemoglu & Zilibotti (2001) speak of MNCs making technologies available to their various LDC subsidiaries according to the relative availability of skilled workers. Moreover, they cite an example of Kenya using the hammer mill to grind maize rather than the roller mill because of abundant unskilled labour. Other examples come from Tanzania and Thailand, where a new method for producing cans was not widely adopted because insufficient skilled workers were available to work with them. Rosenberg (1969) highlights how rifle production in the UK was the preserve of scarce skilled workers who were also strike prone. In response, the UK acquired from the United States the means to produce rifles using mass production methods and unskilled workers. Although they are not developing countries, they provide another example of an existing overseas technology being acquired in response to domestic factor market conditions.¹¹ Fransman (1985) draws on comprehensive case study evidence from a number of Latin American countries (Teitel, 1984) and elsewhere to speak of semi-industrialised countries adapting overseas technologies to local factor supplies. In an econometric study of the transition economies, Esposito & Stehrer (2009) find results that are consistent with a positive relationship between the initial relative quantity of skilled labour and subsequent SBTC.

2.4.2 Modelling technology adoption

With this empirical background in mind, we start by describing the decision of a potential licence holder whether or not to acquire a licence for a technology from abroad.

For the licence-holder, it costs one unit of Y to import one unit of a machine, skilled or unskilled, such that the marginal cost is unity for both machine types. The cost of acquiring a skilled *licence* for a particular skilled machine X_j is C^s and the cost of a licence for an unskilled machine Z_j is C^u units of Y exported. We will assume developing countries are far behind the technology frontier and are price takers in the technology market. However, the price of a licence is inversely related to the research frontier reached by R&D in the developed world. That is, $C^s = \frac{1}{R^s}$ and $C^u = \frac{1}{R^u}$.

$$C \equiv \frac{C^S}{C^u} = \frac{R^u}{R^s} \equiv \frac{1}{R} \tag{10}$$

R is the skill-bias of the world's available technologies such that the relative cost of importing skilled technologies is inversely related to it.

At any time t, the agent considers if the value of the licence exceeds the cost. The agent would incur the cost at t and start receiving profits at t + 1. The value is the discounted present value of all future profits. Because profits for all skilled machine types are equal, the

¹⁰Knight also notes the reliance on imported technologies, which tended to replace unskilled labour.

¹¹There are many examples of technologies being researched and developed in response to factor supplies. Hayami & Ruttan (1970) compare the US and Japan, where differences in elasticities of factor supply meant that increased demand for agriculture led to different courses of technical progress. In Japan, land was more inelastic and became relatively expensive, so innovations were directed towards biological improvements so that crops required less land. In the US, labour became expensive and mechanisation was the result. Mokyr (1990) notes that the spinning jenny and mass production in factories coincided with large rises in the availability of unskilled labour in UK cities, due in part to massive migration from Ireland. Acemoglu (2002) cites this as an example of technical change that favours unskilled workers and contrasts this with the coincidence of rising skill supply and SBTC in the US in the 20th century.

value is the same for all skilled machine types. Thus the value of a skilled licence at time t is $V_t^s = \sum_i^{\infty} (P_{t+i}^X - 1) X_{t+i} (1+r)^{-i}$. Recalling $P^X = \frac{1}{\alpha}$, using (5) and defining $\Omega \equiv (1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}$, the per period profit from a licence for a skilled machine is $\pi^x = \Omega(p_t^s)^{\frac{1}{1-\alpha}} q_t$. Similarly, the per-period profit for an unskilled licence is $\pi^z = \Omega(p_t^u)^{\frac{1}{1-\alpha}} A(1-q_t)$. Therefore, the value of a skilled licence is:

$$V_t^s = \Omega \left[\sum_{i=1}^{\infty} \frac{q_{t+i} \left(p_{t+i}^s \right)^{\frac{1}{1-\alpha}}}{(1+r)^i} \right]$$
(11)

Analogously:

$$V_t^u = A\Omega\left[\sum_{i=1}^{\infty} \frac{(1-q_{t+i})\left(p_{t+i}^u\right)^{\frac{1}{1-\alpha}}}{(1+r)^i}\right]$$
(12)

The ratio of values is:

$$V_{t} = \frac{\left[\sum_{i=1}^{\infty} \frac{q_{t+i}(p_{t+i}^{s})^{\frac{1}{1-\alpha}}}{(1+r)^{i}}\right]}{A\left[\sum_{i=1}^{\infty} \frac{(1-q_{t+i})(p_{t+i}^{u})^{\frac{1}{1-\alpha}}}{(1+r)^{i}}\right]}$$
(13)

For constant values of Q (the relative supply of effective labour) and R (the skill-bias of the technology frontier), we can find an equilibrium in which p, V and T are constant. Under these assumptions, equation (13) can be simplified to:

$$V = Q^{\frac{\sigma-1}{\sigma}} T^{\frac{-1}{\sigma}} \tag{14}$$

Further, use the fact that wage equals marginal revenue product to write (14) as $V = \frac{qw^s}{(1-q)w^u} \frac{1}{T}$. Note $qw^s/(1-q)w^u \equiv \zeta$ is an expression for the relative factor shares of skilled and unskilled labour, so

$$V = \frac{\zeta}{T}.$$
(15)

Equation (15) expresses the relative value of skilled and unskilled technologies in terms of relative factor shares and relative technology availability in the developing country. ζ captures both the induced innovations (Hicks, 1963) and market size (Schmookler, 1966) arguments for factorbiased technical change. Hicks introduces factor saving inventions as those which increase the marginal product of the other factor relative to that factor. Such inventions seek to economise on the use of the more expensive factor, are thus spurred by changes in relative factor prices and are called "induced innovations" (pg 125). A skilled intermediate producer will, ceteris paribus, demand more skilled machines if skilled wages are higher. Thus a given rise in the skill premium would induce innovations in favour of skilled machines. Alternatively, Schmookler (1966) introduces the market-size effect later modelled by Kiley (1999): a higher number of skilled workers raises the marginal product of skilled machines and hence increases demand for skilled machines. Thus, a rise in the proportion of skilled workers makes skilled machines more attractive to import.

The way we have modelled these arguments, it appears that they oppose each other: a rise in the relative scarcity of unskilled labour would make it more expensive and spur the development of unskilled machines. However, we can combine them into "market attractiveness" based on relative shares. Holding technology constant, a rise in the supply of skilled labour will raise its factor share if $\sigma > 1$. In other words, the quantity effect outweights the price effect. Thus, if $\sigma > 1$, a rise in relative skill supply increases the skill share and overall makes the value of adopting a skilled machine licence relatively more attractive. A rise in skill supply lowers its share if $\sigma < 1$ and makes the value of adopting a skilled licence less attractive. This illustrates the equivalence between (15) and (14), which is closer to the treatments in Acemoglu (2002ab).

2.5 Steady-state equilibrium

Anybody is allowed to acquire a licence of either type. By free entry, $V^s = C^s$ and $V^u = C^u$ such that, in steady state,

$$V = C \tag{16}$$

and

$$T = Q^{\sigma-1} R^{\sigma} \tag{17}$$

$$= \zeta R \tag{18}$$

As a natural extension to (14), the ratio of skilled to unskilled technologies is positively related to the relative skill supply when $\sigma > 1$. We have an even simpler expression in which the skillintensity of technology is positively related to the relative attractiveness of the skilled technology market ζ and inversely related to the relative cost of such technologies $C = \frac{1}{R}$. These equations also convey the notion, due to Atkinson & Stiglitz (1969), of technologies being "appropriate" for a country's endowments. By equation (9):

$$W = Q^{\sigma-2} R^{\sigma-1} \tag{19}$$

This is the basis of our simple estimating equation. It gives the net (reduced form) impact of relative quantities on relative prices, but we analyse the comparative statics carefully next.

2.6 Comparative Statics

We can see from (19) that $\frac{d \log W}{d \log Q} = \sigma - 2$. Breaking this down,

$$\frac{d\log W}{d\log Q} = \frac{\partial \log W}{\partial \log T} \frac{d\log T}{d\log Q} - \frac{1}{\sigma}$$
(20a)

$$= \underbrace{\frac{\sigma - 1}{\sigma} \sigma - 1}_{\sigma} - \underbrace{\frac{1}{\sigma}}_{\sigma}$$
(20b)

Technology import effect substitution effect
$$\sigma - 2$$
 (20c)

The substitution effect comes from conventional labour demand theory and this is the effect empirical studies typically measure. However, the substitution effect must be compared to the effect operating through a change in technology imports. A rise in T has two effects on wages. First, it increases the relative (physical) productivity of skilled labour. Second, however, it increases y^s/y^u , which necessitates a fall in p and therefore has a negative effect on the relative marginal revenue product of skilled labour. The net effect on relative wages depends on σ . If $\sigma > 1$, a rise in T will have a positive effect on the skill premium, because the second effect is relatively small. Also, a rise in Q only leads to a rise in T if $\sigma > 1$. As discussed earlier, this is because a rise in skill supply makes the market for skilled technologies more attractive iff $\sigma > 1$. Conversely, $\sigma < 1$ means relative wages will have to adjust a lot so that the overall effect is negative. $\sigma < 1$ also implies that a rise in skill supply reduces the relative share of skilled labour and hence makes skilled technologies less attractive. The technology import effect of skill supply on wages is positive for any $\sigma \neq 1$.

Algebraically, this is consistent with Acemoglu (2002a). For the sake of argument, we will from now on take a short-cut and only consider $\sigma > 1$, as will be empirically supported, such that we can refer to a rise in T and SBTC interchangeably and can say a rise in Q leads to the acquisition of more skilled machines.

We are mainly interested in changes in Q, but we also accommodate changes in R. Berman, Bound & Machin (1998) argue that SBTC is pervasive across the globe, affecting both OECD and developing countries. Furthermore, most of the developing countries in their sample experienced increases in the skill premium and in the skilled share of employment. Berman & Machin (2000) also argue that technology adoption in the South is driven by that in the North. They find that the same industries experiencing SBTC in the South in the 1980s were those experiencing it in the North in prior decades.

Our model captures SBTC in the North by a rise in R, the relative skill bias of the research frontier. In equations (17) and (18), T rises after a rise in R because SBTC reduces the relative cost of a skilled technology. A rise in R over time captures the observation that "...developing countries must be choosing from a menu of best practices that includes an ever-increasing proportion of skill-biased technologies." - (Berman & Machin, 2000:3)

We note that a country opening up to trade might affect its exposure to technologies overall such that the price of acquiring machines or technologies of both types falls. This, however, should not affect the *relative* cost of acquiring skill-biased technologies and is not in of itself a mechanism for steady-state trade-induced skill-biased technical change.¹²

2.7 Changes over time

We have thus far modelled steady state changes, which are empirically best suited to a crosssection of data or a long range panel. We will also use annual observations. If R is constant, in equilibrium, we have $V_t = C$ for all periods. In particular, we have $V_0 = C$ and $V_1 = C$. Therefore, $Q_1p_1 = C$. Given $p_1 = (T_1Q_1)^{\frac{-1}{\sigma}}$ (cf equation (8)), we can write $T_1 = \frac{Q_1^{\sigma-1}}{C^{\sigma}}$. We can extend this to all periods such that

$$T_t = Q_t^{\sigma - 1} R^{\sigma} \tag{21}$$

There are no direct intertemporal effects in wages, so

$$W_t = Q_t^{\sigma-2} R^{\sigma-1}.$$
(22)

If R changes regularly and if prospective licence holders don't expect further changes in R, then we can also attach time subscripts to R.

Our model does not explicitly permit lags in technology adoption. However, with annual observations, it may be appropriate to distinguish between short run and long run responses.

 $^{^{12}}$ One example of such a change in this framework can be found in Acemoglu (2003). If a rich country opens up to trade, skill-intensive goods become more expensive, which induced R&D into technologies used with skill labour.

With reference to (20), the substitution effect can operate with no lags while the directed technical change response is delayed such that the overall relationship is only a long run one. We will briefly consider this distinction with our annual data.

3 The elasticity of substitution revisited

The elasticity of substitution parameter influences what impact schooling will have on the wage premium. In the traditional sense, the reduction is larger if the elasticity is low (they are far from perfect substitutes). In our context, which accounts for technical change, we are interested in whether the elasticity is greater than 2 in developing countries. In this section, we will draw on existing estimates of this elasticity based on relative labour demand equations.

3.1 Existing estimates

The table of studies in Freeman's (1986) handbook chapter contains elasticities ranging from 0.6 to 1000 between college and non-college educated workers, which does not appear to be particularly informative. After surveying about 40 broader studies, Hamermesh (1993) is not prepared to offer a summary range of values. However, Freeman volunteers a range between 1 and 2. This consensus appears to have stuck. In particular, authors have rallied around an estimate of 1.4. This value is due to a US study by Katz & Murphy (1992) and its acceptance is ironic given that the authors were themselves "skeptical of estimates of σ recovered from 25 non-independent time series observations" (pg 69). Besides, our reading of their Figure IV suggests a higher elasticity would fit the data better. Nevertheless, this is not far from more recent work for a panel of US states by Ciccone & Peri (2005), whose preferred estimate is 1.5. Goldin & Katz (2008) have 47 observations going back as far as 1915 to produce a consensus-reenforcing preferred estimate of 1.67. However, estimates with a lower education cutoff produce elasticities from 2 to 5 so they do not volunteer a number.

Focussing on developing countries, Psacharopoulos & Hinchliffe (1973) estimate values of 2.1 to 2.5. We note that the same paper and method is responsible for the value of 1000 cited by Freeman (1986) for developed countries. With a full sample of countries, the Psacharopoulos & Hinchliffe (hence PH) study generates an elasticity of 2.2 when people are skilled if they have higher education and an elasticity of 50 if people are skilled once they have completed primary education. Tinbergen (1974:217), "struck by the high elasticity figures obtained by several others, and wondering how to interpret them", offers 0.6 to 1.2 for developing countries based on education data, but we are not aware of anything newer.

3.2 Re-interpreting the elasticities

Many of the studies, including PH across countries, Katz & Murphy (1992) across years and Ciccone & Peri (2005) for a panel of US states, calculate elasticities on the basis of a function like:

$$\log W = \alpha + \beta \log Q + e, \tag{23}$$

where e is a stochastic term. The elasticity of substitution is then given by $\tilde{\sigma} = -\frac{1}{\beta}$. There may or may not be additional variables like capital and exogenous technical change in the form of a time trend. Endogenising SBTC, as Acemoglu (2002a) does for rich countries and we do

for developing countries endogenises the acquisition of capital by making it a function of skill supply. As we can see from equation (19), such terms drop out completely such that we are left with the parsimonious specification (23). R and A (which is part of Q) are captured by the constant or perhaps a time trend and, more importantly, $\beta = \sigma - 2$. This can be very different to $\beta = -\frac{1}{\tilde{\sigma}}$.

How different? $\tilde{\sigma} = \sigma$ when the elasticity is unity, which corresponds to the case where there is no induced technical change. Calculated values of $\tilde{\sigma}$ and σ for a range of values of β are presented in Table 1. In the first three rows, we represent "consensus" values of $\tilde{\sigma}$ within the 1-2 range in the second column. The values still yield values of σ within that range.

Row 4 gives the actual Katz & Murphy (1992) β estimate, the elasticity they attach to it $(\tilde{\sigma} = 1.41)$ and our new interpretation close to the original ($\sigma = 1.291$). Thus, our alternative measure does not challenge the consensus estimate in a material way. On the contrary, our findings re-enforce the consensus because "implausible" values now fall within the consensus range. Also, results that seem to differ wildly are actually consistent with each other. Row 5 onwards gives elasticities from cross-country studies. For example, an often-cited elasticity between those who completed primary school and those who didn't is reported as $\tilde{\sigma} = 8$ (Bowles, 1970: equation 7). Our model suggests the elasticity is $\sigma = 1.88$. While $\tilde{\sigma} = 8$ is high, it is not as high as the $\tilde{\sigma} = 200$ reported from their equation (6) between those who have 8-11 schooling years and those who have 12 or more. $\tilde{\sigma} = 8$ is far from $\tilde{\sigma} = 200$, but $\sigma = 1.88$ is close to $\sigma = 1.995$. The PH estimate of $\tilde{\sigma} = 1000$ becomes $\sigma = 1.999$.

Taking an inverse of a small coefficient can make very small changes in that coefficient yield dramatic changes in the implied value of $\tilde{\sigma}$, while the effect on σ is not so severe. We also note that a positive estimate for β needn't imply invalid results. While implying an invalid negative value for $\tilde{\sigma}$, it simply means $\sigma > 2$ and that we are seeing a positive relationship between skill supply and wages brought about by a strong directed technical change effect. An example of this from PH is in equation R6 in Table 1, but we would not be surprised if publication bias has prevented similar positive estimates from surfacing. Thus, the uninformative range in Freeman (1986) of 0.6 to 1000 becomes a rather more consistent interval of 1/3 to 2.

Finally, we note the estimate for developing countries taken from PH equation (R5) in which $\tilde{\sigma} = 2.1$ and thus $\sigma = 1.5$. For our purposes, this is the best estimate available so far.¹³ However, this is only between those workers who have a tertiary education and those who have secondary education and is based on data that predates the 1960s. Our next step is to offer an improvement on this state of affairs with newer data covering a broader segment of the population.

4 New data

We use four types of data, namely (i) cross sections, (ii) a long range panel of 40 observations, (iii) time series for Brazil and (iv) an annual panel for Latin America. Cross sections have been used before, but we are not aware of the use of long range panels. While time series have been used before, we are not aware of their use in developing countries. Further, while Ciccone & Peri (2005) have a panel of US states, we are not aware of the use of a panel of developing countries. This section describes the datasets.

 $^{^{13}}$ The functional form is more appropriate than the Tinbergen (1974) study we cited earlier.

Cross sections We have two cross-country cross-section data sets. The results are arguably best interpreted as steady state or long-run elasticities.

- 1. The first is downloaded from Francesco Caselli's website and was used by Caselli & Coleman (2006) (hence CC). Their data on labour supply is from Barro and Lee (2001), who report for each country the share of the labour force who have one of seven categories of educational achievement. To calculate wage premia and to construct aggregates of skilled and unskilled labour, as we describe below, they use the Mincerian coefficients due to Bils and Klenow (2000). The data include unpublished information from Barro & Lee, who report the duration of schooling for each country. Unlike the other data in this paper, there is information on the per-worker capital stock, which CC take from Hall & Jones (1999). Capital data are for 1988 so the labour supply data is taken for 1985. We note that many of the estimates in Bils & Klenow (2000) are taken from Psacharopoulos (1994), which in turn is based on studies and data from earlier.
- 2. We construct another cross-country data set to provide estimates with more recent data. We have 43 developing countries in the sample, which is a third more than the CC data, even though we deliberately exclude any observations before 1985. There is still some overlap between the two data sets. We also use the Barro-Lee labour supply and schooling duration data but make use of two recent sources of Mincerian coefficients, namely Banerjee & Duflo (2005) and Psacharopoulos & Patrinos (2004). The labour supply data are available in 5-year periods, so we use the observations from the period preceding that of the Mincerian estimate. For example, a Mincerian for 1990 or 1994 would be allocated the labour supply information for 1990.

A long range panel for 20 countries Mincerian returns are taken from Psacharopoulos & Patrinos (2004), who have a separate table of estimates they consider to be comparable over time. Some countries have more than two observations but we will report results using observations in their earliest and latest period. The observations are usually separated by long periods of time, which is why we refer to this data as a long range panel and why we can still track long run steady-state changes. Labour supply and duration data are from Barro & Lee as before, where we choose the observation for the five year period preceding the Mincerian return. If more than one return is available within a five-year period, we take the average. For Mexico, we ignored a return that was far out of line with the others for Mexico that period.

Annual observations for a single country Annual data are used in order to produce a developing-country analogue to the Katz & Murphy (1992) study for the USA. We choose Brazil simply because it has the longest time span and the observations are comparable in number to theirs. The data are taken from SEDLAC which, as described in CEDLAS & World Bank (2009),¹⁴ has standardised and collated household data from a number of Latin American countries. SEDLAC define three skill levels. 'High' corresponds closely to having some tertiary education while 'medium' corresponds roughly to having completed at least primary and possibly secondary school.¹⁵ They report the share of the population in each of these categories and their

¹⁴ http://www.depeco.econo.unlp.edu.ar/sedlac/eng/index.php

¹⁵Specifically, 'low' corresponds to people with 0-8 years' schooling, 'medium' to 9-13 years, and 'high' to 14 or more years.

monthly labour income.¹⁶ These data are arguably less suited to steady state changes

A panel with annual data Using the same SEDLAC data, we can run regressions on about fifteen Latin American countries over a number of years such that we have a total of about 180 observations. This allows variation across countries and over time. Within each country, surveys were redesigned periodically. To cater for this, we introduce country-specific dummies corresponding to each survey period.

Aggregating labour supply The Barro-Lee data, which we use for the world-wide analysis, has seven labour supply categories. Following the tradition in this literature, we aggregate the seven categories on labour supply into two. Caselli & Coleman (2006) focus on the distinction between those who have completed primary school and those who have not. They argue this definition roughly separates out the completely illiterate and innumerate from those who can at least read a simple text and perform basic arithmetic. They noted there are many tasks that no number of completely illiterate agents will be able to perform. Furthermore, this sort of cutoff may be more relevant when dealing with developing countries, where literacy and numeracy can by no means be taken for granted. However, we also produce the cutoff between those who have some post-secondary education and those who don't.

With the cutoff at primary school, the aggregate for unskilled labour is constructed as

$$L_{\text{unskilled}} = L_{\text{no education}} + W_{\text{some primary}} L_{\text{some primary}}, \qquad (24)$$

where L_i is the labour share of workers with education level *i* and $W_{\text{some primary}}$ is the ratio of wages of those with some primary education to the wages of those with no education. *W* is constructed using the Mincerian earnings coefficient and the number of years of schooling between categories. Similarly,

$$L_{\text{skilled}} = L_{\text{completed primary}} + W_{\text{some secondary}} L_{\text{some secondary}} + W_{\text{completed secondary}} L_{\text{completed secondary}} + W_{\text{some higher}} L_{\text{some higher}} + W_{\text{completed higher}} L_{\text{completed higher}}, \qquad (25)$$

where W_i is measured relative to those with completed primary education.¹⁷ Having constructed measures of skilled and unskilled labour quantities, we construct an aggregate measure of the skilled/unskilled wage premium using the Mincerian coefficient and the number of years' difference between those with primary school and those with no school. We perform analogous construction for the tertiary cutoff. For more details, see CC.

The SEDLAC data has three categories. We perform an analogous aggregation to above such that one cutoff has skilled labour defined as those who have more than 8 years (medium and high skill). The other cutoff defines skilled labour as those who have more than 13 years. The wages at each level are already in the data, so Mincerians are not needed.

¹⁶We use data for both men and women and the wage ratios we construct are unconditional. They also have data available by gender, which produced similar results. They have a number of alternative measures, including hourly wages and ready-built wage gaps for males. Furthermore, they have the marginal return to college, secondary and primary education based on dummies from earnings functions regressions. These are constructed separately for males and females. However, this does not map accurately to the skill supply cutoffs and must either be analysed by gender or aggregated in some arbitrary way.

¹⁷There is some variation in the duration of school. This is accounted for and standardised across countries in the same way as done by Caselli & Coleman (2006).

Openness We will use Sachs & Warner (1999) measure of openness, in particular the average degree of openness from 1965-90¹⁸ and a dummy dividing the sample into more and less open halves based on this data. With the SEDLAC data, we measure openness in each year in terms of the ratio of trade to GDP, which is taken from the Penn World Tables (Heston, Summers & Aten, 2009).

5 New Estimates

We present estimates based on the two cross-section data sets. We proceed to discuss those for the long range panel before considering the annual data from Brazil. Finally, we present estimates based on the annual panel of South American countries.

5.1 Cross-country Data

5.1.1 Caselli & Coleman data

Primary schooling We start with the skilled/unskilled cutoff defined as the end of primary school. Figure 1 plots a negative relationship between the wage premium (vertical axis, in logs) and relative skill supply (horizontal axis, in logs) for developing countries. The outlier is Jamaica, which is dropped from the least squares regressions but included in least absolute deviation regressions.

In Table 2, we regress the skill premium on the relative quantity of skilled labour (in logs) as in equation 1. Column 1 presents estimates based on the whole sample of rich and poor countries. The point estimate of $\beta = -0.0651$ implies $\tilde{\sigma}$, which ignores technical change, is estimated to be about 15, with a lower bound of about 6 and an upper bound of almost 25 (based on the 95% confidence intervals). It also implies $\sigma = 1.93$ with lower and upper bounds of 1.90 and 1.97.

The coefficient estimate is similar to that in column 2, which is restricted to 32 developing countries and has $\beta = -0.0826$. This coefficient implies $\tilde{\sigma} \approx 12$. Accounting for the standard error in the estimate of β gives an upper confidence band as high as 24 for developing countries and the lower bound is negative. This illustrates the implications of inverting a coefficient estimate to calculate an elasticity and reflects how small differences in point estimates (cf Table 1) can lead to large variations in elasticity estimates. Furthermore, the lower bound for $\tilde{\sigma}$ should be truncated at zero because negative elasticities are invalid.¹⁹

The same estimates imply a value of $\sigma = 1.92$. This is within the consensus range of 1 - 2. Furthermore, the confidence bands are by construction much narrower, yielding a more precise elasticity estimate. Our estimate of β is almost significant at 5%, which corresponds to an upper confidence limit of 2.

Our specification is very simple. One might object that technology adoption is affected by a variety of features, of which the availability of skills may be just one. Examples include policies towards foreign investment and the rule of law. We agree, but note that one would need to argue

¹⁸The data are taken from Jon Temple's website.

¹⁹See Duffy et al (2004). This restriction is imposed by the CES functional form. Other functional forms permit negative elasticities when there are more than two inputs. One example is Behar (forthcoming), where skilled and unskilled labour are complements, not substitutes. Ciccone & Peri (2005) have a translog but only have two inputs, which means the inputs are necessarily substitutes. We are not aware of theoretical models of SBTC that accommodate this type of production technology.

for cross-country institutional differences which would affect the *ratio* of technologies adopted (skilled to unskilled) rather than their levels. One may object that the supply of technologies, captured by R, may differ across countries. Given that the suppliers are the same for everyone, namely a handful of R&D intensive rich countries, it is not clear why this should be the case. This is the pervasiveness argument made earlier. However, if there is a period of technical R&D that is making skilled technologies cheaper, this would be reflected over time by a fall in R. This data is from a single cross-section and is thus best used to measure steady-state relationships. However, we can capture this potential time variation by distinguishing between more open economies, for whom t is big because they have had access to the newest technologies, and closed economies, for whom t is small because they may not have such access yet. If it is true that that open countries have more access to the world's newest technologies and if it is true that shifts in R took place, then we should expect a higher level of T in open economies and hence a higher level of wage inequality.

In column 3, an openness dummy²⁰ is significantly positive, which is consistent with this view. It does not affect our estimate of β and hence σ . In column 4, we repeat the specification but include Jamaica and run a Least Absolute Deviations (LAD) estimator. A relatively innocuous change in the coefficient results in an innocuous change in σ . We discuss column 5, which includes a measure of the capital labour ratio, in section 6.

Higher education We now discuss results in which people are classified as being skilled if they have completed at least some post-secondary education and people are unskilled otherwise. Figure 2 presents a scatter diagram for developing countries. The negative relationship appears to be there, but it is not uniform like Figure 1. Jamaica again generates a very high premium and is excluded from the least squares regressions.

In Table 3, column 1 presents results for both rich and poor countries. The elasticity of $\sigma = 1.75$ is slightly lower than in Table 2. In column 2, we present estimates for developing countries The point estimate of the elasticity, $\sigma = 1.84$, is a bit higher than for the whole sample but slightly lower than in Table 2. The distance between the lower and upper confidence bands is larger than in column 2 of Table 2, reflecting the less precise estimate of β . $\tilde{\sigma}$ is also quite imprecisely estimated, with confidence bands breaching zero. In column 3, the openness dummy is insignificant and leaves the elasticity virtually unchanged. The LAD estimate in column 4 gives slightly lower elasticities than in columns 2 and 3 while we discuss column 5 in section 6.

5.1.2 Newer cross-section data

We continue with cross-country analysis but now use the newer updated data. With Figure 3, we present what appears to be a breakdown of the negative correlation between wages and quantities. The picture is for the higher education cutoff but a very similar one would result from the primary cutoff.

In Table 4, we present regression estimates for just over 40 developing countries with the newer data. The first three columns use the higher education cutoff while the next three use the primary school cutoff. Consistent with Figure 3, the β coefficient is close to zero across all six specifications. Under the traditional interpretation, one must either conclude that the factors

²⁰This specification divided the countries into more and less open halves over the 1965-1990 period, but other Sachs Warner measures are robust.

are perfect substitutes, as in the least absolute deviations estimates in columns 3 or 6, or dismiss the least squares estimates in the other columns as coming from a nonsensical CES technology. Alternatively, our model proposes that the elasticity is consistently about 2.

The openness dummy appears to be significant in the least squares regressions (columns 2 and 5). Furthermore, the coefficient is much higher at the higher education cutoff (columns 2 and 3 as opposed to 5 and 6). This is consistent with the view that openness, possibly as a conduit for SBTC, has increased wage inequality at the top of the wage distribution.

The absence of correlation says that relative factor quantities seem to be playing little or no net role in factor prices. A regression of close to zero means one thing if the scatter diagram is more or less a flat horizontal line. However, the scatter plot reveals much variation and the R^2 is low in some specifications. Furthermore, unobserved country-specific features may be playing a dominant role in determining the wage premium. We begin to consider this possibility through a long-range panel.

5.1.3 Long-range panel

The absence of a correlation might be simply because country-specific factors are what drive wage premia. To allow for country-specific effects but still speak in terms of steady-state changes, we make use of the long range panel. The first three columns treat workers as skilled if they have completed primary school. Columns 4-6 treat workers as skilled if they have some tertiary education. In Table 5, column 1 pools all the data, which identifies variation across countries and over time and implies an elasticity of $\sigma = 2$ as before. Column 2 controls for country-specific fixed effects and only exploits the changes in skill supply and wage premia over time within each country. Column 2 produces a positive correlation, which in our framework implies an elasticity of $\sigma = 2.1$. Allowing for openness over the sample period does not appear to have an effect in column 3.²¹ We have very similar results for the higher education cutoff.

5.2 SEDLAC data

5.2.1 Single time series for Brazil

We demonstrated theoretically that we can think of the steady state equilibrium occurring in all time periods in response to annual changes in Q. At the same time, we questioned whether one should contemplate technology changes over such short time periods. Nonetheless, for the time being, we exploit time variation within Brazil and continue to interpret the results as steady state changes.

Figure 4 shows the proportion of people with at least 9 years of schooling has risen steadily over time and that this has coincided with a fall in the wage premium in Brazil. Figure 5 has a number of outliers, which cannot be explained by the changes in data definition or survey methodology as those took place in 1992 and 2004.²² Nonetheless, it shows that the proportion of those with at least 14 years' education and the corresponding wage premium have both risen. Part of the explanation could be that there was a disproportionately large rise in people in the middle-skill category (9-13 years of education).

²¹We also note that controlling for the year/period of the data does not affect the results materially and in many cases indicates a downward trend in inequality. Results available on request.

²²Using alternative wage definitions produces similar outliers in the same years.

Alternatively, technical change may be raising wages at the top of the skill spectrum. We therefore turn to regression analysis to see if these effects can be disentangled.²³ Because of the outliers, we present specifications which exclude them.²⁴ Furthermore, there are dummies to correct for the two occasions on which the sampling method changed. Katz & Murphy (1992) have a time trend in their specification. They interpret this as exogenous SBTC, but we could also interpret it as an exogenous change in R over time.

In Table 6, we present three specifications for primary schooling (at least nine years of schooling) and five for higher education (at least thirteen).²⁵ The explanatory power is much higher than in the cross-section or long range panels. For primary school, we see estimates that imply the elasticity of substitution is between 1.67 and 1.8 depending on the specification. We see an insignificant positive year coefficient, but a significantly negative openness coefficient. For higher education, we have an elasticity of 2.41 in column 4. This is consistent with the positive relationship in Figure 5. However, the inclusion of a trend in column 5 reduces the elasticity to 1.79, which is in line with our previous estimates. The significantly positive year coefficient can be interpreted as SBTC being driven by external factors like SBTC in the R&D-intensive countries (a change in R). If we believe this is more likely to affect the people at the top of the skill spectrum, these results make sense. Brazil's economy has opened up over time, but the inclusion of the openness measure in column 6 leaves the elasticity unchanged relative to column 4 and the measure itself is insignificant.

Dynamics We have raised the issue of whether annual data are appropriate for estimating our proposed steady-state relationship (equation 1). Technical change may take some time so that we have a short run negative relationship between factor supplies and the skill premium driven by the standard substitution effect and a potentially positive long run relationship after technical change has taken place.

This lends itself to serious time series analysis with sufficiently frequent and/or lengthy data. The Brazilian data is not (yet) ready for such analysis, but a cursory exercise suggests such research would be fruitful. Recall that column 4 of Table 6 yielded a strong positive correlation between the wage premium and factor supplies. Column 7 estimates the relationship in first differences and yields a significantly negative coefficient. This is to be expected since first differences is arguably more appropriate for estimating short-run effects. Further, borrowing from Engle & Granger (1987), we include the residual from the column 5 estimates in our first difference specification presented in column 8.²⁶ With this structure imposed, we can interpret the coefficient on (the first difference of) factor supply as the short run effect such that the elasticity of substitution is -1/0.499 = 2. This is again close to the estimate of 1.8 implied by the long run relationship used to produce the correction term. These are not statistically different, but more rigorous testing can be conducted once longer time series become available.

 $^{^{23}}$ The figures suggest some of the variables have striong trends and that multicolinearity may affect the precision of our estimates. We examined the variance inflation factors and these were below 10, which suggests the issue is not serious.

 $^{^{24}}$ These are in 1986 and 1992 for the primary cutoff and in 1996 & 2007 for the higher cutoff.

 $^{^{25}\}mathrm{As}$ noted in Section 4, these are approximate equivalences.

²⁶We could alternatively estimate the long run and short run parameters jointly in an error correction model or an isomorphic autoregressive distributed lag model. We present these "two-step" results because it leaves us having to estimate fewer parameters with our 20-odd observations.

5.2.2 Latin America Panel

Having taken one country with the longest time series, we now investigate whether we can capture similar patterns in a panel, albeit with a shorter average time span. By including fixed effects, we can continue to examine time series variation. In some specifications, we include dummies for changes in data definition over time in each country (see CEDLAS & World Bank, 2009). Thus, it is as if we have country / data-definition fixed effects and are estimating the within-survey variation.

The first column is a simple pooled estimate at the primary schooling cutoff. The implied elasticity is 1.8. Adding country fixed effects and a year variable tend to raise the elasticity towards 2 (column 2). Including country and data fixed effects brings the elasticity even closer to 2 in column 3 while allowing for trade openness makes no difference in column 4.

Columns 5-10 are for higher education. The pooled estimates imply an elasticity of 1.9 but adding country specific fixed effects raises this coefficient in column 6 to 2.2. However, in column 7, we see a positive year coefficient and a lower implied elasticity of 2.1. The elasticity remains relatively unaffected by the use of alternative specifications. In contrast, while the inclusion of the openness measure does not affect the year coefficient, the use of data controls and countryspecific trend variables does. The latter in particular suggest that trends are different for some countries, which leans against the pervasiveness arguments advanced by Berman & Machin (2000).

5.3 Summary and interpretation

For the cutoff corresponding more or less to primary school, the Latin America panel produces fixed effects elasticities between 1.9 and 2. The CC cross-section data produces the same range. The individual values for Brazil are a bit lower while the long-range world panel elasticity and the cross-section estimates with newer data are a little bit higher. For multiple countries, we can comfortably settle on an elasticity of 2 or just below.

For the cutoff corresponding to higher education, the Latin America panel yields elasticities of 2.1-2.2. The values based on the Caselli & Coleman data and Brazil (with a year trend) are about 1.8 while those from the newer cross-section and the long range panel are inbetween. A first attempt at distinguishing between short run and long run effects also produces an estimate of 2, so we again settle on an elasticity of 2.

Given the variations in country coverage, data source, skill definition and time period as well as in estimation method or specification, this is a robust result. Furthermore, some (but by no means all) of our estimates are precise and produce relatively narrow ranges for the elasticity. The traditional elasticity estimates would have wide confidence intervals and big variations in point estimates, while many would be discarded as nonsense regressions because they produce elasticity values that lie outside of the feasible set.

In a framework that allows for endogenous SBTC, the elasticity of 2 means that increased skill supply leads to the acquisition of more skill-biased technologies and that the effect this has on the wage premium is equal in magnitude to the downward substitution effect. The similarity in magnitude of these two forces is what leads to the small or absent correlation between skill intensity and the wage premium.

6 Alternatives

Some may argue that what appears to be a general absence of a negative correlation is due to specification issues or other empirical difficulties.

Measurement error: convex wages and schooling quality The wage premia and other data are prone to measurement error. Measurement error can cause attenuation bias, which tends to move estimated coefficients towards zero. We first note that this would not "solve" the problem of positive elasticities; the absence of any measurement error would make such elasticities more positive. Second, our newer data sets should have more reliable Mincerians and better matched data, yet the coefficients were closer to zero than in the CC data. Third, it is often the case that the inclusion of fixed effects magnifies the problem of measurement error, but we did not consistently see smaller coefficients when including fixed effects.

One particular form of measurement error could potentially have important consequences for our study. Many authors argue that the return to education is convex.²⁷ This means countries whose people tend to go to school less tend to have lower returns to education. In terms of Figure 3 for example, this means the true observations on the left of the diagram would be higher and those on the right of the diagram would be lower if the Mincerian returns used to construct the data accounted for convexity. This means that the true value of β is more positive / less negative than we have estimated.

This argument is part of the reason why we turned to the SEDLAC data. As described in section 4, the wage differentials were not constructed using Mincerian estimates but were taken directly from the data, so any non-linearities in returns would be taken into account. The SEDLAC estimates did not systematically differ from those elsewhere, which suggests our results are not being driven by convexity in the earnings profile.

Failure to account for schooling quality could also affect the results. However, we don't think this drives ours for three reasons. First, if we assume that those countries with fewer skilled people are also those with worse quality education, then adjusting for school quality would if anything make the correlation smaller and hence bring σ even closer to 2.²⁸ Second, Caselli (2005) finds very little of the observed residuals in cross-country income differences can be explained by schooling quality differences. Caselli & Coleman (2006) use this to argue that the positive correlation between skill supply and the relative productivity of skilled workers across countries is not attributable to schooling quality differentials. Third, Meschi & Vivarelli (2009) use an index of household income inequality and two types of skill supply data, including a measure that adjusts for quality. They have a panel of 65 developing countries and more than 800 observations yet find no significant correlation between relative income inequality and relative skill supply with both types of skill data. Their research suggests that this is not affecting our results.

Capital Some studies include the capital labour ratio in specifications. Fallon & Layard (1975) use two-stage least squares on cross-country data to produce an elasticity between skilled and unskilled labour of 1.67.²⁹ Krusell, Ohanian, Rios-Rull and Violante (2000) employ pseudo-

²⁷See for example the note by Colclough, Kingdon & Patrinos (2009) and the references therein.

²⁸Graphically, it means the observations on the right of the scatterplot should be further to the right and those on the left are further to the left. Whether slightly positive or negative, the slope would become flatter.

²⁹This is based on their "raw labor" approach.

maximum likelihood techniques on US time series to generate an elasticity of (also) 1.67.

Our long run steady-state model makes the quantity and variety of machines and hence the observed level of capital (K) endogenous and hence estimation by OLS is invalid. Nonetheless, we use capital from the CC data set in column 5 of tables 2 and 3. The positive coefficient is consistent with capital-skill-complementarity because a rise in the capital:labour ratio increases the relative marginal product of skilled labour. Capital-skill-complementarity (CSC) is found in many studies, most recently and comprehensively in Duffy et al (2004) and in Henderson (2009) using production functions. It is not obvious how one interprets our estimates of β in our model and with exogenous capital so we do not present elasticity calculations. However, in terms of our framework, $K = T^s X + T^u Z$. We obviously cannot distinguish between skilled and unskilled capital in the data. When $\sigma > 1$, a rise in X and/or T^s would raise the observed capital aggregate and simultaneously have a positive effect on the relative productivity of skilled workers and hence the skill premium. Thus, our model is consistent with what people refer to as CSC.

Nonetheless, Caselli & Coleman (2006) still find evidence of endogenous skill bias even after accounting for CSC. Furthermore, Berman & Machin (2000) argue that, even if CSC holds, capital deepening has not occurred in sufficient quantities to account for labour demand shifts in developing countries. Affording ourselves a generous structural interpretation, we would expect controls for technology/capital to make the correlation between relative wages and the relative skill supply more negative, which can be seen by comparing columns 5 and 2 in tables 2 and 3.

The insignificance of the capital:labour ratio in our relative demand specification can be used to argue that CSC does not feature strongly and hence capital is separable. This can be rationalized because our model endogenises capital. A more traditional explanation is based on Ciccone & Peri (2005). They marshal labour's constant share of output as an argument that capital is separable and hence can be omitted without affecting estimates of the elasticity between skilled and unskilled labour.

One elasticity to rule them all? We have spent much space commenting on the paucity of reliable estimates for the elasticity of substitution, but pause to reflect on the enterprise of estimating a single elasticity for developing countries or even the whole world.

One alternative is to follow the approach of Mello (2008) and numerically calculate the elasticity for each country that reconciles its wage premium with its relative skill supply. He notes the point made by Diamond, McFadden & Rodriquez (1978) that it is impossible to distinguish between factor biased technical change and changes in the elasticity of substitution when characterizing sources of factor-price differentials. Therefore, instead of assuming a constant value of σ across countries and allowing relative productivity (T) to vary as done here and by CC, one can assume a constant T and allow σ to vary. Doing so using similar data to the CC crosssection yields an average value of 3.4 for developing countries at the higher education cutoff.³⁰ The primary education cutoff yields an average of close to zero, which implies the inputs are perfect substitutes on average across the world. However, as noted by Mello (2008), many of these values produce nonsense elasticities for individual countries.

However, for better or worse, researchers seem to have a strong appetite for a single consensus

³⁰Thanks to Marcelo Mello for providing the data.

elasticity parameter to include in their models. With one value of σ , it is possible to back out how T varies across countries. For example, using $T = W^{\frac{\sigma}{\sigma-1}}Q^{\frac{1}{\sigma-1}}$ from equation (9) and estimates from column 4 of Table 3, we plot $\ln(T)$ against the relative factor shares.³¹ In Figure 6, we see a picture entirely consistent with equation (18). In other words, countries where the factor share of skilled labour is relatively high have relatively more skill-biased technologies. Analogously, Caselli & Coleman (2000:23) note a strong positive correlation between relative factor shares and the productivities of skilled workers relative to unskilled workers, which they interpret as the relative numbers of machines skilled workers have. In both cases, this is consistent with the argument that a higher factor share raises the attractiveness of the technology complementing that factor such that technologies are appropriate to that country's endowment (Atkinson & Stiglitz, 1969).

Another alternative is to turn to individual country-level studies. We included an example for Brazil, but the next longest time span was for Argentina with 16 observations. We can wait for this data set to grow, but an alternative is firm-level data. Fajnzylber & Maloney (2001) note that only a handful of firm-level developing country studies exist. For example, Teal (2000) estimates elasticities of 0.28 (fixed effects) or 2.2 (no fixed effects) for Ghanaian firms. Fajnzylber & Maloney (2001) estimate firm labour demand elasticities. Using this, we derive substitution elasticities of 0.33 (Chile), 0.26 (Mexico) and 0.38 (Colombia).³² Knight & Sabot (1987) study East Africa. Their Table 1 produces two negative coefficients, three positive coefficients below 2 and one coefficient of 2.38.

We note however that our framework is not applicable to the estimation and interpretation of estimates using firm level data. For one, it would be questionable to have wages on the left hand side and to condition on labour quantities on the right hand side. While firms may choose inputs like capital, the availability of particular technologies is no longer endogenous in the same sense. The study by Teal (2000) is based on direct estimates of the underlying technology, from which the elasticities are inferred. This raises the question of whether or not this approach is more reliable or appropriate.

Production/cost functions Instead of first order conditions, one can estimate the parameters of an underlying technology and infer the elasticities from that. For example, Caselli & Coleman (2000) estimate a value of 1.32 from a production function directly using a cross-section of countries. The variation in estimates we discussed earlier is in part due to the inversion of the estimated coefficient. For this reason, using a production function approach can also generate high values. For example, Klenow & Rodriguez-Clare (1997) generate a value of 65 for a crosssection of countries. Production function parameters from Duffy et al (2004) imply elasticities ranging from 0.3 to 5.25. This varies according to the choice of cutoff, estimation method and data.

While some firm-level studies mentioned are of cost functions or their derived demands, we are not aware of cross-country or time-series studies based on cost functions. All the education-based studies reviewed in Hamermesh (1993) stem from first-order-conditions. With reference to studies of substitution between production and non-production workers, however, there is tentative evidence that elasticities based on (translog) production functions are higher than

³¹This is for the higher cutoff but similar figures are generated for the primary cutoff or the previous dataset.

 $^{^{32}}$ These are technically Morishima elasticities; see Blackorby & Russel (1989).

those from cost functions. None of these elasticities exceeds 6, which is low given the range we have seen, but Hamermesh (1993) argues that production functions produce less reliable estimates. Analogous to reduced form elasticities calculated by inverting the regression coefficient, Hamermesh suggests the standard errors generated by inverting production function parameters of these sorts are very big. Studies based on CES functions need not have this problem but we have noted the structural assumptions imposed can affect the results (cf Duffy et al (2004); Krusell et al, 2000). As argued in Hamermesh (1993), the sensitivity to choice of cutoff for aggregation purposes strongly suggests that the separability assumptions made to construct the labour aggregates are invalid.³³

Our reading of the Hamermesh (1993) studies on production vs non-production workers is that the use of aggregate vs micro or time series vs cross-section data does not affect the results systematically. Also, the choice between the parsimonious relative demand equation and potentially complex production technologies is not consistently influencing elasticity estimates in a way that could explain the large numbers cited in the literature. We saw that large estimates (65) can be generated by production functions or relative demand equations in new studies or old and across skill definition.

Endogeneity Identification and interprepation of the β coefficient relies on the assumption that quantities affect prices and not the other way around. Empirically, it is more appropriate to model factor quantities as exogenous and factor prices as endogenous with macroeconomic data and vice versa for microeconomic data (Hamermesh, 1993). However, it may be the case that the wage premium affects the skill supply through migration. This simultaneity concern motivates the use of compulsory schooling laws as instruments by Ciccone & Peri (2005) for US States.

Migration is less likely to be an issue for cross-country data, but relative wages can affect the skill supply by influencing the decision to stay in school. In this paper, we take the view that, in developing countries, there is a binding cost constraint on acquiring the level of education desired at given wage premia. From a policy point of view, our thought experiment is a reform that reduces the costs of acquiring education. For example, education access expanded markedly to non-whites after the end of Apartheid in South Africa (van der Berg, 2001) and to women in China (Lavely, Zhenyu, Bohua & Freedman, 1990). Elsewhere in Africa, the specific government objective was the universal availability of primary education (Knight & Sabot, 1987) while, in Taiwan, access to higher education is strictly controlled by the government (Gindling & Sun, 2002). Our final example comes from the West Bank and Gaza Strip, where there were no higher education institutions in 1972 but 20 by the mid 1980s. This increased access - students had to go abroad before - resulted in the small region being flooded with college graduates within a short space of time (Angrist, 1995).

We note that the theory model we have built eliminates the simultaneity issue because demand becomes a function of supply. Furthermore, the results in Acemoglu (1998) suggest that the insights presented here are unchanged after allowing the acquisition of schooling to respond endogenously. Furthermore, we constructed our cross-section data and long range panel such that the labour quantities predate the wages in order to reduce feedback effects.

Nonetheless, we acknowledge that we cannot fully rule out reverse causality, so what would be

³³Clark et al (1988) formally test for separability and reject it convincingly.

the implications for our estimates? Following the standard discussion (for example Wooldridge, 2002:62) on the assumption that there is a positive correlation between shifts in relative labour supply and labour demand, a negative β coefficient estimate is too small (in absolute value terms) relative to the true value, which is more negative. A positive β coefficient estimate would be too high relative to the true value, which is closer to zero, which implies the true value of σ is closer to two. We note that Ciccone & Peri (2005, table 4) yield estimates of $\tilde{\sigma} \approx 3$ based on OLS while their preferred estimate is $\tilde{\sigma} \approx 1.5$. In our framework, this implies $\sigma \approx 1.67$ and $\sigma \approx 1.33$ for the OLS and preferred estimates respectively. Together, this analysis suggests that, if there is any reverse causation, the "true" value of σ for developing countries is not 2 but something slightly lower. We remark that table 6 in Ciccone & Peri suggests that their use of instruments does not make their result different to previous studies based on OLS. Finally, we note that the implications of endogeneity for estimates of σ are mechanically much less severe than for estimates of $\tilde{\sigma}$, making our approach more robust to endogeneity or other potential sources of bias.

7 Conclusion

This paper informs what happens to the wage premium if there is an increase in the relative supply of skilled workers. Drawing on traditional factor demand theory, researchers have sought to estimate the impact by measuring the substitutability between skilled and unskilled workers. Drawing on Acemoglu (1998) and Kiley (1999), we have introduced a model of directed technical change for developing countries. Like these models, the relative attractiveness of skill-biased technologies is affected by the relative supply of skilled labour. However, our adaptation to developing countries notes that these countries have limited R&D. Therefore, we model a potential licence holder in a developing country who is considering whether or not to acquire the right to import machines of a particular type from abroad to sell locally.

The key parameter for understanding the impact of relative skill supply on the wage premium is the elasticity of substitution, σ . This paper has identified two issues with existing estimates of this parameter and addresses them accordingly.

The first is that, despite an enthusiasm for rallying around a parameter value of 1.4, existing estimates vary widely. This is regardless of the specification estimated, the type of data used or the way skilled labour is defined. We make sense of this by using our model of SBTC to justify an alternative interpretation of the regression coefficients. A regression of the wage premium on relative skill supply maps exactly to our model. Because it already incorporates the effects of SBTC, the regression coefficient is $\sigma - 2$, not $-\frac{1}{\sigma}$. Viewed in this way, elasticities within the consensus range are still in the range. More importantly, those coefficient estimates of close to zero, which would traditionally imply near perfect elasticities, actually re-enforce the consensus with elasticities close to 2.

The very low correlation between wage premia and quantities is viewed as technical change cancelling the substitution effect rather than evidence of perfect substitution. In other words, this paper asks you to believe Stata software came into being and features are continually added because more people know some econometrics. The alternative is that regressions could be run by an arbitrarily large number of people who know no econometrics. In our framework, positive correlations that were hitherto nonsensical and hence probably not observed in the literature due to publication bias are in fact plausible because they imply an elasticity in excess of 2.

The second issue is a lack of recent reliable estimates for developing countries. We therefore use four types of data to estimate the elasticity of substitution for these countries. We have used cross sections, a long range panel, Brazilian time series and a Latin American panel. We have defined skilled labour as those who have been to college or whether they need only have completed primary school.

Our estimates consistently imply the elasticity is about 2, though the estimate may be a little high due to endogeneity bias. If inputted into models of this class, a value of 2 implies a rise in the skill supply would neither reduce the skill premium nor raise it. While the data directly shows the absence of a correlation between relative quantities and prices, the model offers a more credible explanation for it. It is not because skilled and unskilled workers are perfect substitutes, but because technology changes endogenously.

While models of this class have been used to account for past increases in wage inequality, this has not been our aim. While the potential roles of trade and other sources of SBTC may be important, our contribution suggests that expanded education access, which may have been a government response to observed rises in wage inequality, would have no downward effect. This would be observationally equivalent to witnessing a simultaneous rise in skill supply and wage inequality.

Our estimate of 2 can also be used in a broad range of models, including those seeking to explain cross-country differences in skill intensity, productivity or income. We have noted that it also implies increasing the relative supply of skills is not an effective way to reduce wage inequality. In turn, this weakens the argument for the deployment of state resources towards education in pursuit of this goal.

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	β	$\tilde{\sigma}=-\frac{1}{\beta}$	σ= β+2
	-1	1	1.000
Consensus Range	-0.667	1.5	1.333
	-0.5	2	1.500
Katz & Murphy (1992)	-0.709	1.41	1.291
Bowles (1970) equation 7	-0.124	8.05	1.876
Bowles (1970) equation 6	-0.005	202	1.995
PH equation R7	-0.001	1000	1.999
PH equation R6	0.050	-20	2.050
PH equation R5	-0.476	2.10	1.524

Table 1: Existing coefficients estimated and implied elasticities: The first three rows make a mapping from the consensus range for the elasticity $(\tilde{\sigma})$ to estimated regression coefficients $(\beta = -\frac{1}{\tilde{\sigma}})$ and to what the elasticity is once one accounts for directed technical change ($\sigma = \beta + 2$). In the remaining rows, β gives the regression coefficients actually estimated in previous studies, together with the elasticities implied by those studies ($\tilde{\sigma} = -\frac{1}{\beta}$) and those implied by the directed technical change framework ($\sigma = \beta + 2$). PH refers to Psacharopoulos & Hinchliffe (1973).

	1	2	3	4	5
	All	Developing	Open	LAD	Capital
log(Q)	-0.0651***	-0.0826*	-0.0814**	-0.0624	-0.137**
	0.0196	0.0408	0.0392	0.0865	0.0547
Openness			0.0962*	0.163	
			0.0516	0.113	
log(K)					0.0637
					0.0438
constant	0.398***	0.412***	0.364***	0.337***	-0.189
	0.0215	0.0274	0.0368	0.0804	0.414
Ν	52	32	32	33	32
R-sq	0.18	0.12	0.214		0.18
$ ilde{\sigma}$ (lower bound)	6.06	-0.10	0.19	-29.36	
$\tilde{\sigma}$ (estimate)	15.37	12.11	12.29	16.03	
$ ilde{\sigma}$ (upper bound)	24.68	24.32	24.39	61.41	
σ (lower bound)	1.90	1.83	1.84	1.76	
σ (estimate)	1.93	1.92	1.92	1.94	
σ (upper bound)	1.97	2.00	2.00	2.11	

Table 2: Cross-country regressions based on Caselli & Coleman (2006) data and where people are skilled if they have completed primary schooling. The dependent variable is the log of the skill premium. Estimation is by OLS except in column 4. Column 1 is for the full sample of rich and poor countries. Column 2 onwards is restricted to developing countries. Column 3 introduces a measure of openness. Column 4 uses a Least Absolute Deviations Estimator. Column 5 controls for the capital stock. $\tilde{\sigma} = -\frac{1}{\beta}$ and $\sigma = \beta + 2$, where β is the coefficient on log(Q). *10% ** 5% *** 1%; standard errors in italics.

	1	2	3	4	5
	All	Developing	Open	LAD	Capital
log(Q)	-0.250***	-0.16	-0.133	-0.263*	-0.222
	0.0776	0.104	0.103	0.148	0.132
Openness			0.302	0.4	
			0.191	0.304	
log(K)					0.115
					0.149
constant	0.602**	0.981***	0.915**	0.579	-0.284
	0.227	0.339	0.333	0.482	1.679
Ν	52	32	32	33	32
R-sq	0.172	0.073	0.146		0.092
$\tilde{\sigma}$ (lower bound)	1.51	-2.05	-4.43	-0.57	
$\tilde{\sigma}$ (estimate)	4.00	6.25	7.54	3.80	
$ ilde{\sigma}$ (upper bound)	6.50	14.56	19.51	8.16	
σ (lower bound)	1.59	1.63	1.66	1.43	
σ (estimate)	1.75	1.84	1.87	1.74	
σ (upper bound)	1.91	2.05	2.08	2.04	

Table 3: Cross-country regressions based on Caselli & Coleman (2006) data and where people are skilled if they have some tertiary education. The dependent variable is the log of the skill premium. Estimation is by OLS except in column 4. Column 1 is for the full sample of rich and poor countries. Column 2 onwards is restricted to developing countries. Column 3 introduces a measure of openness. Column 4 uses a Least Absolute Deviations Estimator. Column 5 controls for the capital stock. $\tilde{\sigma} = -\frac{1}{\beta}$ and $\sigma = \beta + 2$, where β is the coefficient on log(Q). *10% ** 5% *** 1%; standard errors in italics.

	1	2	3	4	5	6	
			Primary				
	Simple	Open	LAD	Simple	Open	LAD	
log(Q)	0.0792	0.0572	-0.0439	0.0182	0.0176	-0.0000	
	0.0783	0.0775	0.135	0.0198	0.0193	0.0339	
Openness		0.231*	0.297		0.0701*	0.0836	
		0.134	0.252		0.0376	0.0681	
constant	1.550***	1.381***	1.101**	0.375***	0.344***	0.372***	
	0.238	0.252	0.457	0.0193	0.0253	0.0457	
Ν	42	42	43	42	42	43	
R-sq	0.025	0.094		0.021	0.101		
$\tilde{\sigma}$ (estimate)	-12.62	-17.48	22.77	-54.85	-56.67	7.28E+17	
σ (estimate)	2.08	2.06	1.96	2.02	2.02	2	

Table 4: Cross-country estimates based on new data for developing countries. The dependent variable is the log of the skill premium. Estimation is by OLS in columns 1,2,4 & 5 and by LAD in columns 3 & 6. *** 1% * 10%; standard errors are in italics. Columns 1-3 present results where the skilled/unskilled cutoff is at the tertiary level and columns 4-6 present results where the cutoff is at primary school.

	1	2	3	4	5	6
			Higher			
	Pooled	FE	Open	Pooled	FE	Open
log(Q)	0.014	0.104*	0.104*	-0.0264	-0.0078	-0.0078
	0.0244	0.0493	0.0493	0.0218	0.0439	0.0439
Openness			-0.066			-0.117
			0.138			0.163
constant	0.441*	0.516*	0.582*	0.344*	0.435	0.552*
	0.0243	0.135	0.109	0.0784	0.273	0.209
Country fe?	Ν	Y	Y	N	Y	Y
Ν	40	40	40	40	40	40
R-sq	0.009	0.566	0.566	0.037	0.466	0.466
$\tilde{\sigma}$ (estimate)	-71.429	-9.615	-9.615	37.879	127.877	127.877
σ (estimate)	2.014	2.104	2.104	1.974	1.992	1.992

Table 5: Estimates based on developing countries in a long-range panel. The dependent variable is the log of the skill premium. Estimation is by OLS but country-specific dummies are included in columns 2, 3, 5 & 6. *** 1% * 10%; standard errors are in italics. Columns 1-3 present results where the skilled/unskilled cutoff is at the end of primary school and columns 4-6 present results where the cutoff is at the tertiary level.

	1	2	3	4	5	6	7	8	
		Primary		Higher			Higher (differences)		
log(Q)	-0.240***	-0.328	-0.197***	0.411***	-0.209	0.415***			
	-0.0579	-0.42	-0.0471	-0.111	-0.289	-0.12			
Year		0.00543			0.0210**				
		-0.0257			-0.00915				
Trade:GDP r	atio		-0.0071***			-0.0003			
			-0.0021			-0.00268			
Δlog(Q)							-0.618*	-0.499**	
							-0.335	-0.177	
Correction te	erm⁺							-0.916***	
								-0.132	
constant	0.627***	-10.25	0.795***	2.151***	-41.27**	2.137***	0.0396	0.0383***	
	-0.0646	-51.47	-0.0699	-0.291	-18.96	-0.362	-0.0249	-0.013	
elasticity	1.76	1.67	1.80	2.41	1.79	2.42	1.62~	2.00~	
Ν	22	22	22	22	22	22	20	20	
R-sq	0.923	0.923	0.955	0.795	0.843	0.795	0.159	0.781	

Table 6: Estimates based on Brazilian (SEDLAC) annual observations. In columns 1-6, the dependent variable is the log of the skill premium, where workers are skilled if they have at least nine years of schooling in columns 1-3 and at least thirteen in column 4-6. In columns 7-8, the dependent variable is the first difference of the log of the skill premium, where workers are skilled if they have at least thirteen years' schooling. Estimation is by OLS. *** 1% * 10%; standard errors are in italics. ⁺ the correction term is residual from regression in column 5; standard errors are only indicative in this specification. ⁻ the elasticity is calculated using the inverse of the $\Delta \log(Q)$ coefficient in columns 7 &8.

	1	2	3	4	5	6	7	8	9	10
	Primary						Hig	her		
log(Q)	-0.196***	-0.0826**	-0.024	-0.0295	-0.0966***	0.197***	0.124**	0.123**	0.202***	0.163***
	0.0173	0.0412	0.0616	0.0619	0.024	0.0323	0.0508	0.0513	0.0703	0.0593
Year		-0.00408*	-0.00606*	-0.00471			0.00384*	0.00375*	-0.000533	0.00952
		0.0021	0.00338	0.00364			0.00206	0.00212	0.00337	0.00996
Trade:GDP				-0.000717				0.000146		
ratio				0.000725				0.000734		
constant	0.437***	8.592**	12.44*	9.78	0.585***	1.403***	-6.833	-6.529	2.194	-17.66
	0.0101	4.165	6.678	7.2	0.0513	0.106	4.187	4.283	6.783	19.96
Sigma	1.8	1.92	1.98	1.97	1.9	2.2	2.12	2.12	2.2	2.16
Ν	182	182	182	182	182	182	182	182	182	182
R-sq	0.416	0.819	0.87	0.871	0.083	0.733	0.739	0.739	0.782	0.809
adj. R-sq	0.413	0.798	0.836	0.836	0.078	0.703	0.708	0.706	0.724	0.762
Country fe	N	Y	Y	Y	N	Y	Y	Y	Y	Y
Data fe	Ν	Ν	Y	Y	N	Ν	Ν	Ν	Y	Ν
Country trends	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Y

Table 7: Panel of Latin American Countries from SEDLAC data. The dependent variable is the log of the skill premium, where workers are skilled if they have at least nine years of schooling (columns1-4) or at least thirteen years of education (columns 5-10). Estimation is by OLS but with country and/or data fixed effects. *** 1% ** 5% * 10%; standard errors are in italics.



Figure 1: Caselli & Coleman (2006) data where people are defined as skilled if they have completed primary school. The wage premium is on the y-axis and relative skill supply is on the x-axis (variables in logs).



Figure 2: Caselli & Coleman (2006) data where people are defined as skilled if they have some tertiary education. The wage premium is on the y-axis and relative skill supply is on the x-axis (variables in logs).



Figure 3: Newer cross-country data (excluding Jamaica) where people are defined as skilled if they have some tertiary education. The wage premium is on the y-axis and relative skill supply is on the x-axis (variables in logs).



Figure 4: Brazilian data (taken from SEDLAC) where people are defined as skilled if they have at least nine years of schooling, which is roughly equivalent to having completed primary school. The wage premium is on the y-axis and relative skill supply is on the x-axis (variables in logs).



Figure 5: Brazilian data (taken from SEDLAC) where people are defined as skilled if they have at least thirteen years of schooling, which is roughly equivalent to having some tertiary education. The wage premium is on the y-axis and relative skill supply is on the x-axis (variables in logs).



Figure 6: Plot of relative technologies (y-axis) against relative factor shares (x-axis) (variables in logs). The factor shares are taken from the data in Caselli & Coleman (2006), where workers are skilled if they have some tertiary education. The relative technologies are calculated using sigma estimates from column 4 of Table 3 and equation (9).