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The Elasticity of Substitution Between Skilled and Unskilled Labor In Developing Countries: A Directed Technical Change Perspective

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The Elasticity of Substitution Between Skilled and Unskilled Labor In Developing Countries: A Directed Technical Change Perspective

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ABSTRACT: We develop a model of endogenous skill-biased technical change in developing countries. The endogenous response to a rise in skill supply counters the traditional substitution effect and dampens its role in reducing wage inequality. The model re-enforces consensus estimates of the elasticity of substitution between more/less educated workers by reconciling dispersed existing estimates. It also rationalizes estimates that were hitherto deemed implausible or model-inconsistent. We produce new estimates for developing countries with a novel global panel (finding values at or just above 2) and with Latin American data that facilitates analysis of dynamics (which reduce estimates to 1.7-1.8). We therefore shed new light on a parameter that is crucial for inequality, growth, and other key macroeconomic questions.

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The elasticity of substitution between skilled and unskilled labor in developing countries: a directed technical change perspective

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1 Introduction

The elasticity of substitution between skilled and unskilled labor, σ, is crucial for determining variations in income within and across countries. By making skilled workers less scarce relative to unskilled workers, expanded education can reduce wage differentials within a country. The effect of such a policy depends on σ. A lower value for σ tends to result in a bigger reduction in inequality, making the parameter crucial for studies of the potential contribution of increases in the supply of educated workers to reducing or containing inequality.[1] In reverse, a higher value for σ means that an exogenous change in relative factor prices, such as a rise in the minimum wage, would have a bigger effect on the demand for skilled and unskilled workers (Hamermesh, 1993).[2] One argument for why education should be subsidized by the state is that there may be positive externalities to education, which can be measured by comparing the returns to education estimated with macroeconomic data to those from microeconomic earnings functions. Such comparisons rely on σ (Teulins & van Rens, 2008). Policy-makers often view educational attainment as a way to improve overall income, yet the growth accounting literature includes an unsettled debate on human capital's importance, in part because of sensitivity of results to σ.[3] σ also informs the potential for skill-biasing effects of trade and the effects of immigration on wages.[4]

Initial attempts to estimate the elasticity produced wildly dispersed results. For example, Freeman (1986) documents values of up to 1000. Authors subsequently coalesced around a value of about 1.5 attributable to Katz & Murphy (1992) and re-enforced by subsequent studies (Ciccone & Peri, 2005). One concern is that these U.S. based studies may not be representative emerging market and developing economies (EMDEs), which tend to have higher inequality and which are the focus of the growth accounting literature. Havrenek, Irsova, Laslopova & Zeynalova (2022) (hence HILZ) note the average of available estimates is higher and that the range is considerable. Moreover, they argue that publication bias excludes many estimates that are deemed implausibly high or of the incorrect sign. Using meta-study methods to control for publication bias pushes the average elasticity to 10. Controlling for econometric bias in estimation brings this value back down partially to 3.7 with a 95% confidence interval of about 18. For the subset of developing countries, the average elasticity is 2.1 with an interval of 3.

The primary contribution of this paper is to explain how a wide range of estimates that includes allegedly implausible values, publication bias (its causes and consequences), and

[1]Fernandez & Messina (2018), Manacorda et.al (2010).

[2]This study is part of a broader body of work on input substitution. Karabarbounis & Neiman (2013) explain part of labor's decreasing share of income in terms of cheaper capital and the elasticity of substitution between labor and capital.

[3]Klenow & Rodriguez-Clare (1997), Hendricks (2002), Caselli (2005), Jones (2014), Caselli & Ciccone (2019).

[4]Epifani & Gancia (2008), Thoenig & Verdier (2003), Borjas, Grogger & Hanson (2012).

econometric estimation bias can be effectively mitigated by reinterpreting the reduced-form empirical relationship between the skill premium and relative skill supply. We illustrate this using existing studies. Another important contribution is our new set of estimates for developing countries.

The canonical approach in this literature is based on derived relative demand curves that produce a relationship between the skill premium (in logs) and the ratio of skilled to unskilled labor (in logs). Our main innovation is to derive this equation from a model incorporating endogenous skill-biased technical change so that

$$\text{skill premium} = (\sigma - 2)^* \,(\text{relative skill supply})\,, \tag{1}$$

where the coefficient, β, on skill supply is $\sigma - 2$, not $-\frac{1}{\sigma}$ as traditionally inferred. Under the traditional usage, even modest differences in β estimates lead to large variations in elasticity estimates. Even modest attenuation bias, which artificially pushes the coefficient estimate to zero, has potentially large effects on the parameter of interest. Formal tests of statistical significance with the null hypothesis that $\beta = 0$ implies a value of infinity for σ, while positive coefficient estimates are outside the feasible set. These factors have likely caused many studies to be discarded. In contrast, equation (1) formally permits a coefficient that is positive, negative or zero in terms of hypothesis testing in a way that is useful to policymakers, produces less uncertainty in elasticity estimates for use in other models, softens the implications of bias, and consequently reduces the risks of unnecessarily discarded studies.

To justify our proposed interpretation, we use a model of endogenous skill-biased technical change (SBTC) in developing countries. New technologies do not automatically favour skilled workers and there are many examples where they didn't. As modelled in Acemoglu (1998) and Kiley (1999) for rich countries, 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. In these models, larger values of σ make the directed effect more likely to dominate the substitution effect. The models help explain why, despite a steady rise in the supply of skilled workers in rich countries, wage inequality increased.

Caselli & Coleman (2006) argue that developing countries also apply technologies according to their endowments using as evidence a cross-country positive correlation between relative skill supply and adoption of skill-biased technologies. This suggests directed technical change is relevant for developing countries too. In our model, $\sigma > 2$ means wage inequality rises while $\sigma < 2$ means it falls following a rise in relative skill supply. Our model also accounts for the possibility that developing countries, particularly middle income countries, absorb more skill-biased technologies if those are the technologies being produced by developed economies (Berman & Machin, 2000, Raveh & Resheff, 2016). Accordingly, our paper fits into the literature on the nature of technological change, which has both positive and normative aspects. As Atkinson (2015) notes, *"The direction of technological change should be an explicit concern of policy-makers"*.

Section 2 builds a formal model with an endogenous skill bias of technical change in developing countries and provides evidence thereof. 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, more robust to bias, and less likely to produce counterintuitive interpretations, and may therefore resurrect some abandoned studies. Section 4 applies the framework to new data with a focus on EMDEs. Specifically, we construct a global panel dataset that to our knowledge is unmatched in country coverage. We also use data from Latin America, which allows us to investigate dynamic effects for the broader region, focus on the hitherto underexplored Central America region, and study Brazil. For the global sample, our estimated β coefficients are slightly positive, which would be theory-inconsistent under the traditional interpretation but imply elasticities of 2 or slightly higher. For our Latin America data, our estimated β coefficients are generally around zero, which implies traditional elasticities that are very large or incorrectly signed but alternatively imply, in our framework, $\sigma \approx 2$. The dynamic approach yields estimates of $\sigma = 1.7 - 1.8$. Section 5 derives implications and proposes extensions to our research.

2 Theory

This section describes the model. Production uses intermediates produced either with skilled labor and multiple varieties of skill-complementary machines or unskilled labor and multiple varieties of machines that complement unskilled labor. Each machine variety is provided by a holder of the licence to that machine. The skill premium is influenced by the supply of skilled labor relative to unskilled labor and by the number of different machines that complement skilled labor relative to the number of different machines that complement unskilled labor. The relative number of skilled machines is determined by the relative supply of skills and by the global relative availability of licences for purchase.

2.1 The population and labor 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

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

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:

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

Final output is produced by perfect competitors using two intermediate inputs purchased from intermediates producers. $\epsilon > 0$ is the finite elasticity of substitution between intermediate inputs. Individual producers take the price of final output (unity) and prices of intermediate inputs as given before choosing their optimal quantities of intermediates. For the economy to be in equilibrium, intermediates must have prices p^s and p^u such that:

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

Building on Romer (1990), intermediates are produced by i perfectly competitive firms, where y^s uses skilled labor, L_{it}^s, and T^s different machines while y^u uses unskilled labor, L_{it}^u, and T^u different machines. Specifically, $y_{it}^s = (L_{it}^s)^{1-\alpha} \sum_{j=1}^{T_t^s} X_{ijt}^{\alpha}$ and $y_{it}^u = A(L_{it}^u)^{1-\alpha} \sum_{j=1}^{T_t^u} Z_{ijt}^{\alpha}$. 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 labor. Similarly, Z_{ijt} is the quantity of each of T^u machines complementing unskilled labor. Capital depreciates fully in each period. $A < 1$ for unskilled labor makes production a function of effective units of labor. We refer to T^s and T^u as the number of skilled and unskilled machines.

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 $X_{ijt} = \left(\alpha \frac{p_t^s}{p_{jt}^X} \right)^{\frac{1}{1-\alpha}} L_{it}^s$.

The price of each skilled machine, p_{jt}^X, is set by the firm holding the licence for that type of machine. Technology importers 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 exported 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 labor. Using the fact that final goods are produced using a constant returns to scale technology, economy-wide demand for each skill-biased machine is:

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

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

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

Economy-wide output of skilled and unskilled intermediates is:

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

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

As in models of this class (Romer, 1990), there are constant returns to increases in the variety of inputs. This is why 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. A change in the ratio of T^s to T^u would also require prices to change. After substituting from (5) and (6), combining (7) and (4), we can write

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

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 labor. 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. Producers of intermediate goods hire labor such that wage equals marginal revenue product. For equilibrium in the economy, relative wages are given by:

$$W_t \equiv \frac{W_t^s}{W_t^u} = T_t p_t = T_t^{\frac{\sigma-1}{\sigma}} Q_t^{\frac{-1}{\sigma}} \tag{9}$$

Equation (9) mirrors the findings of Acemoglu (2002). 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 labor 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 labor. Second, relative technologies, the effect of which can be positive or negative. A rise in T raises the relative physical productivity of skilled labor. 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 endogenous to the skill supply.

2.4 Technology adoption

Empirical background Before proceeding with the model, we present some relevant facts on technical change in developing countries. Most countries do not develop their own technologies but acquire them from abroad through imports or other forms of technology transfer (Eaton & Kortum, 2001; Savvides & Zachariadis, 2005). Importantly, such technical change imports need not be skill-biased. Caselli & Wilson (2004) find that skill-abundant countries import machines that are more complementary with skilled labor. Gallego (2012) finds a strong link between the degree of skill upgrading in the U.S. and skill upgrading in Chile that is consistent with the international transmission of the bias of technical change. Raveh and Reshef (2016) empirically show that some types of imported capital are more complementary to unskilled workers and thus can lower the skill premium. For developing countries, it is therefore pertinent to model technology acquisition as a purchase from abroad rather than as a result of R&D and home production.

More importantly for this paper, countries do not absorb any new methods automatically, but consider domestic factor market conditions before choosing appropriate technologies. For example, Knight (1979) notes that the introduction of the color bar restricted the supply of skills in South Africa and encouraged capital that substituted for skilled workers and that the relaxation of the color bar encouraged substitution of machines for unskilled labor. Acemoglu & Zilibotti (2001) note that multinationals make technologies available to their various developing country subsidiaries according to the relative availability of skilled workers. For example, Kenya used the hammer mill to grind maize rather than the roller mill because of abundant unskilled labor. In Tanzania and Thailand, a new method for producing cans was not widely adopted because insufficient skilled workers were available to work with them. Fransman (1985) presents case studies of countries adapting overseas technologies to local factor supplies, while Esposito & Stehrer (2009) find econometric support for the relationship. Christenko, Martinaitis & Krūminas (2023) concude that the Baltics experienced technological upgrading that favored their abundant unskilled workers.[5]

[5]Blum (2009) find evidence consistent with technical change that favors the more expensive scarce factor (Hicks, 1963), which means that an increase in the supply of skilled labor would have an amplified negative effect on the skill premium. As shown in Behar (2013), technology adoption can easily be expressed as a function of the relative factor share, which is the product of relative quantities and relative prices. If $\sigma > 1$,

The simultaneous presence of mostly skill-biased R&D in developed economies and abundant unskilled labor in EMDEs raises questions on the "appropriateness" of technology for EMDEs (Atkinson Stiglitz, 1969).[6]

Modelling technology adoption With this empirical background, we start by describing the decision of a potential licence holder whether or not to acquire a licence for a technology from abroad.[7] It costs one unit of Y exported to import one unit of a machine 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 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,

$$C_t \equiv \frac{C_t^S}{C_t^u} = \frac{R_t^u}{R_t^s} \equiv \frac{1}{R_t}, \tag{10}$$

where 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 value is the discounted present value of all future profits. Thus the value of any skilled licence at time t is $V_t^s =_i^\infty \left(P_{t+i}^X - 1\right) X_{t+i} (1+r)^{-i}$. 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 $\pi^x = \Omega \left(p_t^s\right)^{\frac{1}{1-\alpha}} q_t$. Therefore, the value of a skilled licence is:

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

The profit for an unskilled licence is $\pi^z = \Omega \left(p_t^u\right)^{\frac{1}{1-\alpha}} A(1-q_t)$ and

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

a rise in skill supply increases its factor share and makes skilled technologies relatively more valuable. For $\sigma < 1$, a rise in skill supply increases unskilled labor's factor share and makes unskilled technologies more valuable.

[6] Li (2020) suggests it has been more costly for MNCs to adapt to China's endowments than to simply use the available developed-country technology. Diao et al (2021) argue that this lack of adapted technology has held back employment in Ethiopia and Tanzania. In contrast, Okoye (2016) argues that it is developing countries' *insufficiently* skill-biased technology adoption that is a large contributor to productivity gaps.

[7] International trade enters this model but in a stylized way, namely developing countries export final goods and import technology (licences) and capital (machines). We are in this way not allowing for the role international trade can play in influencing the relative price of skilled products and hence the skill bias of technologies, as done in Behar (2016).

so that the ratio of values is:

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

For constant values of Q and R, equation (13) can be simplified to:

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

2.5 Steady-state and comparative statics

By free entry, $V^s = C^s$ and $V^u = C^u$ such that, in steady state,

$$V = C \tag{15}$$

and

$$T = Q^{\sigma-1} R^{\sigma} \tag{16}$$

As a natural extension to (14), the ratio of skilled to unskilled technologies is positively related to the relative skill supply when $\sigma > 1$. Moreover, by equation (9), we derive the final equation for the skill premium:

$$W = Q^{\sigma-2} R^{\sigma-1} \tag{17}$$

We remark that the precise exponent on W can be sensitive to functional form. If, as is appropriate for our small open developing country setting, technology is acquired by price takers from an international market, we obtain this particular exponent, which then forms the basis of our simple estimating equation.[8]

From a policy perspective, one can consider a reform that reduces the costs of acquiring education. For example, education access expanded markedly to non-whites in South Africa after the end of Apartheid (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, Province of China, access to higher education was controlled by the government (Gindling & Sun, 2002). In the West Bank and Gaza, there were no higher education institutions in 1972 but 20 by the mid 1980s, so the small area was quickly flooded with college graduates (Angrist,

[8] In rich country models of R&D the same exponent would apply if there are constant returns to R&D. Increasing or decreasing returns can affect the exponent and hence the threshold values of σ.

1995).[9]

Differentiating equation (17) yields:

$$\frac{d\log W}{d\log Q} = \frac{\partial \log W}{\partial \log T}\frac{d\log T}{d\log Q} - \frac{1}{\sigma} \tag{18a}$$

$$= \underbrace{\frac{\sigma-1}{\sigma}\sigma - 1}_{\text{Technology effect}} - \underbrace{\frac{1}{\sigma}}_{\text{substitution effect}} \tag{18b}$$

$$= \sigma - 2 \tag{18c}$$

The substitution effect on the far right comes from conventional labor demand theory and 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 labor. Second, 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 labor. 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. Analogously, the effect of skill supply on technology adoption has two effects and the net effect depends on σ. With reference to equation (14), a rise in skill supply makes the market for skilled technologies more attractive iff $\sigma > 1$. The reason for this is that the increase in available skilled labor, which makes skilled machines more attractive, also produces a reduction in skilled wages, which makes skilled machines less attractive. For $\sigma > 1$, the latter effect is small so that the former effect dominates. Conversely, $\sigma < 1$ means relative wages adjust a lot, so the overall effect is that more skilled labor makes skilled machines *less* attractive. However, as we already mentioned, $\sigma < 1$ also means that a reduction in T has a *positive* effect on the skill premium. Therefore, the technology import effect of skill supply on wages is (strictly) positive for any $\sigma \neq 1$.

Algebraically, this is consistent with Acemoglu (2002). To make the argument smoother from now on, we will take a short-cut and only consider $\sigma > 1$ (this 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 remark that the model captures the relative skill bias of the global technology frontier by R. In equation (16), T rises if there is a rise in R because SBTC reduces the relative cost of a skilled technology, consistent with the view 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).

[9] Acemoglu (1998) suggest that the theoretical insights presented here are unchanged after allowing the acquisition of schooling to respond endogenously.

3 The elasticity of substitution reinterpreted

In this section, we will present existing estimates of this elasticity and re-interpret those estimates using our framework. To accompany the discussion in this section, Table 1 presents various values of β, $\tilde{\sigma}$ (the traditionally inferred elasticity), and σ (as per our framework) from the literature.

3.1 Existing estimates

Many of the studies estimate and calculate elasticities on the basis of a canonical function like (with applicable subscripts ommitted):

$$\log W = \alpha + \beta \log Q + e, \tag{19}$$

where e is a stochastic term. The elasticity of substitution is then given by $\tilde{\sigma} = -\frac{1}{\beta}$.

A study for the U.S. by Katz & Murphy (1992) and subsequent work such as Ciccone & Peri (2005) established a consensus that the elasticity is about 1.5. Yet Freeman's (1986) review contains elasticities ranging from 0.6 to 1000. HILZ (2022) report an (unadjusted) average regression coefficient β whose implied elasticity $\tilde{\sigma}$ is higher than the consensus, specifically 1.8 for all countries and 2.4 for the United States. More importantly, the coefficients imply an interquartile range of 1.4-3.6 for all countries and 1.6-5.2 for the U.S.. After correcting for publication and estimation biases, the corrected global mean is $\tilde{\sigma} = 3.7$ with a 95% confidence band of [2;20].

For developing countries, to our knowledge, the study with the broadest geographical coverage is (still) Psacharopoulos & Hinchliffe (1972), who report values of 2.1 to 2.5 for $\tilde{\sigma}$. More recent studies, which have limited regional coverage, include Avalos & Savvides (2006) and Fernandez & Messina (2018) with reported $\tilde{\sigma}$ ranging from 1 to 2.5. The HILZ meta-study reports a mean $\tilde{\sigma}$ of 2.1 for developing countries. The interquartile range of coefficient estimates is -0.58 to -0.37, which implies $\tilde{\sigma}$ ranging from 1.7 to 2.7. The bias-corrected mean elasticity is also $\tilde{\sigma} = 2.1$ with a [1.4;4.2] interval.

Re-interpreting the coefficients It is easy to map (17) to (19). R is captured by the constant or perhaps an additional time trend and, more importantly, $\beta = \sigma - 2$. In some cases, this can be very different to $\beta = -\frac{1}{\tilde{\sigma}}$. The Psacharopoulos & Hinchliffe (1972) coefficient estimates for EMDEs imply moderately lower σ of 1.5-1.6 in a directed technical change framework than under the traditional interpretation. Similar comparisons apply at the mean of EMDE studies analyzed by HILZ. This pattern, $\sigma =< \tilde{\sigma}$, is quite general, with exceptions only observed at the extreme low end of coefficient estimates. For example, the first percentile of EMDE estimates reviewed by HILZ has $\tilde{\sigma} \approx 1$, which corresponds to the case where there is no directed technical change.

The directed technical change framework produces much smaller variation in implied elasticity estimates. For example, the interquartile range for $\tilde{\sigma}$ of 1 referred to earlier corresponds to an interquartile range of only 0.2 for σ. This is because 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 severe. For illustrative purposes, we extend the comparison to the global sample.[10] The range in Freeman (1986) becomes 0.3 to 2. In HILZ, the interquartile range of β estimates implies considerable variation in $\tilde{\sigma}$ but not σ, which remains close to the consensus of 1.5.

3.2 Estimation bias, publication bias, and hypothesis testing

The data are prone to measurement error, which can cause attenuation bias, which tends to move estimated coefficients towards zero. Since most coefficient estimates are negative, this would tend to overestimate $\tilde{\sigma}$. In our framework, the bias would be towards values of $\sigma = 2$ from either direction. Systematic mismeasurement could also bias the coefficient, though not necessarily towards zero.[11]

Identification and interpretation of β relies on the assumption that quantities affect prices and not the other way around. However, it may be the case that the wage premium affects the skill supply through migration or education choices. To address the issue, Ciccone & Peri (2005) use compulsory schooling laws as instruments. Carneiro, Liu, and Salvanes (2023) exploit exogenous variation in school colleges and synthetic controls. In the absence of such options, another way to mitigate reverse causation is to use lags of quantities. If reverse causality is not fully dealt with, then (Wooldridge, 2002:62), if there is a positive correlation between shifts in relative labor supply and labor demand, a negative β coefficient estimate is too small (in absolute value terms) relative to the true value and a positive β coefficient is too high relative to the true value. Endogeneity of this form would tend to re-enforce attenuation bias for true negative coefficients, which seem to apply in most published studies, and thus lead to overestimates of $\tilde{\sigma}$. In our framework, it would lead to overestimates of σ regardless of the coefficient sign.

HILZ document the role of attenuation and endogeneity bias. Observing that IV methods can address both issues, they find that coefficients are on average 0.1 more negative than

[10] Because this includes some advanced economies that engage in R&D, the model developed in this paper is not strictly applicable. However, the directed technological change approach could plausibly formally justify the calculations under the assumption of constant returns to technology development. In any case, such model uncertainty's implications for σ are likely smaller than those generated for $\tilde{\sigma}$ by taking the inverse of a coefficient estimated with error.

[11] For example, Bowlus et al (2021) find that failure to account for demographic composition and ad hoc SBTC assumptions contributes to "incorrectly" signed coefficients. Their corrected approach reduces the coefficient to -0.2 from -0.6. This has the effect of raising $\tilde{\sigma}$ to 5 from about 1.5 but raises σ only to 1.8.

OLS coefficients. We calculate a similar difference when restricting ourselves to EMDEs using their data. This implied difference is only 0.1 for σ but implies a $\tilde{\sigma}$ that is 0.4 lower. More generally, our framework makes inferred elasticities much more robust to estimation error.

The HILZ finding that estimation biases tend to overestimate substitution elasticities is countered by publication bias, which they show leads to an underestimate of substitution elasticities. In particular, studies with β coefficients that are low or insignificantly different from zero, which fails to reject the null hypothesis of perfect substituability between inputs, are less likely to be published. Following their logic, we suspect that publication bias may understate the number of studies that produce positive coefficients, which would imply theoretically-inconsistent negative values for $\tilde{\sigma}$. This may explain why the share of weakly positive coefficient values is less than 5 percent for the full set of studies and also for the EMDE subsample.

Further use of our proposed framework would limit the incentive for publication bias because there is nothing problematic about small negative coefficients or even positive coefficients. Indeed, hypothesis tests take on a different interpretation under the proposed approach. Testing for "significance", $\beta = 0$, in a 2-sided manner allows for reduced-form testing of whether a higher skill supply increases or decreases the wage premium. In our context, if σ is insignificantly different from 2, the technology and substitution effects are approximately equal and there is no change in wage inequality. Testing whether the types of labor can't be substituted at all (as per a Leontief production function) amounts to testing whether $\beta = -2$ in our framework, but would be awkward in the traditional approach. $\sigma = 1$ ($\beta = -1$) is the only condition under which a rise in the supply of skilled labor does not lead to technical change that favors skilled workers and implies skilled and unskilled labor combine according to the Cobb Douglas production technology.

Our framework also reduces the implications of biases for the consensus estimate. After controlling for publication bias, HILZ find that OLS estimates decline to almost zero, which increases $\tilde{\sigma}$ to 10 yet is consistent with $\sigma \approx 2$. Their preferred estimate, which accounts for estimation and publication bias, is $\beta = -0.27$ and thus $\sigma \tilde{=} 3.7$, which is well above the consensus, and $\sigma = 1.73$, which is close to it. Their 95% confidence interval of this estimate is [2;20] while ours is [1.5;1.9]. For EMDEs, the combined effects of publication and estimation bias result in a bias-adjusted estimate that is very close to the uncorrected mean at 2.1 and has an interval of [1.4;4.2]. It alternatively implies $\sigma = 1.53$ with an interval of about [1.3;1.8].

3.3 Dynamics

It is straightforward to develop a time-series (and, by extension, panel data) analogue to equation (19), namely $logW_t = \alpha_0 + \alpha_1 logR_t + \beta \log Q_t + e_t$ with R represented by a trend term. Dynamic specifications allow for a distinction between a shorter run substitution effect and longer-run technology responses such that wage premia initially contract after a rise in skill supply but subsequently expand (Serrano & Timmer, 2002). For example:

$$\Delta logW_t = \gamma_0 - \frac{1}{\sigma}\Delta logQ_t + \gamma_1[logW_{t-1} - (\sigma - 2)logQ_{t-1}] + e_t, \tag{20}$$

γ_0 can capture the linear trend although additional trend terms could be incorporated. The coefficient on the first difference of relative skill supply represents the short-run substitution effect and its negative inverse provides an estimate of σ. The square brackets indicate the static or long-run equilibrium. γ_1, the coefficient on the lagged wage premium, indicates the speed of adjustment to that equilibrium. Together with the coefficient on lagged skill supply, $\gamma_1(\sigma - 2)$, it can be used to back out another estimate of σ. This framework is also amenable to estimation with a non-linear restriction that exploits the presence of σ in both the first-difference and lagged labor supply terms.

4 New data and estimates

We use two types of data. First, we construct a global panel that to our knowledge is the literature's broadest in terms of geographical representation and the number of countries. Second, we use data for Latin America to explore dynamics.

4.1 Data construction

Global Panel Building on Caselli & Coleman (2006), who constructed a single cross section, we construct a panel from 1970 to 2010 and extend country coverage to about 60 developing countries across all applicable continents. To construct the panel, we take the 2018 update of data on labor supply from Barro and Lee (2013). The data reports the share of the population aged 15-64 who have one of seven categories of educational achievement. To calculate wage premia and to construct aggregates of skilled and unskilled labor, as we will describe below, we use the Mincerian coefficients in Psacharopoulos & Patrinos (2018) and unpublished information from Barro & Lee (2001) taken from Caselli & Coleman (2006) on the duration of schooling for each country. The labor supply data are available in 5-year periods, while the Mincerians have varying frequencies. To allow for some lags in transmission from quantities to wages, we use the observations from the period preceding that of the Mincerian estimate. For example, either a Mincerian for 2000 or 2004 (or the average of both) would be allocated the labor supply information for 2005.[12]

[12]An earlier version of this paper (Behar, 2009) used the Caselli & Coleman dataset or updated cross section data with similar results. It also used a long-range global panel with two observations per country, which drew on Mincerian returns taken from Psacharopoulos & Patrinos (2004), to exploit within-country variation. Behar (2013) uses indices of household inequality.

We aggregate the seven categories on labor supply into two.[13] Caselli & Coleman (2006) focus on the distinction between those who have completed primary school and those who have not, which may be appropriate for developing countries. We also produce the cutoff between those who have some post-secondary education and those who don't. For the cutoff at primary school, the aggregate for unskilled labor is constructed as

$$L_{\text{unskilled}} = L_{\text{no education}} + W_{\text{some primary}} L_{\text{some primary}}, \tag{21}$$

where L_i is the labor 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,

$$\begin{aligned} L_{\text{skilled}} &= L_{\text{completed primary}} + W_{\text{some secondary}} L_{\text{some secondary}} + W_{\text{completed secondary}} L_{\text{completed secondary}} \\ &\quad + W_{\text{some higher}} L_{\text{some higher}} + W_{\text{completed higher}} L_{\text{completed higher}}, \end{aligned} \tag{22}$$

where W_i is measured relative to those with completed primary education. Having constructed measures of skilled and unskilled labor 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 Caselli & Coleman (2006).

Latin America data We take the December 2022 update of the data from SEDLAC which, as described in CEDLAS & World Bank (2009), has standardized and collated household data from a number of Latin American countries. SEDLAC defines 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. Specifically, 'low' corresponds to people with 0-8 years' schooling, 'medium' to 9-13 years, and 'high' to 14 or more years. They report the share of the population in each of these categories and their monthly labor income. We perform an analogous aggregation to above. One cutoff defines skilled labor as those who have more than 8 years' schooling (medium and high skill, roughly equivalent to completed primary school). The other cutoff defines skilled labor as those who have more than 13 years (high skill only, roughly equivalent to some tertiary education). The wages at each level are already in the data, so Mincerians are not needed. The frequency of

[13] Collapsing to two categories requires some assumptions on the separability of the production function (Berndt & Christensen, 1973). Our approach implicitly assumes perfect substitution between the combined categories. An alternative approach would focus on any two categories of interest and assume excluding some categories does not bias the estimates of interest.

the data is typically annual.

For regression analysis, we explore different parts of the data. We start with an analysis for twelve countries who have time series that are now just-about long enough. We also study Brazil, which has the longest time series in our dataset. We also study Central American countries individually and as a group; these countries have relatively long time series and have received less attention than those in South America.

4.2 New Estimates

Global panel In Tables 2 and 3, we present regressions from the global panel with skilled workers defined as those having some tertiary/higher education. The former presents results for EMDEs using different estimation techniques and the latter presents results where we alter the sample. In all specifications, the estimated skill supply coefficient is slightly positive. Under the traditional interpretation, one would have to conclude that the estimates represent a nonsensical CES technology. In particular, the "Elasticity (inverse)" row shows negative $\tilde{\sigma}$ values. Using the interpretation proposed in this paper, "Elasticity (beta+2)", σ is slightly higher than 2, and the small positive coefficient represents a substitution effect that is slightly outweighed by the directed technology effect.

For example, column 1 in Table 2 presents estimation by random effects, which allows for variation across and within countries. The coefficient of 0.15 yields a nonsensical traditional elasticity, $\tilde{\sigma}$, of -6.73 but, under our interpretation, an elasticity of $\sigma = 2.15$, which in turn implies a substitution effect of -0.47 and a technology effect of 0.61. In column 2, estimation by fixed effects gives a higher coefficient. The between effects coefficient in column 3, which only allows for cross country identification, yields a slightly lower coefficient. Allowing for different error term properties (for example country-specific AR(1) in column 4) or for alternatives to a single time trend (for example period dummies in column 5 or higher-order trend terms, available on request) does not materially alter the results. Column 1 is reproduced in Table 3 for comparison with a sample for advanced economies (column 2). Subsequent columns trim the sample of EMDEs by excluding low income countries (column 3), the Latin America & Caribbean region (column 4), and pre-1985 data - all using random effects for illustration. The estimates are fairly consistently around 0.15, which implies $\sigma = 2.15$.

In Tables 4 and 5, we repeat the analysis but define skilled workers as those having at least primary education. The coefficients are again positive across the board, but much closer to zero. A traditional interpretation would render the results nonsensical, while, under our interpretation, $\sigma \approx 2$. [14] In all four tables discussed so far, the standard errors in parentheses

[14] An earlier version with a single cross section also estimated coefficients that were close to zero and, depending on the estimation method, slightly positive or slightly negative. That single cross section also including specifications that control for trade openness or the capital/labor ratio, though such a specification would be inconsistent with a framework in which capital is endogenized to labor.

suggest the elasticity is significantly greater than 1, which would have implied a Cobb Douglas Technology and the absence of any directed technical change effects. $\sigma > 1$ also means that a rise in skill supply would raise its share of labor income. The trend term and period dummies were insignificant or negative, which could suggest that earlier findings of rising inequality trends, perhaps driven by imported skill-biased technology, no longer hold.

Latin America Panel We apply our framework to the SEDLAC data for Latin America. Figures 1 and 2 plot the data for the twelve countries in our full sample. As documented for some of the countries elsewhere for earlier decades, there has been a broadbased increase in skill supply. However, the skill premium has not fallen as consistently or clearly, especially at the higher education cutoff.[15]

In Table 6, we present three results for the higher education cutoff. In all cases, estimation includes dummies for changes in the survey method and thus subsumes country fixed effects. Various tests did not suggest the underlying variables or the residuals from the regressions are non-stationary. The first column uses the canonical static approach. In contrast to the global panel, we find a significantly negative coefficient. Under the traditional interpretation, the elasticity of substitution is above 5, while our framework implies an elasticity of 1.81 and a substitution effect that slightly outweighs the technology effect. The second column presents a dynamic specification as per equation 20, where the negative and insignificant inverse of the coefficient on the first difference term (-0.11) implies an inverse elasticity of 9.2. Unlike for the static specification, this is an appropriate interpretation under our framework, but the value is high and is substantially different from the elasticity based on the steady state / long-run relationship of 1.71; these two elasticities should strictly speaking be the same. We use the steady-state elasticity to calculate substitution and technology effects of -0.59 and 0.29, respectively. Column 3 presents a regression that forces the theoretical equivalence of the two elasticity values by imposing non-linear constraints. The results in column 3 are very close to those implied by the steady-state relationship in the unrestricted regression.

In Table 7, we present the results for the primary education cutoff. Consistent with the global static specifications, the coefficient in column 1 is positive. This implies an unfeasible $\tilde{\sigma}$ under the traditional interpretation but an $\sigma = 2.2$ in our framework, with the positive reduced-form relationship explained by a technology effect exceeding the substitution effect. In column 2, our estimates are problematic because the coefficient on the first difference term is positive. which, even under our framework, implies an unfeasible negative elasticity. The constrained approach estimates an elasticity of 1.88.

[15] Manacorda et. al (2010) show a rise in the supply of secondary education since the 1980s in Latin America and Asia. Also see Gallego (2012) for Chile and Fernandez & Messina (2018) for Argentina, Brazil, and Chile. Some studies also document a rise in the skill premium.

Single time series for Brazil Tables 8 and 9 follow the format for the Latin America panel but focus on Brazil, which has data from 1981-2021, for primary and higher education cutoffs. We again include dummies for changes in the survey method. In Table 8, the coefficient value of -0.67 implies $\tilde{\sigma} = 1.5$ under the traditional interpretation and $\sigma = 1.33$ in our framework. The second column presents the dynamic specification. The negative inverse of the coefficient on the first difference term (-0.45) implies an elasticity of 2.25, which is not very different from the elasticity based on the steady state / long-run relationship of 1.7. Column 3, which constrains the elasticities to be equal, yields the same results as those for the steady state in column 2. In Table 9, the static specification yields an non-feasible traditional elasticity while the dynamic specification's low first-difference coefficient implies a very high inverse elasticity. The elasticity from the dynamic model's steady-state relationship and from the constrained estimate is 1.8, bringing it closer to the value for the tertiary cutoff.

Central American Countries We proceed to conduct similar analysis for Costa Rica, the Dominican Republic, El Salvador, Honduras, and Panama. These countries now have reasonably long time series (around 1991-2021) and have to our knowledge not been studied in this literature. For these countries, the supply of skills has also increased notably (Figures 1 and 2), but a decline in the wage premium seems even less apparent.

Table 10 presents the canonical static specification for each country and for the panel as a whole using the higher education cutoff. Estimation includes dummies for changes in the survey method and thus (in the case of the panel) subsumes country fixed effects. Coefficient estimates range from -0.21 in Honduras to 0.20 (El Salvador). The panel coefficient of 0.04 in our framework implies $\sigma = 2.04$ and a directed technology effect that marginally outweighs the substitution effect. Table 11 presents results of the constrained dynamic specification.[16] This approach estimates $\sigma = 1.67$ for the region, with most countries being close to that value.

Tables 12 and 13 repeat the analysis for the primary education cutoff. Most static specifications estimate positive coefficients and thus, in our framework, elasticity values of over 2. The dynamic specifications yield estimates of around 1.8. The trend terms in the static specifications are generally negative.

Summary and interpretation To recap the results, for the Central America region, many static specifications for higher and primary cutoffs imply unfeasible elasticities under the traditional interpretation, as is found for the broader sample with the primary cutoff. By our interpretation, $\sigma \approx 2$ for higher education and a little more for primary education. Turning to dynamic specifications, Central American elasticities of 1.7-1.8 match those for

[16]Unconstrained dynamic specifications produced positive coefficients on the first-difference terms so we ommited the results for brevity.

Brazil and Latin America as a whole. Looking at the individual country results, variation within Central America seems at least as large as that between the region and the rest of Latin America. Mollick (2008) finds coefficients of $\tilde{\sigma} \approx 2$ and thus $\sigma \approx 1.5$ for Mexico.

For the global data, our coefficient estimates differ from the negative coefficients produced by Psacharopoulos & Hinchliffe (1972) and are toward the extreme end of the HILZ meta study for EMDEs. Our global estimate for the value of the elasticity is accordingly also comparatively high. This is intuitive because our positive estimates would be more prone to exclusion owing to publication bias. Importantly, even extreme values of σ are not that different, but the same cannot be said for traditional interpretations. Our regional analysis, especially specifications that permit dynamics, are more closely aligned with existing studies. In addition to those regional studies shown in Table 1, estimates in Manacorda et al (2010) imply values of 1.6-1.8 for σ. Our Latin America analysis is aligned with the HILZ bias-adjusted mean for all countries.

5 Conclusion

Drawing on Acemoglu (1998) and Kiley (1999), we have introduced a model of directed technical change for EMDEs, which are assumed to be price takers in the technology market. We model a potential licence holder in an EMDE considering whether or not to acquire the right to import machines of a particular type to sell locally. The relative attractiveness of skill-biased technologies is affected by the relative supply of skilled labor. We use the approach to reinterpret existing estimates of the elasticity of substitution between skilled and unskilled labor and apply it to a standalone set of empirical contributions.

Our reinterpretation rests on the insight that, in our framework, the coefficient on the canonical reduced-form regression of relative wages on relative quantities is $\sigma - 2$, not $-\frac{1}{\sigma}$. Viewed in this way, elasticities near the existing consensus range are still close. Negative coefficient estimates of close to zero, which would traditionally imply very high elasticity values, would yield σ values of just below 2 and thus re-enforce the consensus. Our framework also permits positive coefficient estimates, is more robust to estimation error, and mitigates a source of publication bias. Taking the HILZ bias-adjusted coefficient estimates as indicators of preferred estimates in the literature, our framework implies $\sigma = 1.7$ for the global sample and 1.5 for the subset of EMDEs.

Our empirical contributions include construction of global panel of relative skill supply and relative quantities to permit analysis on a large panel of data and a Latin America panel to facilitate dynamics. Global results indicate a slightly positive relationship between the relative supply of skills and the wage premium, which imply an elasticity of 2-2.2. Latin America results, which include results for Central America, indicate elasticities of around 2 or, once one accounts for dynamics, 1.7-1.8, and thus align with the consensus.

In our framework, the absence of a large correlation between wage premia and quantities is viewed as technical change approximately cancelling the substitution effect rather than evidence of perfect substitution. The existing and new results suggest the effect on wage premia may be modest. From a policy perspective, prioritizing expanded education access to reduce within-country wage inequality may not be justified. Furthermore, our finding of imperfect substitution even if the reduced form correlation is weak (Banerjee & Duflo, 2005) justifies efforts to account for imperfect substitution in human capital measurement, which enriches the debate on the role of human capital in explaining cross-country income differences (Jones, 2014; Caselli & Ciccone, 2019). Imperfect substitution also implies, other things equal, more broad-based effects of immigration on wages of the local population (Borjas et. al, 2012).

Although the traditional interpretation may have condemned some previous studies, we hope our new framework encourages those to be brought to light and stimulates more research. Extensions may include in-depth analysis of more countries with perhaps more observations. There may be alternative forms of aggregating skill types or ways to apply our framework to innovations that account for worker experience. Alternative proxies for external drivers of technology availability or adoption could also be explored. Potential proxies include observables like trade, investment, or measures of upskilling in advanced economies, or unobservables backed out for advanced economies using the directed technical change modelling framework .

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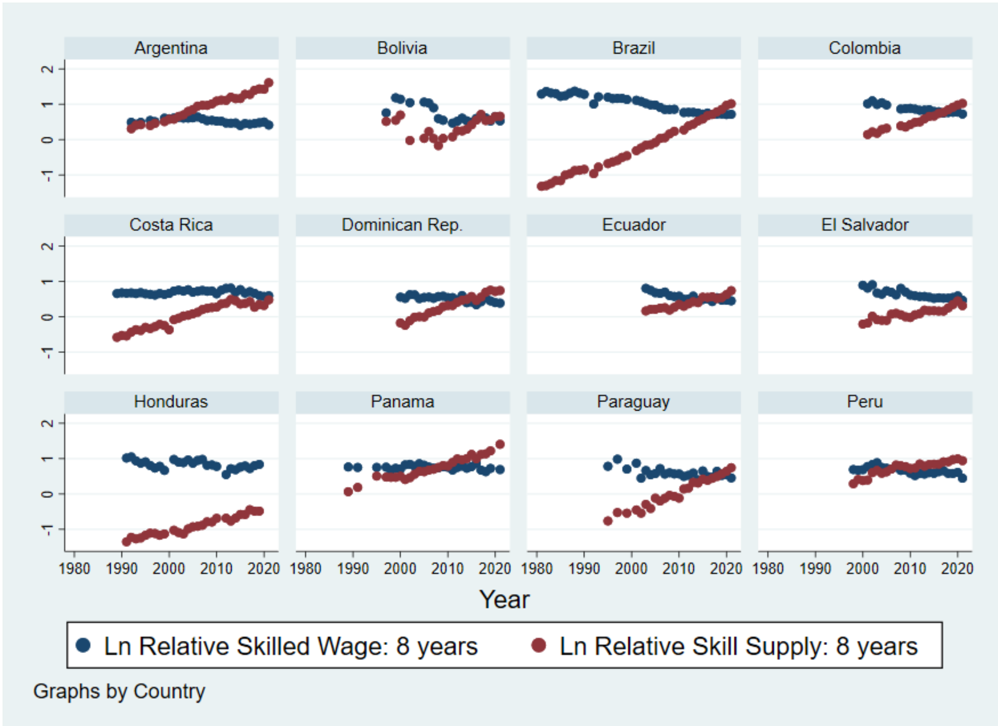

Figure 1: Skill supply and wage premium (primary)

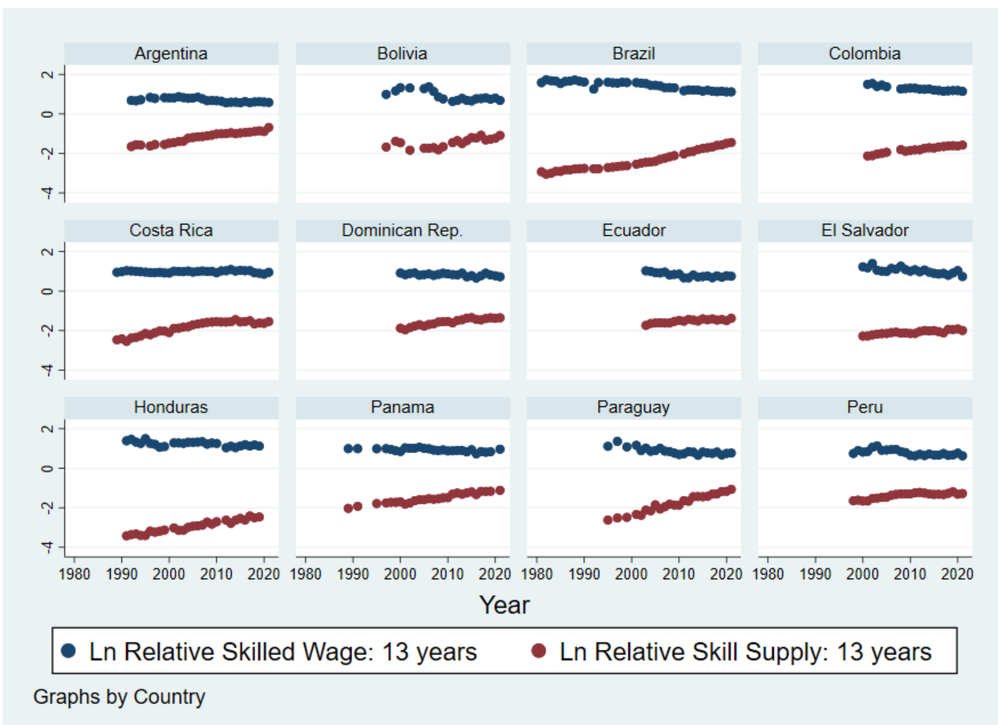

Figure 2: Skill supply and wage premium (tertiary)

Table 1: Existing literature: coefficients and implied elasticities

Developing Countries			
Psacharopoulos & Hinchliffe (1972): Global sample of 9 EMDEs			
Equation R7	-0.395	2.53	1.61
Equation R5	-0.476	2.10	1.52
Avalos & Savvides (2006) Table 3: LAC and Asia			
Highest estimate LAC	-0.401	2.49	1.60
Lowest estimate LAC	-0.771	1.30	1.23
Highest estimate Asia	-0.643	1.56	1.36
Lowest estimate Asia	-0.986	1.01	1.01
Fernandez & Messina (2018): Argentina, Brazil, and Chile			
Highest (Secondary education)	-0.398	2.51	1.60
Lowest (Secondary education)	-0.459	2.18	1.54
Highest (Tertiary education)	-0.696	1.44	1.30
Lowest (Tertiary education)	-0.865	1.16	1.14
HILZ (2022) meta-study *			
mean	-0.474	2.11	1.53
p1	-0.986	1.01	1.01
p25	-0.579	1.73	1.42
p75	-0.370	2.70	1.63
p99	0.200	-5.00	2.20
bias corrected mean**	-0.470	2.13	1.53
Other country coverage* **			
HILZ (2022) meta-study (all countries) *			
mean	-0.550	1.82	1.45
p1	-2.960	0.34	-0.96
p25	-0.734	1.36	1.27
p75	-0.276	3.62	1.72
p99	0.200	-5.00	2.20
bias corrected mean **	-0.270	3.70	1.73
HILZ (2022) meta-study (USA)			
mean	-0.416	2.40	1.58
p1	-1.460	0.68	0.54
p25	-0.610	1.64	1.39
p75	-0.194	5.15	1.81
p99	0.330	-3.03	2.33
bias corrected mean **	-0.160	6.25	1.84
Freeman (1986) literature review			
Lowest	-1.667	0.6	0.33
Highest	-0.001	1000	2.00

* HILZ values calculated by the author using unweighted winsorized data. Also see HILZ Table A2.
** As reported in HILZ Table 5, first column.
*** Sigma values use an advanced economy analogue to equation (17) that assumes constant returns to scale in R&D. For illustrative purposes only.

Table 2: Global panel, higher cutoff, by estimation method

	(1) RE	(2) FE	(3) BE	(4) Panel AR	(5) RE
Skill supply	0.15***	0.25***	0.05	0.12***	0.14***
	(0.04)	(0.08)	(0.06)	(0.01)	(0.04)
trend	-0.01	-0.03		-0.01	
	(0.02)	(0.02)		(0.00)	
1975					-0.08
					(0.15)
1980					-0.10
					(0.12)
1985					-0.17
					(0.11)
1990					-0.18
					(0.11)
1995					-0.14
					(0.10)
2000					-0.13
					(0.12)
2005					-0.17
					(0.11)
Constant	1.66***	2.01***	1.35***	1.62***	1.73***
	(0.17)	(0.29)	(0.15)	(0.04)	(0.16)
Elasticity (inverse)	-6.73***	-4.03***	-19.67	-8.02***	-6.94***
	(2.03)	(1.35)	(22.07)	(0.76)	(1.89)
Elasticity	2.15***	2.25***	2.05***	2.12***	2.14***
	(0.04)	(0.08)	(0.06)	(0.01)	(0.04)
Subs. effect	-0.47***	-0.44***	-0.49***	-0.47***	-0.47***
	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)
Tech. effect	0.61***	0.69***	0.54***	0.60***	0.61***
	(0.04)	(0.07)	(0.04)	(0.01)	(0.03)
Observations	204	204	204	190	204

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Clustered standard errors in parentheses. Dependent variable is wage premium where skilled workers are those with some tertiary education. Columns show estimation by random effects, fixed effects, between effects, GLS with panel-specific autocorrelation, and random effects with period dummies. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 3: Global panel, higher cutoff, by sample

	(1)	(2)	(3)	(4)	(5)
	EMDEs	AEs	No LICs	No LAC	Post 1985
Skill supply	0.15***	0.16*	0.25***	0.08	0.14***
	(0.04)	(0.09)	(0.06)	(0.05)	(0.05)
trend	-0.01	0.02	-0.04*	0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Constant	1.66***	1.32***	1.93***	1.34***	1.51***
	(0.17)	(0.20)	(0.20)	(0.24)	(0.23)
Elasticity (inverse)	-6.73***	-6.19*	-4.05***	-12.91	-7.00***
	(2.03)	(3.35)	(0.97)	(8.58)	(2.38)
Elasticity	2.15***	2.16***	2.25***	2.08***	2.14***
	(0.04)	(0.09)	(0.06)	(0.05)	(0.05)
Subs. effect	-0.47***	-0.46***	-0.45***	-0.48***	-0.47***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Tech. effect	0.61***	0.62***	0.69***	0.56***	0.61***
	(0.04)	(0.07)	(0.05)	(0.04)	(0.04)
Observations	204	146	178	127	127

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Clustered standard errors in parentheses. Dependent variable is wage premium where skilled workers are those with some tertiary education. Columns show estimates for all EMDEs, AEs, EMDEs excluding low-income countries, EMDEs excluding the LAC region, and EMDEs post-1985. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 4: Global panel, secondary cutoff, by estimation method

	(1)	(2)	(3)	(4)	(5)
	RE	FE	BE	Panel AR	RE
Skill supply	0.04***	0.09***	0.00	0.01***	0.03***
	(0.01)	(0.03)	(0.02)	(0.00)	(0.01)
trend	-0.00	-0.02**		0.00***	
	(0.01)	(0.01)		(0.00)	
1975					-0.02
					(0.05)
1980					-0.02
					(0.04)
1985					-0.04
					(0.03)
1990					-0.04
					(0.03)
1995					-0.03
					(0.03)
2000					-0.03
					(0.03)
2005					-0.04
					(0.03)
Constant	0.34***	0.37***	0.35***	0.36***	0.36***
	(0.03)	(0.02)	(0.02)	(0.00)	(0.03)
Elasticity (inverse)	-26.21***	-11.21***	-1682.32	-80.32***	-31.61***
	(7.30)	(3.52)	(45258.42)	(0.86)	(9.59)
Elasticity (beta+2)	2.04***	2.09***	2.00***	2.01***	2.03***
	(0.01)	(0.03)	(0.02)	(0.00)	(0.01)
Subs. effect	-0.49***	-0.48***	-0.50***	-0.50***	-0.49***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Tech. effect	0.53***	0.57***	0.50***	0.51***	0.52***
	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)
Observations	204	204	204	190	204

*** p<0.01, ** p<0.05, * p<0.10. Clustered standard errors in parentheses. Dependent variable is wage premium where skilled workers are who completed primary education. Columns show estimation by random effects, fixed effects, between effects, GLS with panel-specific autocorrelation, and random effects with period dummies. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 5: Global panel, secondary cutoff, by sample

	(1) EMDEs	(2) AEs	(3) No LICs	(4) No LAC	(5) Post 1985
Skill supply	0.04***	0.04*	0.05***	0.03**	0.03***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
trend	-0.00	0.01	-0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.34***	0.21***	0.34***	0.31***	0.32***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)
Elasticity (inverse)	-26.21***	-26.89*	-19.21***	-35.51**	-31.59***
	(7.30)	(15.48)	(4.82)	(14.95)	(10.90)
Elasticity (beta+2)	2.04***	2.04***	2.05***	2.03***	2.03***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Subs. effect	-0.49***	-0.49***	-0.49***	-0.49***	-0.49***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Tech. effect	0.53***	0.53***	0.54***	0.52***	0.52***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Observations	204	146	178	127	127

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Clustered standard errors in parentheses. Dependent variable is wage premium where skilled workers are those who completed primary education. Columns show estimates for all EMDEs, AEs, EMDEs excluding low-income countries, EMDEs excluding the LAC region, and EMDEs post-1985. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 6: Latin America panel, higher cutoff

	(1) Static	(2) Dynamic	(3) Constrained NL
main			
Ln Relative Skill Supply: 13 years	-0.19**		
	(0.08)		
Year	-0.01***		
	(0.00)		
D.Ln Relative Skill Supply: 13 years		-0.11	
		(0.06)	
L.Ln Relative Skill Supply: 13 years		-0.15***	
		(0.05)	
L.Ln Relative Skilled Wage: 13 years		-0.52***	
		(0.10)	
_cons	21.50***	0.41***	0.13
	(6.62)	(0.12)	(0.08)
a1			
L.Ln Relative Skilled Wage: 13 years			-0.51***
			(0.13)
a2			
L.Ln Relative Skill Supply: 13 years			-0.14**
			(0.05)
Elasticity (inverse)	5.39**	9.20*	
	(2.18)	(5.17)	
Elasticity (beta+2)	1.81***	1.71***	1.73***
	(0.08)	(0.07)	(0.07)
Subs. effect	-0.55***	-0.59***	-0.58***
	(0.02)	(0.02)	(0.02)
Tech. effect	0.37***	0.29***	0.31***
	(0.05)	(0.05)	(0.04)
Observations	246	227	232

*** p<0.01, ** p<0.05, * p<0.10. Dependent variable is wage premium where skilled workers are those with more than 13 years' schooling. Estimation by OLS (columns 1 and 2) and constrained non-linear least squares (column 3) with survey method dummies and standard errors clustered by country in parentheses. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 7: Latin America panel, primary cutoff

	(1) Static	(2) Dynamic	(3) Constrained NL
main			
Ln Relative Skill Supply: 8 years	0.20*		
	(0.10)		
Year	-0.02***		
	(0.01)		
D.Ln Relative Skill Supply: 8 years		0.15	
		(0.09)	
L.Ln Relative Skill Supply: 8 years		-0.09**	
		(0.04)	
L.Ln Relative Skilled Wage: 8 years		-0.55***	
		(0.15)	
_cons	41.41***	0.52***	0.44**
	(10.51)	(0.17)	(0.15)
a1			
L.Ln Relative Skilled Wage: 8 years			-0.61**
			(0.20)
a2			
L.Ln Relative Skill Supply: 8 years			-0.07
			(0.05)
Elasticity (inverse)	-4.98**	-6.77	
	(2.41)	(4.15)	
Elasticity (beta+2)	2.20***	1.84***	1.88***
	(0.10)	(0.06)	(0.06)
Subs. effect	-0.45***	-0.54***	-0.53***
	(0.02)	(0.02)	(0.02)
Tech. effect	0.66***	0.39***	0.41***
	(0.08)	(0.04)	(0.05)
Observations	246	227	232

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Dependent variable is wage premium where skilled workers are those with more than 8 years' schooling. Estimation by OLS (columns 1 and 2) and constrained non-linear least squares (column 3) with survey method dummies and robust standard errors clustered by country in parentheses. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 8: Brazil, higher education cutoff

	(1) Static	(2) Dynamic	(3) Constrained NL
main			
Ln Relative Skill Supply: 13 years	-0.67***		
	(0.16)		
Year	0.02**		
	(0.01)		
D.Ln Relative Skill Supply: 13 years		-0.45*	
		(0.22)	
L.Ln Relative Skill Supply: 13 years		-0.24***	
		(0.05)	
L.Ln Relative Skilled Wage: 13 years		-0.81***	
		(0.13)	
_cons	-32.51**	0.55***	0.68***
	(14.45)	(0.11)	(0.10)
a1			
L.Ln Relative Skilled Wage: 13 years			-0.81***
			(0.11)
a2			
L.Ln Relative Skill Supply: 13 years			-0.24***
			(0.05)
Elasticity (inverse)	1.50***	2.25**	
	(0.37)	(1.09)	
Elasticity (beta+2)	1.33***	1.70***	1.70***
	(0.16)	(0.04)	(0.04)
Subs. effect	-0.75***	-0.59***	-0.59***
	(0.09)	(0.01)	(0.01)
Tech. effect	0.08	0.29***	0.29***
	(0.07)	(0.03)	(0.03)
Observations	36	32	32

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Dependent variable is wage premium where skilled workers are those with more than 13 years' schooling. Estimation by OLS (columns 1 and 2) and constrained non-linear least squares (column 3) with survey method dummies and robust standard errors in parentheses. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 9: Brazil, primary education cutoff

	(1) Static	(2) Dynamic	(3) Constrained NL
main			
Ln Relative Skill Supply: 8 years	0.32		
	(0.28)		
Year	-0.04*		
	(0.02)		
D.Ln Relative Skill Supply: 8 years		-0.09	
		(0.20)	
L.Ln Relative Skill Supply: 8 years		-0.07	
		(0.05)	
L.Ln Relative Skilled Wage: 8 years		-0.34*	
		(0.19)	
_cons	73.19*	0.29*	0.71***
	(37.84)	(0.17)	(0.15)
a1			
L.Ln Relative Skilled Wage: 8 years			-0.48**
			(0.18)
a2			
L.Ln Relative Skill Supply: 8 years			-0.09*
			(0.05)
Elasticity (inverse)	-3.09	11.70	
	(2.62)	(26.99)	
Elasticity (beta+2)	2.32***	1.80***	1.82***
	(0.28)	(0.12)	(0.06)
Subs. effect	-0.43***	-0.56***	-0.55***
	(0.05)	(0.04)	(0.02)
Tech effect	0.75***	0.35***	0.37***
	(0.22)	(0.08)	(0.04)
Observations	36	32	32

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Dependent variable is wage premium where skilled workers are those with more than 8 years' schooling. Estimation by OLS (columns 1 and 2) and constrained non-linear least squares (column 3) with robust standard errors in parentheses. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 10: Central America: Static specification, higher education cutoff

	(1) C. Rica	(2) Dom. Rep.	(3) El Salv.	(4) Honduras	(5) Panama	(6) All
Ln Relative Skill Supply: 13 years	0.10	-0.07	0.20	-0.21	-0.10	0.04
	(0.10)	(0.31)	(0.39)	(0.29)	(0.26)	(0.11)
Year	-0.01**	-0.01	-0.02***	-0.01	-0.00	-0.01**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Constant	20.67**	15.73	39.97***	16.47	6.64	25.58**
	(9.36)	(30.06)	(11.81)	(22.80)	(20.30)	(8.09)
Elasticity (inverse)	-9.86	15.11	-5.02	4.80	9.92	-24.19
	(10.01)	(70.68)	(9.84)	(6.71)	(25.93)	(66.25)
Elasticity (beta+2)	2.10***	1.93***	2.20***	1.79***	1.90***	2.04***
	(0.10)	(0.31)	(0.39)	(0.29)	(0.26)	(0.11)
Subs. effect	-0.48***	-0.52***	-0.45***	-0.56***	-0.53***	-0.49***
	(0.02)	(0.08)	(0.08)	(0.09)	(0.07)	(0.03)
Tech. effect	0.58***	0.45**	0.65**	0.35*	0.43**	0.53***
	(0.08)	(0.23)	(0.31)	(0.20)	(0.19)	(0.09)
Observations	33	22	22	27	27	128

*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses (clustered by country in panel setting). Dependent variable is wage premium where skilled workers are those with more than 13 years' schooling. Estimation by OLS with survey method dummies. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 11: Central America: Constrained dynamic specification, higher education cutoff

	(1) C. Rica	(2) Dom. Rep.	(3) El Salv.	(4) Honduras	(5) Panama	(6) All
g0						
Constant	-39.90	-14.89	-121.64***	-133.48***	0.53***	0.32***
	(.)	(.)	(0.91)	(0.26)	(0.16)	(0.09)
a1						
Lagged premium	-0.66**	-1.10***	-0.99***	-0.43**	-0.98***	-0.73***
	(0.27)	(0.24)	(0.29)	(0.18)	(0.31)	(0.11)
a2						
Lagged skill supply	-0.14*	-0.42**	-0.85*	-0.16	-0.26*	-0.24***
	(0.08)	(0.17)	(0.49)	(0.12)	(0.14)	(0.06)
Elasticity (beta+2)	1.79***	1.62***	1.14***	1.64***	1.74***	1.67***
	(0.14)	(0.18)	(0.39)	(0.19)	(0.09)	(0.07)
Subs. effect	-0.56***	-0.62***	-0.87***	-0.61***	-0.58***	-0.60***
	(0.04)	(0.07)	(0.30)	(0.07)	(0.03)	(0.02)
Tech. effect	0.35***	0.24**	0.02	0.25**	0.31***	0.27***
	(0.10)	(0.11)	(0.09)	(0.12)	(0.06)	(0.04)
Observations	32	21	21	24	22	120

*** $p<0.01$, ** $p<0.05$, * $p<0.10$. Robust standard errors in parentheses (clustered by country in panel setting). Dependent variable is wage premium where skilled workers are those with more than 13 years' schooling. Estimation by Constrained Non-linear Least Squares with survey method dummies. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 12: Central America: Static specification, primary cutoff

	(1)	(2)	(3)	(4)	(5)	(6)
	C. Rica	Dom. Rep.	El Salv.	Honduras	Panama	All
Ln Relative Skill Supply: 8 years	0.28***	0.80***	0.31	0.29	-0.35*	0.23***
	(0.09)	(0.24)	(0.18)	(0.25)	(0.19)	(0.05)
Year	-0.01***	-0.06***	-0.02***	-0.03**	0.01	-0.02**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Constant	27.71***	112.51***	42.48***	52.82**	-22.94	33.35**
	(7.76)	(29.16)	(11.41)	(20.30)	(17.75)	(8.93)
Elasticity (inverse)	-3.52***	-1.25***	-3.26*	-3.39	2.82*	-4.44***
	(1.14)	(0.38)	(1.95)	(2.82)	(1.52)	(0.93)
Elasticity (beta+2)	2.28***	2.80***	2.31***	2.29***	1.65***	2.23***
	(0.09)	(0.24)	(0.18)	(0.25)	(0.19)	(0.05)
Subs. effect	-0.44***	-0.36***	-0.43***	-0.44***	-0.61***	-0.45***
	(0.02)	(0.03)	(0.03)	(0.05)	(0.07)	(0.01)
Tech. effect	0.72***	1.15***	0.74***	0.73***	0.25**	0.67***
	(0.07)	(0.21)	(0.15)	(0.20)	(0.12)	(0.04)
Observations	33	22	22	27	27	128

*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses (clustered by country in panel setting). Dependent variable is wage premium where skilled workers are those with more than 8 years' schooling. Estimation by OLS with survey method dummies. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

Table 13: Central America: Constrained Dynamic Specification Primary, by country

	(1) C. Rica	(2) Dom. Rep.	(3) El Salv.	(4) Honduras	(5) Panama	(6) All
g0						
Constant	0.43**	0.59***	0.79***	72.22***	0.56***	0.60**
	(0.19)	(0.18)	(0.20)	(0.12)	(0.15)	(0.14)
a1						
Lagged premium	-0.73**	-1.05***	-1.19***	-0.38**	-0.70***	-0.65**
	(0.29)	(0.29)	(0.30)	(0.15)	(0.19)	(0.15)
a2						
Lagged skill supply	-0.16*	-0.27	-0.51**	-0.06	-0.03	-0.13
	(0.08)	(0.17)	(0.19)	(0.09)	(0.06)	(0.07)
Elasticity (beta+2)	1.78***	1.74***	1.58***	1.83***	1.96***	1.80***
	(0.14)	(0.18)	(0.13)	(0.22)	(0.08)	(0.10)
Subs. effect	-0.56***	-0.57***	-0.63***	-0.55***	-0.51***	-0.55***
	(0.04)	(0.06)	(0.05)	(0.07)	(0.02)	(0.03)
Tech. effect	0.34***	0.32***	0.21***	0.38**	0.47***	0.36***
	(0.09)	(0.12)	(0.08)	(0.16)	(0.06)	(0.07)
Observations	32	21	21	24	22	120

*** p<0.01, ** p<0.05, * p<0.10. Robust standard errors in parentheses (clustered by country in panel setting). Dependent variable is wage premium where skilled workers are those with more than 8 years' schooling. Estimation by Constrained Non-linear Least Squares with survey method dummies. Elasticity (inverse) is traditional interpretation and Elasticity (beta+2) follows proposed framework. Technology and substitution effects are estimated using equation 18.

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