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Abstract

Why has schooling not countered the pervasive rises in wage inequality driven by skill-biased technical change? Using data and a model of directed technical change in which developing countries acquire technology licenses from abroad, we show technological change is skill-biased in the South simply because it is in the North. This causes permanently rising wage inequality in the South. We model expanded schooling access as producing relatively educated new cohorts of labor market entrants. This makes the market for skill-biased technologies more attractive, which generates accelerated skill-biased technical change, which leads to higher wage inequality and possibly stagnant unskilled wages.

KEYWORDS: skill-biased technical change, income inequality, technology absorption, inclusive growth

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1 Introduction

It is well documented that there has been a contemporaneous increase in skill supply and in income inequality in the US and other OECD countries. A broad consensus has emerged that skill-biased technical change (SBTC) has been a major cause (Katz & Autor, 1999) of the observed increases. There is evidence that developing countries have also experienced technical change that favors skilled workers (Berman & Machin, 2000) and seen rises in income inequality (Berman, Bound & Machin, 1998). Berman & Machin present evidence that SBTC is pervasive globally and that technology adoption patterns in developing countries follow those of developed countries. Because developing countries acquire machines and technologies from abroad (Caselli & Wilson, 2004), this suggests SBTC in the South is driven primarily by SBTC in the North. As we document later in the paper, developing countries have also experienced expanded schooling that coincides with rising inequality. Furthermore, after controlling for trends over time, it appears that schooling has had an at best limited effect in reducing inequality and perhaps an upward influence. Given that schooling is a potential tool against inequality, this relationship is puzzling and worrisome.

One set of explanations for the relationship in rich countries is that the supply of skills creates its own demand (Machin & Manning, 1997; Kiley, 1999; Acemoglu, 2002a). Within this set, some argue that the degree of skill-bias is endogenous. According to this view, the rise in the supply of skills in the UK and USA made it relatively more profitable to produce skill-biased technologies and raise the relative productivity of skilled workers. This mitigates the negative effect of expanded skill supply on inequality and can in some cases lead to a rise in inequality. Data from a cross section of countries reveal a positive correlation between relative skill endowments and the relative productivity of skilled workers (Caselli & Coleman, 2001). Insofar as relative productivities reflect the relative availabilities of skill-biased and non- skill-biased technologies, this is consistent with endogenous skill-bias in developing and developed countries alike.

After providing examples of cases where technology adoption was endogenously skill-biased in developing countries, this paper adds to the literature by modelling the skill-bias of technology in developing countries. In our theoretical model, the skill-bias of technologies adopted depends on both international research and development (R&D) trends and local skill supply. In keeping with prior work on directed technical change in developed countries (Acemoglu, 2002ab; Kiley, 1999), we base our explanation on an endogenous growth model with two types of workers (skilled and unskilled), but our departures from the existing literature are threefold.

First, instead of firms in an intermediate goods sector paying to develop technologies, firms in an import sector acquire the licence for a new product in exchange for output exported. Because their economies are still developing, countries in the South are not able to engage in R&D to develop their own technologies, but they can pay to acquire technologies developed by the North.

Second, we allow for different rates of basic research into skill-biased and non- skill-biased technologies by the North. Specifically, we assume that skill-biased technologies advance faster than non- skill-biased technologies, which feeds directly into the pace at which technologies are imported by the South. In our model, this means there can be a pervasive rise in wage inequality simply because of R&D in a handful of developed countries.

Third, instead of one-off changes in skill supply, we allow for a gradual change in the skill composition. To capture the effects of education reforms on the entire population more realistically, we employ a Markov model of changes in the proportion of cohorts being educated as they enter the labor force and replace those cohorts that die. This generates periods of growth in the skill composition of the population. In the context of the skill-biased technical progress driven by Northern R&D, we therefore see accelerated growth in income inequality, potentially corresponding with a long period of stagnant unskilled wages.

Section 2 provides emprical evidence of a contemporaneous rise in schooling levels and income inequality for developing countries. Regression analysis provides evidence of pervasive rises in wage inequality over time and evidence that schooling does not have a large downward effect on inequality and possibly raises it. To motivate our candidate explanation, section 2 draws on the existing literature to justify the claim that skill bias in developing countries is influenced both by external drivers - SBTC driven by R&D in the North - and by domestic conditions like relative skill supply. Section 3 builds a model that captures these features and also describes the demography of the labor force. Section 4 nests our key formal results; it describes the evolution of the economy and the two sources of persistent SBTC. Section 5 considers the dynamics more closely. It models a one-off rise in the economy's skill composition before employing the demographic model to show how expanded access to schooling generates persistent accelerations in SBTC. Section 6 provides a short conclusion, including a note of caution against the deployment of schooling in the fight against inequality and to make growth more inclusive.

2 Patterns of inequality and skill-biased technical change

In this section, we will present data on skill supply and inequality in developing countries. Using the literature for developed countries, we will distinguish between technical change that is inherently skill-biased and that which is skill-biased because of increased skill supply. We then introduce and motivate analogues for developing countries, namely technical change that is skill-biased due to exogenous drivers from developed countries and technical change that is appropriate to domestic skill endowments.

Figures 1-3 plot the average years of schooling and income inequality since the mid 1960s (see Appendix 1 for data details). In low income countries (LICs), lower middle income countries (LMICs) and upper middle income countries (UMICs), we see a steady rise in the average provision of schooling. For LICs, it tripled from 0.9 to 2.7 years; in LMICs, it rose from 2.4 to 5.5 years and in UMICs, the average rose from 4.2 to 7.5 years. LICs saw a rise in the household income inequality index from 44.5 in the late 1960s to 48.1 in the early 2000s. Inequality fell in the LMICs in the 1970s but rose overall from 44.4 to 47.8. UMICs experienced a sharp rise in the household income inequality index in the late 1980s and early 1990s such that the index rose from 38.3 to 43.7. Meschi & Vivarelli (2009) also document rises in inequality for low and middle income countries from 1980-1999.

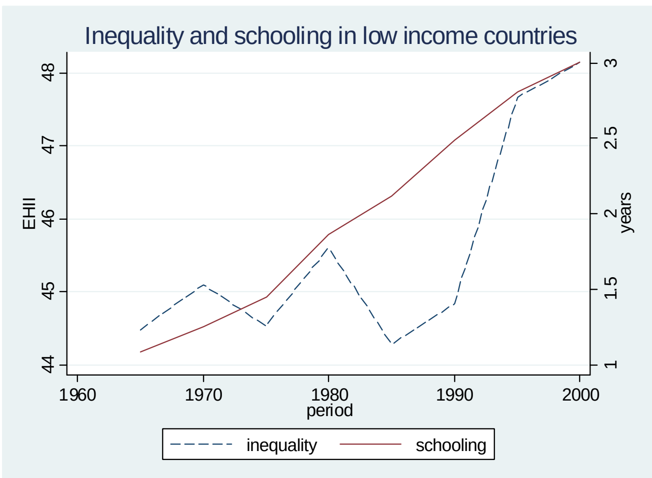

Figure 1:

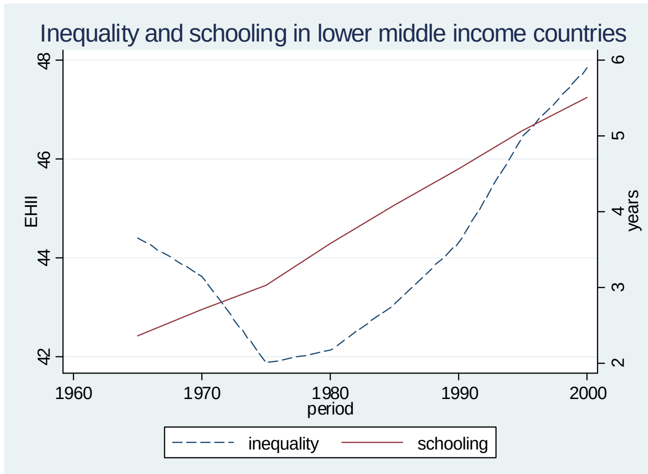

Figure 2:

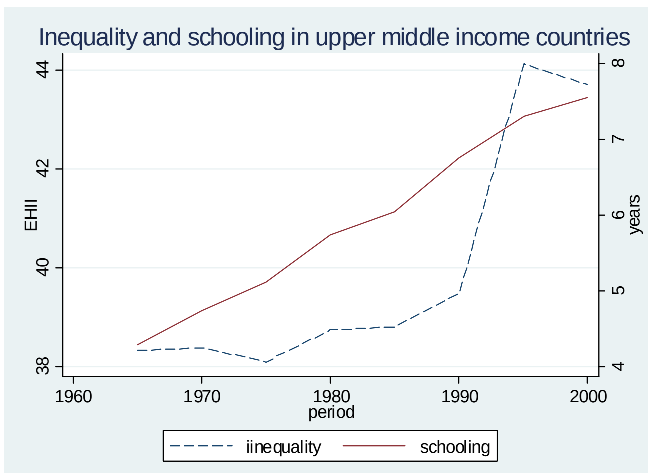

Figure 3:

While the graphical evidence is informative, it is difficult to distinguish between trends in inequality over time and the relationship between inequality and skill supply. Therefore, we regress the inequality index on the average years of schooling in each country and dummies for each 5-year period. Not surprisingly, the dummies in Table 1 clearly depict evidence of increased inequality over the latter half of the century. The first column is a regression for all developing countries while the others coincide with the diagrams. The relationship between schooling and inequality is negative, but appears to be driven by the UMICs. Overall, the coefficient of -0.936 is quite small because a 1-year rise in the average, which is a big amount relative to existing averages, would reduce the inequality index by less than

Table 1: Regressions of inequality

	Overall	LIC	LMIC	UMIC
Schooling	-0.936**	-1.142	-0.431	-2.174**
	(0.416)	*(1.128)*	*(0.531)*	*(0.877)*
Early 70s	0.125	0.552	-0.636	1.266
	(0.748)	*(1.465)*	*(0.839)*	*(1.832)*
Late 70s	-0.196	1.15	-1.689*	1.376
	(0.783)	*(1.593)*	*(0.897)*	*(1.867)*
Early 80s	0.927	3.109*	-1.345	3.462*
	(0.872)	*(1.819)*	*(1.040)*	*(2.073)*
Late 80s	1.46	2.1	0.0714	3.897*
	(0.978)	*(1.969)*	*(1.239)*	*(2.248)*
Early 90s	2.585**	2.871	1.129	6.148**
	(1.144)	*(2.304)*	*(1.460)*	*(2.705)*
Late 90s	5.983***	6.337**	2.884*	11.76***
	(1.311)	*(2.546)*	*(1.702)*	*(3.109)*
Early 00s	7.343***	5.935*	4.334**	13.52***
	(1.532)	*(3.016)*	*(2.142)*	*(3.397)*
Constant	45.07***	45.42***	45.30***	48.26***
	(1.190)	*(1.561)*	*(1.359)*	*(3.983)*
N	353	96	152	105
R^2	0.228	0.17	0.264	0.347

Regressions on schooling and period dummies by country group. Country fixed effects omitted from table. * 10% ** 5% *** 1%.

1 unit. In the wake of strong upwards trends in inequality, it seems that schooling is having a moderate effect. For example, columns 1 and 4 imply it would take a rise in average schooling of approximately seven years to counteract the change in inequality represented by the Early 00s dummy.

Table 2 summarizes the coefficients from a number of regressions. Like Table 1, the dependent variable is the inequality index. However, instead of average schooling years, we calculate the proportion of the population that is skilled. Along the columns, we use different cutoffs for the skills level. The first column defines people who have some primary education (roughly 2-3 years of school) as skilled and the rest as unskilled. Analogously, we have columns where people are only skilled if they have completed Primary, Secondary or Tertiary education. Along the rows, we distinguish between income-group and have an overall measure.[1] All in

[1]In the interests of space, we have omitted the time dummies, which were the same as those in Table 1.

Table 2: Further results from regressions of inequality on schooling

		Some	Primary	Secondary	Tertiary
UMIC	Coefficient	0.010	0.042	0.075*	0.273*
	Standard Error	*(0.050)*	*(0.031)*	*(0.041)*	*(0.143)*
	Observations	83	93	93	83
LMIC	Coefficient	-0.002	-0.004	-0.005	-0.055
	Standard Error	*(0.018)*	*(0.021)*	*(0.036)*	*(0.102)*
	Observations	135	135	135	128
LIC	Coefficient	-0.163***	-0.055	-0.309	-0.067
	Standard Error	*(0.048)*	*(0.061)*	*(0.253)*	*(0.941)*
	Observations	77	82	82	74
Overall	Coefficient	-0.015	0.016	0.047*	0.136
	Standard Error	*(0.018)*	*(0.017)*	*(0.027)*	*(0.087)*
	Observations	295	310	310	285

Schooling coefficients and standard errors together with the number of observations from regressions of inequality on the proportion of people with education, by education cutoff and by country group. * 10% ** 5% *** 1%.

all, we have the results from 16 regressions in Table 2. Strikingly, the only significant negative coefficient is for Some primary school in the low income countries. Otherwise, we see coefficients that are very close to zero or even significantly positive.[2] This raises the issue of why schooling is offering at best moderate resistance to rising inequality and introduces the possibility that increased skill supply leads to rising inequality.

In the United States, inequality fell in the 1970s and rose from the 1980s onwards. Goldin & Katz (2008) present evidence that skill supply decelerated and hence began to lose ground against demand-side shifts in favor of skilled labor. This view is contested; Acemoglu (2002b) and others prefer an explanation based on accelerating relative demand. In the LMICs, we also see a fall in inequality in the 60s and much of the 70s. However, the rise in inequality started at the same time as an *acceleration* in skill supply. For the UMICS and LICs, inequality was initially flat and then started rising even though skill supply continued rising at the same speed. Deceleration of skill supply does not appear to be a plausible explanation for developing countries.

[2]These results are consistent with Meschi & Vivarelli (2009), who use the same inequality measure. Furthermore, many studies that use the skill-premium as the dependent variable rather than overall inequality measures find correlations of practically zero; see Behar (2009) for a comprehensive review.

Therefore, it appears there was an acceleration of demand for skilled workers in developing countries. In developed countries, a consensus emerged that demand shifts were due in large part to skill-biased technical change (SBTC), but the causes and nature of SBTC are still debated. One view holds that technical change by its very nature favors skilled workers. Griliches (1969) advances capital skill complementarity: skills and the technology embodied in machines are relative complements in the production function such that the elasticity of substitution between capital and unskilled workers is higher than that between capital and skilled workers. Building on this, Krusell, Ohanian, Rios-Rull & Violante (2000) posit a dramatic fall in the price of capital and the resulting capital adoption as the main cause of the relative labor demand shifts in the US. In some developing countries, a rise in the quantity of capital - facilitated by the lifting of sanctions or the opening up of domestic markets to foreign investors for example - could favor the wages of skilled workers. Nelson & Phelps (1966) refer to skilled workers as intrinsically complementary to new technologies precisely because they are new; skilled workers have the ability to understand and implement new machines and/or processes. An exogenous boom in new technologies would temporarily favor skilled workers because they are needed to apply them.

The view that new technologies are intrinsically skill-biased relies on an exogenous boost in technology growth to explain the labor demand shifts. There is support for this in the form of ICT adoption (Katz & Autor, 1999) but Acemoglu (2002b) argues total factor productivity has not accelerated sufficiently to support the claim that there has been a pronounced revolution. Berman & Machin (2000) argue that, even if Capital Skill Complementarity holds, developing countries have not had nearly the extent of capital deepening required to generate the observed relative labor demand shifts. So, it seems this can only be part of the explanation.

Furthermore, we have noted that it is really far from clear that increased schooling leads to a reduction in inequality even after conditioning on skill-biased trends over time. Why might this be? In addition to the wage compression effect - skills become less scarce and hence cheaper - Knight & Sabot (1983) refer to the wage composition effect, in which expanded education increases the proportion of people earning high incomes and can initially raise many indices of income inequality. Furthermore, De Gregorio & Lee (2002) analyze how income inequality is influenced not just by the level of schooling, but by the dispersion of schooling. While a higher variance in schooling leads to higher variance in income, the effect of the level depends on how rates of return to education are dispersed across schooling levels. For example, if the return to education is convex and everyone gets an extra year, income inequality rises. Martins & Pereira (2004) show that skilled workers benefit from an incremental year of education more than unskilled workers, which leads to higher income inequality.

Another possibility is that increased skill supply raises inequality by increasing the demand for skilled labor. For example, Machin & Manning (1997), motivated by a surge in "A-levels" graduates induced by a policy reform in the UK, use a matching model to describe how increased availability of skilled labor can lead firms to create more vacancies for skilled workers. Returning to a technology-based explanation, Kiley (1999), Acemoglu (2002a) and others build endogenous growth models of directed technical change where demand for machines that complement skilled labor is positively related to the availability of skilled labor. Thus the market for skill complementary technologies is relatively more attractive if there are more skilled workers. Because the researchers are driven by profits, they will find it relatively more attractive to do R&D in skill-biased technologies if the proportion of skilled workers is higher. These models present a different view of the process by which technologies become skill-biased. Rather than favoring skilled workers by nature, they favor them by design. In other words, the skill-bias of technical change is endogenous or directed. By these arguments, a rise in the skill supply can contribute to a rise in wage inequality.

Directed technical change models can be illuminating but those which currently exist are of R&D and developing countries do not develop their own technologies. Calculations based on data from the OECD licenses database for 2003 show the top five sources of licences account for more than 80% of those worldwide while 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 and Caselli & Wilson (2004) argue that equipment imports are a good proxy for investment in technology. Licensing is an important form of international technology transfer, especially in those developing countries that offer better protection of intellectual property. About 10% of firms have licensed a foreign technology in the recent past (Almedia & Fernandes, 2008). Licensing often includes the right to distribute the product domestically and in some cases access to the underlying know-how (Hoekman, Maskus & Saggi, 2005).

Because developing countries tend to import technologies from the R&D leaders, they are likely to be affected by the relative costs of technologies that favor skilled or unskilled workers. In particular, the technologies they import will be influenced by the skill-bias of the technologies produced abroad. Berman & Machin (2000) also argue that technology adoption in the South is driven by that in the North. Using skill-upgrading as an indicator of skill-biased technology transfer, they find that the same industries experiencing SBTC in the South in the 1980s were those experiencing it in the North in prior decades. They suggest the choices of technologies available to developing countries are becoming increasingly skill-biased. Berman, Bound & Machin (1998) find 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.

The data in Figures 1-3 and the dummies in Table 1 are consistent with this pattern of pervasiveness. Furthermore, of the 40 countries listed in Appendix 2, 34 exerienced a rise in inequality in the last quarter century. Thus, analogous to the exogenous-trends view of SBTC in rich countries, "*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).

However, developing countries do not absorb any new methods automatically, but consider domestic factor market conditions before choosing from the menu of technologies. For example, Knight (1979) notes that capital can replace skilled or unskilled labor. The introduction of the color bar restricted the supply of skills in South Africa and may have led to capital substituting for skilled workers. Tellingly, when the color bar was relaxed, a large degree of substitution of machines for *unskilled* labor took place.[3] Acemoglu & Zilliboti (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 labor. Fransman (1985) draws on comprehensive case study evidence from a number of Latin American countries and elsewhere to speak of semi-industrialized countries adapting overseas technologies to local factor supplies. In an econometric study of the transition economies, Esposito & Stehrer (2009) find a positive correlation between the initial relative quantity of skilled labor and subsequent SBTC. Furthermore, Caselli & Coleman (2001) display a positive cross-country correlation between skill endowments and the skill-bias of technologies used and thus argue that technological choice is directed in rich and poor countries alike.[4]

To summarize this section, the data show a contemporaneous rise in schooling levels and income inequality. The regression analysis indicates strong upward trends in inequality over time but also the absence of a downward effect of schooling or skill supply on inequality. As possible explanations, there is evidence from the literature that skill bias in developing countries is influenced both by external tech-

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

[4]There are a number of examples from rich countries or from history. Lewis (2011) presents systematic econometric evidence of increased skill supply leading to the adoption of more automation machinery in the United States. 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.

nical progress and by domestic conditions like endowments. Put differently, technology adoption can be "inappropriate", in the sense given by Atkinson & Stiglitz (1969), because it is driven by international factors, but also "appropriate" to local skill supply, as in Caselli & Coleman (2006). The next section builds a model that captures these features. In so doing, it proposes to contribute explanations for why inequality appears to be pervasively growing across developing countries and why schooling has failed to arrest this trend.

3 Model set up

We start by describing the demography of our economy, particularly the way in which the skill composition might change over time. We then describe the production side of the economy and the forces driving the level of skill-biased and non-skill-biased technologies in the developing economy. Thereafter, we show the link between the state of technology and wage inequality.

3.1 The population and labor force

Any improvement in the quantity and quality of education will raise the skill composition of school-age cohorts rather than an economy as a whole. Rather than experiencing an instantaneous shift, an economy's skill composition can rise only gradually as cohorts of people dying are replaced by those being born and schooled. To model this for our economy, we assume people can exist in one of three states. They can either be skilled, unskilled or deceased. The labor force (people that are not deceased) is fully employed and normalized to one such that proportion q_t of the labor force is skilled and $(1-q_t)$ is unskilled. In each period, both skilled and unskilled workers have probability f of dying. In turn, proportion Ψ of those in the deceased state are reborn as skilled people and $(1-\Psi)$ are reborn unskilled. These dynamics are captured by the following Markov process:

$$\begin{pmatrix} L^s_{t+1} \\ L^u_{t+1} \\ D_{t+1} \end{pmatrix} = \begin{pmatrix} 1-f & 0 & \Psi \\ 0 & 1-f & 1-\Psi \\ f & f & 0 \end{pmatrix} \begin{pmatrix} L^s_t \\ L^u_t \\ D_t \end{pmatrix} \tag{1}$$

Assuming a starting point where proportion q_0 of the population is skilled, the solution is:

$$\begin{pmatrix} L^s_{t+1} \\ L^u_{t+1} \\ D_{t+1} \end{pmatrix} = \begin{pmatrix} q_{t+1} \\ (1-q_{t+1}) \\ D_{t+1} \end{pmatrix} = \begin{pmatrix} \Psi \\ (1-\Psi) \\ f \end{pmatrix} + (\Psi - q_0) \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} (1-f)^t \tag{2}$$

q_0 is the proportion of skilled workers at the initial date $t = 0$. At any given time, the number of deceased people is constant at f; all f people are reborn to replace the f who die, maintaining a constant living population.

If the proportion of the new cohort being schooled Ψ is the same as the proportion of the labor force that is skilled, then the proportion of skilled workers remains constant. If $\Psi \neq q_0$, we see that the proportion of skilled workers approaches its steady state Ψ as t gets large. In particular,

$$\frac{q_{t+1}}{q_t} = 1 + \left(\frac{\Psi - q_t}{q_t}\right) f \tag{3}$$

and

$$\frac{1 - q_{t+1}}{1 - q_t} = 1 - \left(\frac{\Psi - q_t}{1 - q_t}\right) f. \tag{4}$$

When alive, consumer i has utility function:

$$U_{it} = \sum_{h=t}^{\infty} C_{ih} (1 + r)^{-h+t} \tag{5}$$

where C is output consumed. It is linear and pins down the interest at r for all t.[5]

3.2 Production and technology adoption

In addition to the consumers and insurance companies, the economy has perfectly competitive producers of final output and monopolist suppliers of a variety of intermediates. The intermediate suppliers are monopolists because they had to acquire the exclusive licence to sell a new intermediate variety. In aggregate, final output can be used for consumption of final goods, to import intermediates for further production, or to import the rights to new technologies.

[5]Because each consumer's lifespan is uncertain, agents may leave unexpected and unintended bequests or debts. Therefore, building on Blanchard (1985) and Yaari (1965), each consumer takes a bet offered by insurance companies. If the consumer dies during the time period, she gives up all her assets. If she remains alive, she receives a certain portion of her assets. Insurance companies offer this risklessly and without profit. The actuarially fair portion they pay out contingent on the consumer staying alive is $f/(1-f)$. In other words, insurance companies collect the assets from the f people dying every year and turn proportion $f/(1-f)$ of these assets over to the $1-f$ people who stay alive.

Using a variety expansion model (Romer, 1990), the production technology for final goods is:

$$Y_{it} = (L_{it}^{s})^{1-a} \sum_{j=1}^{N_t} \left(X_{ijt}\right)^{a} + (AL_{it}^{u})^{1-a} \sum_{j=1}^{M_t} \left(Z_{ijt}\right)^{a} \tag{6}$$

Y_{it} is output for firm i at time t. L_{it}^{s} and L_{it}^{u} are skilled and unskilled labor. X_{ijt} is intermediate input of type j used by firm i at t. It is the skill-biased intermediate input. Similarly, Z_{ijt} is the non- skill-biased intermediate input. Intermediates depreciate fully in each period. $A < 1$ for unskilled labor makes production a function of effective units of labor, with the coefficient for skilled labor normalized to one. We will refer to N and M as the number of skilled and unskilled machines.

Firms in the final output sector are perfect competitors and the price of their final output is unity. Using the first order conditions from (6) and conditioning on exogenous labor quantities, each profit-maximizing firm's demand for the skill-biased intermediates is $X_{ijt} = L_{it}^{s}\left(\frac{a}{P_{jt}^{s}}\right)^{\frac{1}{1-a}}$. Because final goods are produced using a constant returns to scale technology, economy-wide demand for each skill-biased intermediate j is

$$X_{jt} = q_t \left(\frac{a}{P_{jt}^{s}}\right)^{\frac{1}{1-a}}, \tag{7}$$

where q_t is the quantity of skilled labor available to the economy at time t. P_{jt}^{s}, the price of each skill-biased intermediate, is set by the firm holding the infinite licence for that intermediate. Firms acquire this licence by importing it in exchange for exports of Y, as described below. Firms in the technology import sector must receive ex post profits to persuade them to incur the ex ante licence cost. Once the fixed cost has been incurred, it costs 1 unit of Y, which has a price of 1, to produce that intermediate. Using (7), the own price elasticity of demand is $\frac{1}{1-a}$ and the profit maximizing price is $\frac{1}{a}$ for all j. Thus, demand for each and every skill-biased intermediate good in the economy is equal and given by

$$X_t = a^{\frac{2}{1-a}} q_t \tag{8}$$

while non- skill-biased intermediates demand is

$$Z_t = Aa^{\frac{2}{1-a}}(1-q_t). \tag{9}$$

Thus, output for the economy is given by

$$Y_t = a^{\frac{2a}{1-a}}\left[N_t q_t + AM_t(1-q_t)\right] \tag{10}$$

The fact that the intermediates enter additively ensures constant returns to increases in the variety of inputs. The value of holding a licence for all skill-biased intermediates is the same and is given by:

$$V_t^s = \sum_{h=t+1}^{\infty} (P_h^s - 1)\, X_h\, (1+r)^{-h+t} \tag{11}$$

Using (8), (2) and defining $\Omega \equiv (1-a)a^{\frac{1+a}{1-a}}$

$$V_t^s = \Omega \left[\frac{p}{r} - \frac{(p-q_0)\,(1-f)^{t+1}}{r+f} \right] \tag{12}$$

$Lim_{t\to\infty}\, V_t^s = \Omega \frac{p}{r}$ so that, when the skilled population is constant at q,

$$V^s = \Omega \frac{q}{r}. \tag{13}$$

Similarly,

$$V_t^u = A\Omega \left[\frac{1-p}{r} + \frac{(p-q_0)\,(1-f)^{t+1}}{r+f} \right] \tag{14}$$

and the constant-population value is

$$V^u = A\Omega \frac{1-q}{r}. \tag{15}$$

The cost of acquiring a licence for a new intermediate depends on how many intermediates of a particular type exist in the economy relative to the stock of internationally developed machine varieties of that type. An economy that is relatively far from the technology frontier finds it relatively cheaper to acquire its next skilled or unskilled technology. Building on Kiley (1999), this is described by:

$$\Gamma_t^s = \left(\beta^s \frac{N_t}{R_t^s} \right)^k \tag{16}$$

$$\Gamma_t^u = \left(\beta^u \frac{M_t}{R_t^u} \right)^k \tag{17}$$

$k > 1$ ensures an increasing marginal cost in $\frac{N_t}{R_t^s}$ and $\frac{M_t}{R_t^u}$. β^s and β^u allow for possible differences in the ability to adopt technologies across developing countries and between skill- and non- skill-biased technologies. Factors affecting these parameters might be the regulatory environment or proximity to technological leaders for example. To ensure no country goes beyond the frontier, $\frac{N_t}{R_t^s} \leq 1$ for all values of q, assume $\Omega \leq r(\beta^s)^k$, which one can do by setting β^s arbitrarily large. Similarly, assume $A\Omega \leq r(\beta^u)^k$ to ensure $\frac{M_t}{R_t^u} \leq 1$. The stock of available skill-biased and non-skill-biased machines is assumed to evolve exogenously according to:

$$R_{t+1}^s = g^s R_t^s, g^s > 1 \tag{18}$$

$$R_{t+1}^u = g^u R_t^u, g^u > 1 \tag{19}$$

The treatment of R as exogenous is appropriate here. A developing country is unable to influence the decisions by first world producers to develop new technologies. Our paper allows for different stocks and growth rates of R&D for skilled and unskilled technologies. For example, $g^s > g^u$ denotes exogenous skill-biased technical change in the North.

Any firm may enter the technology import sector and start making a new intermediate. A firm considering doing so must compare the one-off cost of importing the licence to the net flow of benefits generated by holding that licence in perpetuity. As explained earlier, we know each intermediate it sells costs the licence holder 1 unit and can be sold at price $\frac{1}{a}$. It takes one period to adopt a new technology and start selling it. By free entry, the value of importing a licence can never exceed the marginal cost. By this condition, $V_t^s \leq \Gamma_t^s$ and $V_t^u \leq \Gamma_t^u$ such that:

$$\Omega\left[\frac{\Psi}{r} - \frac{(\Psi - q_0)(1-f)^{t+1}}{r+f}\right] \leq \left(\beta^s \frac{N_t}{R_t^s}\right)^k \tag{20}$$

$$A\Omega\left[\frac{1-\Psi}{r} + \frac{(\Psi - q_0)(1-f)^{t+1}}{r+f}\right] \leq \left(\beta^u \frac{M_t}{R_t^u}\right)^k \tag{21}$$

Producers import technologies such that (20) and (21) hold with equality at time $t+1$. Letting $\phi^s \equiv \Omega^{1/k}/\beta^s$ and $\phi^u \equiv (A\Omega)^{1/k}/\beta^u$, the varieties of skill-biased and non- skill-biased technologies are given by:

$$N_t = \phi^s R_t^s \left[\frac{\Psi_t}{r}\right]^{1/k} \tag{22a}$$

$$= \phi^s R_t^s \left[\frac{\Psi}{r} - \frac{(\Psi - q_0)(1-f)^t}{r+f}\right]^{1/k} \tag{22b}$$

$$M_t = \phi^u R_t^u \left[\frac{1-q_t}{r}\right]^{1/k} \tag{23a}$$

$$= \phi^u R_t^u \left[\frac{1-\Psi}{r} + \frac{(\Psi - q_0)(1-f)^t}{r+f}\right]^{1/k} \tag{23b}$$

Recall q_t is the proportion of skilled workers at time t, q_0 is the original proportion and Ψ is the proportion of people being schooled. Furthermore, letting $\phi = \phi^s/\phi^u = \frac{A^{1/k}\beta^u}{\beta^s}$

$$\frac{N_t}{M_t} = \left(\frac{\beta^u R_t^s}{\beta^s R_t^u}\right)\left(\frac{q_t}{A(1-q)_t}\right)^{1/k} \tag{24}$$

$$= \phi \frac{R_t^s}{R_t^u}\left(\frac{q_t}{(1-q)_t}\right)^{1/k} \tag{25}$$

Equation (24) makes it clear that the ratio of skilled to unskilled technologies is a function of the relative costs of adopting those technologies (first bracket) and the relative values of holding the licences (second bracket). The key driver of costs over time is the rate at which the technology frontiers advance. Relative values change over time if the skill composition of the labor force is changing.

3.3 Wages

In the model, inequality is measured in terms of the skilled wage premium. Skilled and unskilled wages equal the marginal product of skilled and unskilled labor. Holding the level of technology and intermediates constant, skilled and unskilled wages are

$$w_t^s = (1-a)\,N_t\left(\frac{X_{jt}}{q_t}\right)^a \tag{26a}$$

$$w_t^u = A^{1-a}(1-a)\,M_t\left(\frac{Z_{jt}}{1-q_t}\right)^a, \tag{26b}$$

but (8) and (9) imply

$$w_t^s = (1-a)\,a^{\frac{2a}{1-a}}N_t \tag{27a}$$

$$w_t^u = A\,(1-a)\,a^{\frac{2a}{1-a}}M_t. \tag{27b}$$

Equations (27a) and (27b) expose a feature of the production function (cf equation 6). The terms in labor and intermediates cancel, revealing a constant positive correlation between wages and the number of intermediate varieties. By (22a) and (23a), we see this translates into a positive relationship between wages and labor supply and between wages and the research frontier:

$$w_t^s = \theta^s R_t^s \left(\frac{q_t}{r}\right)^{1/k} \tag{28a}$$

$$w_t^u = \theta^u R_t^u \left(\frac{1-q_t}{r}\right)^{1/k} \tag{28b}$$

where $\theta^s \equiv \frac{\left[(1-a)^{1+k} a^{\left(\frac{1+a+2ak}{1-a}\right)}\right]^{1/k}}{\beta^s}$ and $\theta^u \equiv \frac{\left[A^{1+k}(1-a)^{1+k} a^{\left(\frac{1+a+2ak}{1-a}\right)}\right]^{1/k}}{\beta^u}$. Relative wages are

$$\frac{w_t^s}{w_t^u} = \left(\frac{\beta^u R_t^s}{\beta^s R_t^u}\right)\left(\frac{q_t}{A^{1+k}(1-q)_t}\right)^{1/k} = \frac{N_t}{AM_t}. \tag{29}$$

In order to confine our setting to that of a developing economy, which consists mostly of unskilled technologies - $M_t > N_t$ - and still has a positive skill premium - $w^s > w^u$ - for all possible population levels, we impose the restriction that[6]

$$\frac{1}{A}\left(\frac{\beta^u R_t^s}{\beta^s R_t^u}\right)^k < \frac{1-q_t}{q_t} < \left(\frac{1}{A}\right)^{1+1/k}\left(\frac{\beta^u R_t^s}{\beta^s R_t^u}\right)^k. \tag{30}$$

4 Evolution of the economy

We can use (18) and (22a) to describe the rate at which skill-biased technologies are imported:

$$\frac{N_{t+1}}{N_t} = g^s\left(1+\frac{\Psi-q_t}{q_t}f\right)^{1/k} \tag{31}$$

$$= g^s\left(1+\frac{rf(\Psi-q_0)(1-f)^t}{\Psi(r+f)-r(\Psi-q_0)(1-f)^t}\right)^{1/k} \tag{32}$$

If the skill proportion remains constant, new skill-biased technologies are imported at the same rate as the technology frontier advances - g^s. However, if $\Psi > q_0$ such

[6]The first inequality implies that the expense of acquiring non- skill-biased intermediates relative to skill-biased intermediates is sufficiently low to overcome the lower productivity of unskilled workers, so there are more non- skill-biased technologies. The second inequality implies that the greater varieties of unskill-biased intermediates used by unskilled workers, which makes them more productive, is not sufficient to overcome their inherently lower productivity relative to skilled workers. The implied additional criterion $\frac{1}{A} < \left(\frac{1}{A}\right)^{1+1/k}$ is naturally met when $A < 1$. These conditions are not needed for the main results of this paper, only those on the impact on growth.

that the population is becoming increasingly skilled, the rate of technology adoption exceeds g^s.[7] Thus, while advances in the technology frontier reduce the marginal cost of adopting a new technology, holding the level of technology constant, rises in the skilled population increase the value of adopting it. Both act together to expand the variety of skill-biased intermediates. As t gets large, $q_t \to \Psi$ and the growth rate converges to g^s.

In contrast, the forces affecting the rate of non- skill-biased technology adoption work against each other if the skill composition of the population is rising. Using (19) and (23a), the rate at which unskilled technology is imported is:

$$\frac{M_{t+1}}{M_t} = g^u \left(1 - \frac{\Psi - q_t}{1 - q_t} f\right)^{1/k} \tag{33a}$$

$$= g^u \left(1 - \frac{rf(\Psi - q_0)(1-f)^t}{(1-\Psi)(r+f) + r(\Psi - q_0)(1-f)^t}\right)^{1/k} \tag{33b}$$

If the population is constant, unskilled technology is adopted at rate g^u. However, if $\Psi > q_0$ such that the population is becoming increasingly educated, the rate of technology adoption is less than g^u. While advances in the technology available reduce the marginal costs of adopting the technology, the decreasing availability of unskilled workers reduces the attractiveness of unskilled technologies over time.

The possibility remains that the latter effect is stronger than the former, but we assume for now that this is not the case so that there is strictly positive growth in the stock of unskilled technologies. As t gets large, the growth rate converges to g^u.

Furthermore, assuming the skill composition is constant, we can measure the skill-bias of technical progress over time:[8]

$$\frac{\frac{N_{t+1}}{N_t}}{\frac{M_{t+1}}{M_t}} = \frac{g^s}{g^u} \tag{34}$$

This simple expression conveys the persistent skill-biased technical progress observed in developing countries and delivers one of the key messages of the paper: holding skill composition constant, product variety expansion can be skill-biased simply because technical change research is skill-biased in the North ($g^s > g^u$).

This phenomenon occurs even if the population is largely unskilled. Rather than complementing their abundance of unskilled labor, such countries acquire

[7] To confirm this for 32, note $\Psi(r+f) - r(\Psi - q_0)(1-f)^t$ is minimised when $t = 0$. If $t = 0$, this expression is $\Psi f + rq > 0$. It is therefore positive for all t. $rf(\Psi - q_0)(1-f)^t$ is positive for $\Psi > q_0$.

[8] (34) implies that, eventually, (30) will cease to hold. This can be interpreted as the end of a country's status as a developing economy.

technologies that increasingly complement their skilled workers, giving rise to the phenomenon of inappropriate technology transfer.

An economy in which the skill composition is rising will have accelerated skill-biased technical progress:

$$\frac{\frac{N_{t+1}}{N_t}}{\frac{M_{t+1}}{M_t}} = \frac{g^s}{g^u}\left[\frac{1+\frac{\Psi-q_t}{q_t}f}{1-\frac{\Psi-q_t}{1-q_t}f}\right]^{1/k} > \frac{g^s}{g^u} \tag{35}$$

It follows from (27a) and (27b) that:

$$\frac{w^s_{t+1}}{w^s_t} = g^s\left(1+\frac{\Psi-q_t}{q_t}f\right)^{1/k} \tag{36a}$$

$$\frac{w^u_{t+1}}{w^u_t} = g^u\left(1-\frac{\Psi-q_t}{1-q_t}f\right)^{1/k} \tag{36b}$$

and the skill premium evolves according to:

$$\frac{\frac{w^s_{t+1}}{w^s_t}}{\frac{w^u_{t+1}}{w^u_t}} = \frac{g^s}{g^u}\left[\frac{1+\frac{\Psi-q_t}{q_t}f}{1-\frac{\Psi-q_t}{1-q_t}f}\right]^{1/k} = \frac{\frac{N_{t+1}}{N_t}}{\frac{M_{t+1}}{M_t}} \tag{37}$$

The skill premium is more likely to rise if technical change is skill-biased in the North and if the skilled population grows at the expense of the unskilled population. Even if the skill composition is constant, we still see persistent rises in wage inequality at rate $\frac{g^s}{g^u}$. Unlike existing models of endogenous technology adoption, the increase in the skill premium is not a transitory phenomenon that occurs as the skill composition changes, but a permanent one. Furthermore, wage inequality accelerates as the skill composition of the economy evolves.

Output and consumption Equations (34) to (37) constitute our main results. Before going into some detail in the next section, we briefly consider the evolution of output and consumption. GDP growth is given by

$$\frac{Y_{t+1}}{Y_t} \equiv g^y = \frac{N_{t+1}q_{t+1} + AM_{t+1}(1-q_{t+1})}{N_t q_t + AM_t(1-q_t)} \tag{38}$$

If the skill composition is constant and $g^s = g^u = g$, $\frac{Y_{t+1}}{Y_t} = g$. This is a standard result of endogenous growth models (see for example Romer, 2001). GDP (and hence GDP per capita) grows at a pace matching the rate of technological progress. We complete the description of the model by analyzing how GDP is allocated.

We assume the skill composition is constant. Consumers earn income in the form of wages and returns on any claims on licences for intermediates they hold. Aggregate wages are $w^s q_t + w^u(1-q_t) = (1-a)Y_t$. Returns on licences are $r(N_t V_t^s + M V_t^u)$. By (13) and (15), returns are $\Omega\left[N_t q_t + A M_t (1-q_t)\right] = (1-a)aY_t$. Thus consumer income is $Y_t - a^2 Y_t$. But, using (8) and (9), $a^2 Y_t = N_t X_{jt} + M_t Z_{jt}$. Thus aggregate consumer income is given by $Y_t - X_t - Z_t$. The result is analogous to that presented in Barro & Sala-i-Martin (2004).

As expected from the production technology, the wage share of output is $(1-a)$ and the capital share is a, of which a^2 is lost in foregone/depreciated inputs and the remaining $a - a^2$ is earned as monopoly profits. Let all assets (licences) owned in the economy $W_t = N_t V_t^s + M V_t^u$. Analogous to Barro & Sala-i-Martin (2004), consumption in the economy is thus given by

$$C_t = Y_t - X_t - Z_t - (W_{t+1} - W_t) = (1-a^2)Y_t - (W_{t+1} - W_t), \tag{39}$$

where $(W_{t+1} - W_t)$ is the consumption foregone in the form of exports in exchange for new licences (for both types of intermediate). Using the fact that $(W_{t+1} - W_t) = \frac{\Omega}{r}\left[q_t N_t (g^s - 1) + A(1-q_t)M_t(g^u - 1)\right]$, algebra shows $\frac{C_{t+1}}{C_t} = \frac{r(1-a^2)Y_{t+1} - \frac{Y_{t+2} - Y_{t+1}}{a(1-a)}}{r(1-a^2)Y_t - \frac{Y_{t+1} - Y_t}{a(1-a)}} = g^y$, so consumption grows at the same rate as output. If $g^s = g^u = g$, consumption, GDP, wages and income from licences all grow at g.

5 A rise in the skill composition

This section provides more details on the effects of changes in the skill composition. It uses a one-off rise in the supply of skilled labor to work through some adjustment issues before analyzing a gradual rise brought about by expanded schooling access.

5.1 A one-off rise

An economy can experience a relatively fast rise in the skill composition if race- or gender-based barriers to highly skilled jobs are removed. In South Africa for example, people who may have been skilled were effectively barred from participating in the skilled labor force and were in general forced to take unskilled jobs. In the West bank and Gaza Strip, there were no higher education institutions in 1972 but 20 barely a decade later (Angrist, 1995). We therefore compare a rise in the skilled labor force from q_0 to q_1 in time period $t = 0$. For comparative statics, it is helpful to see that (22a) and (23a) make explicit the following relationships:

$$N_t = \frac{R_t^s}{\beta^s} (V_t^s)^{1/k} \tag{40a}$$

$$M_t = \frac{R_t^u}{\beta^u} (V_t^u)^{1/k} \tag{40b}$$

Inspection of (13) shows that the elasticity of the value of a licence with respect to the skilled labor supply is unity: $\frac{V_{jt}^s|q_1}{V_{jt}^s|q_0} = \frac{q_1}{q_0}$. A rise in the number of skilled workers raises demand for each available skill-biased intermediate in a period and therefore raises the present value of profit received for holding a licence. The number of varieties at $t = 0$ is not affected as it takes one period to acquire new licences. However, the economy can jump to the optimal quantity the following period. (40) shows the ratio is:

$$\frac{N_t|q_1}{N_t|q_0} = \left(\frac{q_1}{q_0}\right)^{1/k}, t > 0 \tag{41}$$

The ratio holds for all t as variety expansion continues at rate g^s - as it would have if there had been no change in skill supply.[9] Similarly, $\frac{V_{jt}^u|(1-q_1)}{V_{jt}^u|(1-q_0)} = \frac{1-q_1}{1-q_0}$ and the *optimal* value of non- skill-biased technologies falls:

$$\frac{M_t|(1-q_1)}{M_t|(1-q_0)} = \left(\frac{1-q_1}{1-q_0}\right)^{1/k}, t \geq t^* \tag{42}$$

However, the number of varieties available cannot fall as the technologies have already been acquired. The *actual* number of non- skill-biased intermediates remains constant until the research frontier has advanced sufficiently. Because the value of non- skill-biased intermediates has fallen, the marginal cost must fall sufficiently before technology adoption can resume. This occurs when $\frac{M_{t^*}|(1-q_1)}{M_0|(1-q_0)} > 1$. By 19 and (40), $(g^u)^{t^*} > \left(\frac{1-q_1}{1-q_0}\right)^{1/k}$ so that

$$t^* > \frac{\ln \frac{1-q_0}{1-q_1}}{k \ln g^u} \tag{43}$$

The time required is shorter if the population change is smaller and the research frontier advances quicker. A large value of k means marginal cost falls fast as the

[9]The negative effect of k can be explained as follows: to restore equilibrium, the rise in value generated by higher q must be matched by a rise in marginal cost. The higher the value of k, the faster marginal cost rises as N_t moves closer to the technology frontier and thus the smaller the rise in N_t needed to restore the equivalence.

economy falls further behind the advancing frontier. After t^*, technology imports resume at rate g^u.

At $t = 0$, the number of intermediates and technologies is unaffected by the change in skill composition. Holding the number of intermediates demanded and technology adoption constant, (26a) shows skilled wages are lower than they would have been, in accordance with downward sloping labor demand. Similarly, (26b) shows unskilled wages are higher than they would have been. We thus see a fall in the skill premium when $t = 0$. However, intermediates demand can adjust to the new skill composition for $t > 0$.

Equation (27b) confirms that, because the variety of non- skill-biased intermediates remains constant, unskilled wages also remain constant until t^*. Thereafter, they rise at rate g^u. Because, in the absence of the fall in unskilled labor, unskilled wages would have grown at g^u even before t^*, wages are forever lower than they would have been. We will shortly confirm that inequality rises, but we can immediately see that unskilled workers lose out not only relative to skilled workers but also in absolute terms by $\left(\frac{1-q_1}{1-q_0}\right)^{1/k}$ in all time periods. However, because the number of varieties does not fall, unskilled wages never fall below the actual level attained at t_0.

Similarly, (27a) implies skilled wages jump when the population rises before resuming their normal rate of increase of g^s. Skilled wages and hence wage inequality jump by $\left(\frac{q_1}{q_0}\right)^{1/k}$ at $t = 1$ and continue to grow at g^s until $t < t^*$. Once unskilled technology adoption resumes, wage inequality grows at $\frac{g^s}{g^u}$ as before and

$$\frac{\frac{w^s}{w^u}|q_1}{\frac{w^s}{w^u}|q_0} = \left(\frac{q_1(1-q_0)}{q_0(1-q_1)}\right)^{1/k}, t \geq t^*. \tag{44}$$

The results presented are so far consistent with this class of model. It is important to stress that the one-off change in population causes annual rises in inequality only as long as M_t is stagnant.[10] The main effect is a levels effect. If one believes the skill-biased technical change observed in developing countries is more than simply a transition, the one-off changes in the skill composition produced by models in this class are an inadequate explanation for developing economies. Steady state skill-biased technical progress is generated only by the fact that $g^s > g^u$.

Output effects Before turning to gradual population changes, we consider the effects of the rise in the skill composition on GDP and GDP growth. Partially

[10] To illustrate, a rise in q from 20% to 40% with $k = 2$ and $g^u = 1.02$ generates a value of $t \approx 7$ years.

differentiating (10), holding the levels of technology constant, $\frac{\partial Y_t}{\partial q} = N_t - AM_t$. Allowing for technology to change, $\frac{dY_t}{dq} = \frac{1+k}{k}\left(N_t - AM_t\right)$. It is clear that GDP rises if $N_t > AM_t$. It can be shown that the conditions for this to hold are precisely those in (30). We can also show[11] that $\frac{d\frac{Y_{t+1}}{Y_t}}{dq} > 0$ as long as $g^s > g^u$. Hence, in aggregate, a rise in the skill composition of the economy allows the economy to exploit the skill-biased research being done in the North and grow quicker.

The finding that a rise in skill composition can boost growth is also consistent with theoretical models and cross country empirical growth studies that document a positive correlation between human capital and growth (e.g. Barro & Sala-i-Martin, 2004). It also accords with the view in policy circles that skills acquisition is a key component of any developing country growth strategy (Lopez-Claros, Altinger, Blanke, Drzeniek & Mia, 2006). Furthermore, even if unskilled workers lose out in wage terms, the overall gain should be large enough for them to be compensated. However, we have not accounted for any resource costs.

5.2 An expansion of schooling access

We now model the effects of a new education policy that gradually raises the proportion of skilled workers in the economy. We implicitly assume the main driver of educational attainment is ease of access through the supply of schooling, not shifts in demand by individuals. This assumption is appropriate in the context of widening access to formerly barred segments of the population, but Acemoglu (1998) and Rahman (2005) endogenise the availability of skilled labor without affecting their results.

The economy initially has skill proportion q_0, with the proportion of people being educated $\Psi = q_0$ so that the proportion is constant. At $t_{0,}$ better access to education raises Ψ to $q_1 > q_0$. This is credibly announced at t_0 but only starts to take effect one period later as given by (2). Over time, the economy's skill composition will move towards q_1. We still refer to q_t as the proportion of skilled labor as it evolves over time. These demographics are known to all agents in the economy. We will see that, although the instantaneous change in the skill supply is small, there is still a jump in the value of licences as the expected future profits are adjusted.

Addressing skill-biased technologies first, (12) can be used to compare the values of a skill-biased licence with and without the change in policy. Noting that

[11] Let $g^s = \lambda g^u$ and hold q constant.

Using (38), $\frac{d\frac{Y_{t+1}}{Y_t}}{dq} = \left(\frac{g^u}{(Y_t)^2}\right)\left[\left(\lambda N_t - AM_t\right)\left(N_t q + (1-q)AM_t\right) - \left(N_t - AM_t\right)\left(\lambda N_t q + (1-q)AM_t\right)\right]$. This is strictly positive iff $\lambda > 1$; that is, if $g^s > g^u$.

$V_t^s|q_0 = V_0^s|q_0$ because the population would have remained constant,

$$\frac{V_t^s|q_1}{V_t^s|q_0} = \frac{q_1}{q_0} - \frac{r}{r+f}\left(\frac{q_1}{q_0} - 1\right)(1-f)^t \tag{45}$$

and $\lim_{t\to\infty} \frac{V_{jt}^s|q_1}{V_{jt}^s|q_0} = \frac{q_1}{q_0}$ so the value eventually changes by the same amount as reported for the one-off change. Along the adjustment path, the change in value is lower for large r because future changes in the population are heavily discounted. A large value of f means more people are being educated in absolute terms in a given period and this speeds up the rise in skill composition, which means the change in value is bigger. To characterize what happens initially, we set $t = 0$ and drop all terms in rf because they will have a second order effect on the jump.[12] In this case $\frac{V_{j0}^s|q_1}{V_{j0}^s|q_0} \approx \frac{q_1}{q_0} + \frac{r}{r+f}\left(1 - \frac{q_1}{q_0}\right)$. This shows that the initial jump in value is bigger if f/r is bigger. If we set $f = r$, the initial change is approximately half of the eventual change. After the initial jump, the value continues to rise in small increments towards its steady state value.

Using (45) and (40) (or 22a), the level of licences in period one relative to what it would have been is given by $\frac{N_1|q_1}{N_1|q_0} = \left[\frac{q_1}{q_0} - \frac{r}{r+f}\left(\frac{q_1}{q_0} - 1\right)(1-f)\right]^{1/k}$. It is easy to verify that $\frac{N_1}{N_0} > g^s$. In particular, if we assume $f = r$, $\frac{N_1}{N_0} \approx g^s\left[\frac{q_0+q_1}{2q_0}\right]^{1/k}$. After the initial jump, skill-biased varieties expand as given in (31). This rate is gradually decreasing over time and approaches g^s. The change in the value of unskilled licences is similarly:

$$\frac{V_{jt}^s|q_1}{V_{jt}^s|q_0} = \frac{1-q_1}{1-q_0} + \frac{r}{r+f}\left(1 - \frac{1-q_1}{1-q_0}\right)(1-f)^t \tag{46}$$

The initial jump can be approximated by $\frac{V_{j0}^u|q_1}{V_{j0}^u|q_0} \approx \left(\frac{1-q_1}{1-q_0}\right) + \frac{r}{r+f}\left(\frac{1-q_1}{1-q_0}\right)$ such that, for $f = r$, the downward jump is half the jump of the steady state jump. Therefore, it is feasible for adoption of non- skill-biased technologies to cease. M will not rise in the first period; that is, $\frac{M_1}{M_0} = 1$ if $g^u < \left(\frac{V_{j1}^s|q_1}{V_{j0}|q_0}\right)^{-1/k}$. Generally, the degree of variety remains constant until t^+, when $(g^u)^{kt^+} > \left(\frac{V_{jt^+}^s|q_1}{V_{j0}^s|q_0}\right)$. Over time, the research frontier advances to reduce the marginal cost of importing a new technology, but the value of acquiring a licence is also falling as the population falls. Whether

[12] Beyond the jump, rf is not second order because the incremental changes each period are themselves small.

marginal cost or value fall quicker depends on the parameters. Over time, the fall in value decelerates to 0 while the research frontier keeps advancing. Eventually, marginal cost will fall faster. However, technology adoption resumes only once the fall in marginal cost has caught up and exceeded the fall in value. t^+ denotes this period and is given by:

$$t^+ > \frac{\ln(1-q_0)(r+f) - \ln\left[(1-q_1)(r+f) + r(q_1-q_0)(1-f)^t\right]}{k \ln g^u} \tag{47}$$

t appears on both sides of the inequality. To characterize the solution for t^+, note that the total fall in value is given by the steady state fall, such that t^* given by (43) is an upper bound. Similarly, the approximation for the initial jump provides an approximate lower bound for t^+. So, for example, a rise in the skill proportion from 20% to 40%, setting $k = 2$ and $g^u = 1.02$, the upper bound is 8 years and the approximate $(f = r)$ lower bound is 4 years.

Once technology imports resume, the rate of technology adoption is given by (33) with $\Psi = q_1$ so that the rate of technology import is below g^u but accelerates until it reaches the rate of frontier growth.

Turning to wages, recall that the one off change in skill composition modelled in the previous section generated a one-period fall in the wage premium. This does not happen here. At t_0, the level of skill supply has not changed yet. By the time it does start to change from period 1 onwards, demand for intermediates can adjust as the population change was anticipated. Thus, holding the level of technology constant, there is no initial adjustment in inequality. The effect of the initial jump in N is to raise skilled wages at t_1 by approximately $\frac{w_1^s|q_1}{w_1^s|q_0} \approx \left[\frac{q_1}{q_0} - \frac{r}{r+f}\left(\frac{q_1}{q_0} - 1\right)(1-f)\right]^{1/k}$.

Wages continue to grow at $\frac{w_{t+1}^s}{w_t^s} = g^s\left(1 + \frac{q_1 - q_t}{q_t} f\right)^{1/k}$ and decelerate to g^s as $q_t \to q_1$. While skilled wages jump and grow fast, unskilled wages are stuck at w_0. They remain there until t^+, when unskilled technology adoption resumes. Because unskilled wages grow at $\frac{w_{t+1}^u}{w_t^u} = g^u\left(1 - \frac{q_1 - q_t}{1 - q_t} f\right)^{1/k}$, which is slower than g^u, wage inequality grows faster than before the change in p. As unskilled wage growth approaches g^u, inequality once again grows at $\frac{g^s}{g^u}$. This can be confirmed by inspecting (37).

We therefore have potentially long periods of accelerating inequality because the continuous rise driven by differential advances in the research frontiers is compounded as the skill composition of the workforce gradually rises. Furthermore, at t_1, there is a one-off jump in relative wages. The fact that the unskilled labor force falls for a long time makes it possible for unskilled wages to remain stagnant for long periods while skilled wages advance at a higher (although decelerating) rate.

6 Conclusion

This paper draws on evidence from other studies and the data to observe that developing countries have experienced pervasive skill-biased technological change and growing income inequality. Rising skill supply has been an ineffective counter against these trends, with no robust evidence of a clear negative relationship between schooling and inequality and some indications of a positive relationship. In terms of Tinbergen's (1975) race between education and technology, it seems education is standing still or even running backwards.

With this motivation, we drew on the literature for developed countries to distinguish between R&D that is inherently skill-biased and that which is endogenously skill-biased due to rising skill supply. However, developing countries engage in little R&D but acquire technologies from abroad. Irrespective of the reasons for observed SBTC in rich countries, this produces an external source of SBTC in poorer countries. Furthermore, we provided examples that developing countries also adapt the skill-bias of the technologies acquired to local skill supply.

We develop an endogenous technical change model for developing countries that analyzes the interplay between these sources of SBTC and provides an explanation for why increased skill supply can lead to a rise in inequality including stagnant unskilled wages. In particular, our endogenous growth model established how skill-biased R&D in the North leads to SBTC in the South. Furthermore, it establishes how a rise in skill supply makes it relatively more attractive to acquire skill-biased technologies from abroad. In an era of technical change driven by R&D in the North, our Markov process shows how expanded schooling access, which generates periods of increasing skill supply, leads to accelerated wage inequality.

With this model, we can interpret the coordinated rise in inequality observed in Figures 1-3 in the last two decades as SBTC in the South driven by SBTC in the North. Increased schooling has not been an effective counterweight because its acceleration stimulated further SBTC, especially in the LMICs.

The World Competitiveness Report views an increase in the skills base through expansion of both primary and higher education as a key ingredient for competitiveness in the light of these observed shifts in demand away from unskilled labor (Lopez-Claros et al, 2006). Thus expanded education may be a response to global labor demand shifts. Similarly, while technical change is seen as a key component of increased growth, education is proposed as a way to make this growth more inclusive. However, because it would lead to additional SBTC, this policy response would be counter productive. The model implies that expanded education access would increase GDP growth rates, but it would also result in long periods of accelerated growth in income inequality and flat unskilled wages. Together with the other factors complicating the relationship between skill supply and inequality, the model provides a reason to be cautious about the efficacy of schooling in reducing income disparities.

Appendix 1: Data description

The inequality data is taken from the UTIP-UNIDO database. We use the EHII, which is an index from 0-100 of estimated household income inequality. The data is currently available annually from 1963 to 2003 and covers 150 countries. It is an unbalanced panel but is unmatched in terms of coverage and consistency. We are currently not aware of an individual and/or wage premium panel dataset with this degree of world-wide coverage.

The schooling data is taken from Barro & Lee (2001); in particular, we use the average years of schooling completed in the population. This is available in five year intervals and we start in 1965 and end in 2000. As a result, we build equivalent period averages for the inequality data, corresponding the 1963-1969 inequality data to the 1965 schooling data, the 1970-1974 inequality to the 1970 schooling data and so on. The 2000 schooling data corresponds to the 2000-2003 inequality data. The graphs are based on simple averages taken across each income grouping (low, lower middle, upper middle) for each five-year period.

The regressions use the same data as the graphs but also use data on the proportion of skilled workers, which is downloaded from Francesco Caselli's web site and was used by Caselli & Coleman (2006). Their data on labor supply is from Barro and Lee (2001), who report for each country the share of the labor force who have one of seven categories of educational achievement. We aggregate the seven categories into skilled and unskilled labor following the method in Caselli & Coleman (2006). We use estimates of Mincerian coefficients to assign higher weights to higher categories and also take account of differences in duration across countries. The countries in Appendix 2 below are those for which data is available in sufficiently early/late periods.

Appendix 2: Country changes in schooling and inequality

Country	Inequality	Schooling	Country	Inequality	Schooling
Algeria*	7.4	2.83	Kenya	-1.9	1.53
Bangladesh*	3.6	1.3	Malawi*	5.3	0.38
Bolivia	3.7	1.54	Malaysia	-1.3	3.39
Bulgaria	14	3.06	Mauritius*	-5.7	1.69
Cameroon*	10.7	2.31	Mexico	3.9	2.72
Chile	1.5	1.34	Pakistan*	5.2	0.76
Colombia	2.2	1.93	Panama	4.7	1.99
Costa Rica	-5.2	1.07	Philippines*	1.8	1.87
Ecuador*	8.6	1.31	Poland	11.9	1.25
Egypt	9.2	2.26	Senegal	2.4	0.31
El Salvador*	4.2	2.84	South Africa	1.8	3.05
Fiji*	0.4	1.48	Sri Lanka	0.2	0.91
Ghana*	3.3	2.56	Swaziland*	-5.0	2.36
Guatemala*	12.6	1.68	Syria*	6.6	3.04
Honduras*	3.2	1.18	Taiwan*	3.1	2.99
Hungary	5.9	0	U.S.S.R/Russia	12.1	2.28
India	3.2	2.05	Uganda	-12.2	1.56
Indonesia	5.9	1.62	Uruguay	5.8	1.26
Iran	9.7	2.73	Venezuela*	6.5	1.5
Jordan	2.2	4.44	Zimbabwe*	5.3	1.97

40 countries, of which 39 had rises in schooling and 34 had higher inequality

* late 1970s to early 1990s; otherwise early 1980s to early 2000s

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