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# Skill-biased technological change, unemployment and brain drain

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# 1 Introduction

Models of skill-biased technological change have become increasingly popular for explaining the increase in the relative wage of skilled workers (skill premium) that has been observed around the world over the last decades (see e.g., Acemoglu (2003), Thoenig and Verdier (2003), Epifani and Gancia (2008)). More recently, they have also been used to to explain cross-country differences in income per worker (e.g., Acemoglu and Zilibotti (2001), Caselli and Coleman (2006), Gancia, Mueller and Zilibotti (2011)). A major challenge when testing these models in a cross-country context is that their main empirical prediction is on the relationship between the skill premium and the relative abundance of skilled workers. However, comparable cross-country data on skill premia, which are required to test this hypothesis, are scarce and of questionable quality, making it hard to test. In this paper, we develop two useful extensions of Acemoglu's (1998, 2002) model of directed technological change. We augment the standard model for two components: skill-specific frictional unemployment and skill-specific migration. With these extensions, the model has clear predictions on the relationship between skill ratios and relative unemployment rates of skilled workers on the one hand, and on the relationship between skill ratios and the relative emigration rate of skilled workers (brain drain), on the other hand, for which comparable cross-country data are readily available.

To illustrate the idea, Figure 1 plots relative unemployment rates of skilled relative to unskilled workers for a panel of both OECD and non-OECD countries against relative skill endowments.[1] It is apparent that countries with a higher skill ratio have a substantially lower unemployment rate of skilled relative to unskilled workers. Figure 2 plots log changes in relative unemployment rates against log changes in skill ratio. Again, there is a strong negative correlation. Such a negative relation is not consistent with models where the relative demand for skill is downward sloping, since in this case higher relative abundance of skill should imply higher relative unemployment rates of skilled workers.[2] Moreover, the observed links between the skill ratio and skill-specific labor market outcomes affect the relationship between the skill ratio and emigration rates of the skilled and unskilled accordingly: more skill-abundant countries have a significantly lower migration rate of skilled relative to unskilled workers (brain drain). Figure 3 provides a scatter plot of brain drain against countries' skill ratios.[3] Clearly, more skill-abundant countries suffer much less from brain drain than skill-scarce ones. In Figure 4 we plot log changes in brain drain against log changes

[1]Skilled workers are defined as workers with at least some tertiary education in the population over 25 years. Unemployment rates by skill are constructed from the ILO Key Indicators of the Labor Market (see the Appendix for a description), data on educational attainment are from Barro and Lee (2000). Data are in 5-year intervals from 1980-2005, pooled over time.

[2]This is true even though relative wages of the skilled decrease, as shown in our model.

[3]Data on migration by skill to the OECD are from Beine, Docquier and Rapoport (2008). Data are for 1990 and 2000.

in skill ratio. Again, we observe that countries that increase their skill ratio tend to experience a fall in the brain drain.

Motivated by these correlations, we build a model of directed technological change, skill-specific unemployment and migration. Towards this end, we combine a version of the canonical model of directed technological change (Acemoglu (1998, 2002), Gancia and Zilibotti (2008)) with matching frictions in the labor market (Mortensen (1970), Pissarides (1990/2000)). We show that two conditions are necessary for the skill premium and relative employment rates of skilled workers to be increasing in the skill ratio. First, the elasticity of substitution between skilled and unskilled labor needs to be sufficiently large. This guarantees that the relative demand for skill rises with the skill ratio, as technological innovations complementing the relatively more abundant employed factor become more profitable (market size effect). Second, labor markets need to be sufficiently frictional, such that an increase in the skill ratio does not increase relative labor supply by too much. Otherwise, skill premia need to fall to absorb the additional factor supply, leading to relatively lower employment rates of skilled and inducing technological change – via the market size effect – that is biased towards the factor that has become relatively more scarce. Moreover, we also show that the higher matching elasticities are, the more skill-biased technological change manifests itself not so much in the form of increasing skill premia but, rather, in increasing employment opportunities for the skilled.

In an extension, we introduce labor market institutions into the model, considering unemployment benefits and firing costs. We show that in the presence of these regulations, the previous conditions for an increase in the skill ratio to increase the relative employment rate of skilled workers are no longer sufficient. In addition, unemployment benefits and firing costs need to be sufficiently low, otherwise an increase in the skill ratio can actually reduce relative employment rates of skilled workers.

Turning to the predictions on migration, we show that the same conditions that guarantee that an increase in the skill ratio increases the relative employment rate of skilled workers, are also sufficient for the brain drain to drop when the skill ratio rises. In this case, an increase in the skill ratio, by increasing relative employment rates and wages, increases relative expected wages of skilled workers, thereby reducing relative incentives to emigrate.

Next, we provide empirical evidence for the model's implications and show that skill upgrading: first, does not lead to a reduction in the skill premium but induces skill-biased technological change; second, it reduces the relative unemployment rate of skilled workers; third, we show that this result is conditional on labor market regulation being sufficiently flexible (i.e., unemployment benefits and firing cost must be sufficiently low); and fourth, we demonstrate that skill upgrading lessens the brain drain.

Finally, we use a calibrated version of our model to show that it does reasonably well in replicating both qualitatively and quantitatively the cross-sectional correlations referred to above (e.g., the positive relation between skill ratio and relative productivity of skilled, the negative relation between skill ratio and relative unemployment of skilled, the negative relation between skill ratio and brain drain), as well as the negative correlation between skill upgrading and the drop in brain drain that occurred during the 1990's. In addition, we show that at the levels of skill ratios that are currently prevailing in many developing countries, increases in the skill ratio can potentially result in sizeable decreases in the brain drain.

We contribute to the literature in several ways. We are the first to introduce search and matching frictions (Mortensen (1970), Pissarides (1990, 2000)) into a model of directed technological change (Acemoglu (1998), (2002), Gancia and Zilibotti (2008)) in order to examine the effects of the skill ratio on skill-specific labor market outcomes. As a result, we are able to study the interactions of labor market frictions and directed technological change and provide several interesting results that are new to the literature. Moreover, our predictions can be used to provide new evidence for models of directed technological change. So far, there is only a small number of studies that test this kind of model in a cross-country context. Caselli and Coleman (2006) back out productivities of skilled and unskilled workers from a cross-section of wage premia and income data by calibrating a reduced form model of directed technological change. They find that relative productivities of skill are positively correlated with income per worker. Acemoglu and Zilibotti (2001) show that skill-technology mismatch can partially explain cross-country income differences when all countries use the technologies developed by the U.S. More recently, Gancia, Mueller and Zilibotti (2011) use a full-fledged quantitative model of directed technological change featuring skill-technology mismatch, technology adoption costs and international trade that can endogenously generate skill-specific productivity differences. They estimate technology adoption costs by fitting predicted income per worker to the data and find that the model can replicate observed income differences extremely well. However, none of these papers try to match data other than income and wages. By focusing on unemployment rates and migration, we provide new evidence supporting models of directed technological change.

We also contribute to the literature on brain drain, which shows that increases in the skill ratio can coincide with decreases in the brain drain. On the one hand, this is because workers may invest more in education when their emigration probability increases. If the net effect on the domestic skill ratio is positive – i.e., if relatively few of the workers that obtain higher education because of the migration perspective emigrate – then higher skilled emigration prospects can reduce the brain drain.[4] According to this strand of the literature, an increase in the migration probability can cause

[4] Then, the brain drain corresponds in fact to a so-called brain gain. See for example Mountford (1997), Stark, Helmenstein and Prszkawetz (1997, 1998), Beine, Docquier and Rapoport (2001, 2008).

an increase in human capital in the source country. On the other hand, as has been observed more recently, an increase in human capital in the source country can lead to an increase in domestic wages if returns to skilled labor are increasing and, thereby, reduce emigration incentives. This is the case in De la Croix and Docquier (2010) and Grossmann and Stadelmann (2011), where productivity is assumed to be increasing in skilled labor endowments. In our model, causality also runs from skill ratio to migration, but in contrast to the existing literature, we do not look exclusively at wages as determinants of the brain drain but also at unemployment rates: In our opinion, wages are definitely an important determinant of the decision of workers to emigrate, but their employment probability is likely to be at least as important.[5] Finally, we contribute to the literature by providing empirical evidence for the link from skill upgrading to skill-biased technological change, unemployment and migration.

In terms of policy implications, our findings suggest that educational policies that serve to improve the skills of the workforce may be even more important than commonly acknowledged. First, public investment in education should – via endogenous technology adjustment – improve the employment prospects of skilled workers, while reducing those of unskilled ones. Second, countries that face a deterioration in their skilled workforce through emigration might be able to turn around emigration trends by increasing their skill share and thereby improving demand for skilled labor and thus labor market conditions for the skilled at home. If unmet by an adequate policy response, however, emigration of the skilled workforce might develop a self-enforcing momentum, as labor market conditions for the skilled deteriorate further and emigration incentives are reinforced.

The paper is organized as follows. In section 2, we set up a model of skill-biased technological change and unemployment. We first derive the equilibrium without migration, both for the case where technology is exogenous and where it is endogenous. Next, we investigate the effect of labor market institutions. We then extend the model to allow for migration. In section 3, we calibrate the model and perform several comparative statics exercises, and we provide empirical evidence for the model's predictions in section 4. Section 5 presents our conclusions.

# 2 The Model

## 2.1 Production

We use a model with two different types of labor, skilled and unskilled workers, and factor-biased (directed) technical progress based on Acemoglu (1998, 2002) and Gancia and Zilibotti (2008).[6]

[5] In fact, we find that wage differences are no longer significant once we control for unemployment rates.

[6] While our model is static for reasons of tractability, the comparative statics of skill endowment effects on technology are the same as the steady-state ones in a dynamic model such as Acemoglu (1998, 2002).

Final output can be used for consumption, to pay for the fixed cost of innovation and for the hiring costs of workers in the intermediate sector. The final output sector is perfectly competitive, and final output is produced according to the aggregate production function

$$Y = \left[Y_L^{\frac{\epsilon-1}{\epsilon}} + Y_H^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}}, \tag{1}$$

where $Y_L$ and $Y_H$ are sectoral aggregate goods produced with unskilled labor $L$ and skilled labor $H$, respectively, and $\epsilon > 1$ is the elasticity of substitution between them. From the final producers' profit maximization problem, we obtain the aggregate demand and the relative demand for sectoral aggregates:

$$P_H = \left[\frac{Y}{Y_H}\right]^{\frac{1}{\epsilon}} \tag{2}$$

$$P_L = \left[\frac{Y}{Y_L}\right]^{\frac{1}{\epsilon}} \tag{3}$$

$$\left[\frac{P_H}{P_L}\right] = \left[\frac{Y_L}{Y_H}\right]^{\frac{1}{\epsilon}}, \tag{4}$$

where we have already assumed that final output is the numéraire, which implies

$$P = P_H^{1-\epsilon} + P_L^{1-\epsilon} = 1. \tag{5}$$

Sectoral final output is produced under perfect competition using a constant elasticity of substitution aggregator over a measure $A_L$ ($A_H$) of sector-specific differentiated intermediate inputs, $y_L(i)$ ($y_H(i)$) with elasticity of substitution $\sigma > 1$:

$$Y_L = E_L \left[\int_0^{A_L} y_L(i)^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \quad \text{and} \quad Y_H = E_H \left[\int_0^{A_H} y_H(i)^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \tag{6}$$

The range of available intermediates captures the state of technology and will be endogenously determined in equilibrium. The terms $E_L \equiv A_L^{\frac{\sigma-2}{\sigma-1}}$ and $E_H \equiv A_H^{\frac{\sigma-2}{\sigma-1}}$ are externalities that conveniently pin down a degree of increasing returns that makes sectoral production functions linear in $A_L(A_H)$ and simplify the algebra. Note that this normalization does not change any of the qualitative implications of the model (compare Gancia and Zilibotti (2008)).

From the sectoral final producers' profit maximization problem, we obtain the inverse demand functions for intermediate goods

$$p_L(i) = y_L(i)^{-\frac{1}{\sigma}} Y_L^{\frac{1}{\sigma}} P_L E_L, \qquad p_H(i) = y_H(i)^{-\frac{1}{\sigma}} Y_H^{\frac{1}{\sigma}} P_H E_H. \tag{7}$$

Producers in the intermediate sectors are monopolistically competitive and use skilled (unskilled) labor in production. Their production technology is given by $y_L(i) = l(i)$ and $y_H(i) = Zh(i)$.

Using the demand functions for intermediates (7) it follows that revenue of intermediate producers in the two sectors is given by

$$p_L(i)y_L(i) = Y_L^{\frac{1}{\sigma}} l(i)^{\frac{\sigma-1}{\sigma}} P_L E_L, \qquad p_H(i)y_H(i) = Y_H^{\frac{1}{\sigma}} (Zh(i))^{\frac{\sigma-1}{\sigma}} P_H E_H. \tag{8}$$

Firms in the intermediate sectors face labor market frictions which we model following Helpman and Itskhoki (2010). A firm in the L (H) sector that wants to hire l (h) workers must pay a hiring cost of $b_L l$ $(b_H h)$, where $b_j$, $j \in \{H, L\}$, is exogenous to the firm but depends on labor market frictions to be discussed below. As a consequence, workers cannot be replaced without a cost and this makes workers inside the firm different from workers outside the firm. In particular, workers have bargaining power once they have been hired. We assume strategic wage bargaining with equal weights between the h (l) workers and the firm à la Stole and Zwiebel (1996 a,b). This leads to a distribution of revenue according to Shapley values. The revenue function (8) implies that the firm gets a fraction $\sigma/(2\sigma - 1)$ of the revenue and workers get a fraction $(\sigma - 1)/(2\sigma - 1)$. Then, the firm chooses an employment level that maximizes profits, which are given by

$$\pi_L(i) = \frac{\sigma}{2\sigma - 1} Y_L^{\frac{1}{\sigma}} l(i)^{\frac{\sigma-1}{\sigma}} P_L E_L - b_L l(i) - \mu, \qquad \pi_H(i) = \frac{\sigma}{2\sigma - 1} Y_H^{\frac{1}{\sigma}} (Zh(i))^{\frac{\sigma-1}{\sigma}} P_H E_H - b_H h(i) - \mu. \tag{9}$$

Here, $\mu$ is the fixed cost of producing a variety of intermediates in terms of the final good (the innovation cost).

The solution to this profit maximization problem implies that the optimal employment of firms equals

$$l(i) = l = \left[\frac{\sigma - 1}{2\sigma - 1} \frac{1}{b_L} P_L E_L\right]^{\sigma} Y_L, \qquad h(i) = h = \left[\frac{\sigma - 1}{2\sigma - 1} Z^{\frac{\sigma-1}{\sigma}} \frac{1}{b_H} P_H E_H\right]^{\sigma} Y_H, \tag{10}$$

which is decreasing in hiring costs.

Using this together with demand (7) and production technologies $y_L = l$, $y_H = Zh$, we find that optimal prices are given by constant markups over the hiring costs:

$$p_L(i) = p_L = \left(\frac{2\sigma - 1}{\sigma - 1}\right) b_L, \qquad p_H(i) = p_H = \left(\frac{2\sigma - 1}{\sigma - 1}\right) \frac{b_H}{Z}. \tag{11}$$

Since wages equal a fraction $(\sigma - 1)/(2\sigma - 1)$ of revenue (8) divided by employment (10), we obtain:

$$w_j = b_j, \quad j \in \{L, H\} \tag{12}$$

Note also that given the pricing condition (11) and employment (10) optimal profits can be written as

$$\pi_L = \frac{1}{2\sigma - 1} p_L y_L - \mu \qquad \pi_H = \frac{1}{2\sigma - 1} p_H y_H - \mu \tag{13}$$

## 2.2 Labor Market

Each country is populated by two types of individuals that are in fixed supply. There are $H$ skilled workers and $L$ unskilled workers who maximize expected utility from consumption, $U_j = E(C_j)$, where $j \in \{H, L\}$, given their expected income. Let $H_E$ ($L_E$) be the aggregate employment of skilled (unskilled) workers. A skilled (unskilled) individual that searches for work finds a job with probability $x_H = H_E/H$ ($x_L = L_E/L$), where $x_j$ measures the degree of labor market tightness in sector $j$. Thus, her expected income equals $x_H w_H$ if she is skilled ($x_L w_L$ if she is unskilled).

As in the standard model of job search and unemployment (e.g. Diamond (1981), Mortensen (1970), Pissarides (1990/2000)), we assume that firms have to post vacancies in order to attract workers. This implies that the cost of hiring, $b_j$, depends on labor market tightness. Following Blanchard and Gali (2008) and Helpman and Itskhoki (2010), we assume that

$$b_j = a_j x_j^{\alpha}, \quad j \in (L, H) \quad a_j > 1 \quad \text{and} \quad \alpha > 0, \tag{14}$$

where $b_j$ is the cost of hiring per worker, $x_j$ is the employment rate measuring the degree of sectoral labor market tightness, $a_j$ is a measure of frictions in the labor market[7] and $\alpha$ is the elasticity of the wage with respect to the employment rate $x$. Using (12) together with (14), we obtain a first expression for the wage premium as a function of the relative employment rate of skilled:

$$\frac{w_H}{w_L} = \frac{a_H}{a_L} \left( \frac{x_H}{x_L} \right)^{\alpha} \tag{15}$$

Following the labor market literature, we label this relation between the wage premium and relative labor market tightness the relative wage curve (see e.g., Pissarides (1990,2000)) (we may also refer to this relation as the relative matching curve). It represents the equivalent to the labor supply curve in the presence of matching frictions and is increasing in the relative employment rate of skilled workers – a relatively tighter labor market implies relatively higher wages. Note that a lower value of $\alpha$, which is equivalent to less frictional labor markets, makes this relation flatter.

[7] Higher values of $a_j$ correspond to greater frictions in the labor market.

## 2.3 Exogenous Technology

We now solve for the equilibrium of the economy, assuming for the moment that the level of technology, $A_H, A_L$, is exogenously given.

From the labor market clearing conditions

$$L_E = \int_0^{A_L} l(i)di$$
$$H_E = \int_0^{A_H} h(i)di$$

we get $l(i) = \frac{L_E}{A_L}$ and $h(i) = \frac{H_E}{A_H}$. Substituting these in the sectoral production functions (6), we can express sectoral output as

$$Y_L = A_L L_E \quad \text{and} \quad Y_H = A_H Z H_E \tag{16}$$

and the sectoral relative price according to (4) as

$$\frac{P_H}{P_L} = \left[\frac{A_L L_E}{A_H Z H_E}\right]^{\frac{1}{\epsilon}}. \tag{17}$$

Now, we can derive a second expression for the skill premium – for given levels of technology $A_H, A_L$ – by using (11), (12) and (16), observing that the revenue of the intermediate sectors equals expenditure on sectoral intermediates, $p_L L_E = P_L Y_L$ and $p_H Z H_E = P_H Y_H$, and then substituting for prices using (17) :

$$\frac{w_H}{w_L} \equiv \omega = \frac{P_H Z A_H}{P_L A_L} = \left[\frac{Z A_H}{A_L}\right]^{\frac{\epsilon-1}{\epsilon}} \left[\frac{x_H}{x_L}\right]^{-\frac{1}{\epsilon}} \left[\frac{H}{L}\right]^{-\frac{1}{\epsilon}} \tag{18}$$

We call this relation the relative labor demand curve. According to equation (18) the skill premium is increasing in the relative productivity of the skilled and decreasing in the relative employment rate of skilled workers (since $\epsilon > 1$). Moreover, an increase in the relative supply of skill results in a lower skill premium for given employment rates.

In equilibrium, relative employment unambiguously increases in relative labor supply, but relative wages and employment rates decrease. To see this, use (15) together with (18) – where $A_H$ and $A_L$ are taken as given – to derive

$$\frac{H_E}{L_E} = \left[\frac{a_L}{a_H}\left(\frac{H}{L}\right)^{\alpha}\left(\frac{Z A_H}{A_L}\right)^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\alpha\epsilon+1}} \tag{19}$$

$$\frac{x_H}{x_L} = \left[ \left(\frac{a_H}{a_L}\right)^{-\epsilon} \left(\frac{H}{L}\right)^{-1} \left(\frac{ZA_H}{A_L}\right)^{\epsilon-1} \right]^{\frac{1}{\alpha\epsilon+1}} \tag{20}$$

$$\frac{w_H}{w_L} = \left[ \frac{a_H}{a_L} \left(\frac{H}{L}\right)^{-\alpha} \left(\frac{ZA_H}{A_L}\right)^{\alpha(\epsilon-1)} \right]^{\frac{1}{\alpha\epsilon+1}} \tag{21}$$

Therefore, we get:

**Remark 1.** *Assume technologies $A_H$, $A_L$ are given. Then, an increase in the relative number of skilled individuals always results in a decrease in their wage and employment rate relative to the unskilled.*

Figure 5 provides an illustration of the labor market equilibrium with exogenous technology. As the relative supply of skilled, $H/L$, increases, the relative labor demand curve (18) shifts down – for constant employment rates the relative wage must fall, which in turn leads to lower relative labor market tightness. In the new equilibrium, relatively more skilled are employed than before, but both their (relative) wage and employment rate are now lower.

### 2.4 Endogenous Technology

We now allow for free entry in the intermediate sectors to pin down the state of technology $A_H, A_L$ endogenously.

Using optimal profits (13), free entry implies that intermediate producers make zero profits.

$$\pi_L = \frac{1}{2\sigma - 1} p_L l - \mu = 0 \qquad \pi_H = \frac{1}{2\sigma - 1} p_H h - \mu = 0 \tag{22}$$

Further, using the fact that $p_L L_E = P_L Y_L$, $p_H Z H_E = P_H Y_H$, labor market clearing $L_E = A_L l$, $H_E = A_H h$, sectoral output (16) and relative prices (17), we can write the ratio of the free entry conditions as

$$\frac{\pi_H + \mu}{\pi_L + \mu} = \frac{P_H Z H_E}{P_L L_E} = \left(\frac{A_H}{A_L}\right)^{-\frac{1}{\epsilon}} \left(\frac{ZH_E}{L_E}\right)^{\frac{\epsilon-1}{\epsilon}} = 1 \tag{23}$$

Equation (23) shows that relative profitability has two components, which go in opposite directions: a 'price effect', whereby profits are higher in those sectors that produce more expensive goods, and a 'market size effect', whereby profits are higher in larger sectors (i.e. in sectors that employ more workers).

Solving for relative technologies, we obtain:

$$\frac{A_H}{A_L} = \left(\frac{ZH_E}{L_E}\right)^{\epsilon-1} \tag{24}$$

Thus, technology is biased towards the *employed* factor that is relatively more abundant, if the elasticity of substitution between factors is greater than unity (i.e., factors are gross substitutes). In this case, a fall in the relative price of the skilled aggregate good increases the relative expenditure on the skilled aggregate good, making entry in that sector more profitable (i.e., the market size effect dominates the price effect). Substituting (24) into the expression for the skill premium (18), we get an expression for the skill premium as a function of relative employment when technology is endogenously determined:

$$\frac{w_H}{w_L} = Z^{\epsilon-1}\left(\frac{x_H}{x_L}\right)^{\epsilon-2}\left(\frac{H}{L}\right)^{\epsilon-2} \tag{25}$$

Hence, the skill premium with endogenous technology is increasing in the relative employment rate of skilled workers as long as $\epsilon > 2$. This means that sectoral aggregates have to be sufficiently substitutable for the skill premium to increase in relative employment rates: then, the indirect positive effect of the skill ratio via an increase in the relative productivity of skilled workers ('technology effect') dominates the direct negative supply effect – compare equation (18). Moreover, an increase in the relative supply of skilled workers shifts up the relative demand for skill and increases the skill premium for given employment rates as long as $\epsilon > 2$.

In equilibrium, we obtain the following expressions for relative employment and employment rates (combining wages (12) and hiring costs (14)) and the skill premium (using (15) with (25)) as functions of relative endowments:

$$\frac{H_E}{L_E} = Z^{-\frac{\epsilon-1}{\epsilon-2-\alpha}}\left[\left(\frac{a_H}{a_L}\right)\left(\frac{H}{L}\right)^{-\alpha}\right]^{\frac{1}{\epsilon-2-\alpha}} \tag{26}$$

$$\frac{x_H}{x_L} = Z^{-\frac{\epsilon-1}{\epsilon-2-\alpha}}\left[\left(\frac{a_H}{a_L}\right)\left(\frac{H}{L}\right)^{-(\epsilon-2)}\right]^{\frac{1}{\epsilon-2-\alpha}} \tag{27}$$

$$\frac{w_H}{w_L} = Z^{-\frac{\alpha(\epsilon-1)}{\epsilon-2-\alpha}}\left[\frac{a_H}{a_L}\left(\frac{H}{L}\right)^{-\alpha}\right]^{\frac{\epsilon-2}{\epsilon-2-\alpha}} \tag{28}$$

Relative employment and relative employment rates are increasing in relative endowments of workers, if $0 < \epsilon < 2 + \alpha$. The same is true for relative wages. The reason is as follows. First, relative wages are increasing in relative employment rate, if the relative labor demand function (25) is increasing (if $\epsilon > 2$). This is because, while sectoral prices decrease with sector size (price effect), which implies lower revenues and lower wages, technology improves in sector size (market size effect) and, therefore, revenue and wages increase (given $\epsilon > 1$). When $\epsilon > 2$ the technology effect is sufficiently strong to make the overall labor demand curve upward-sloping. Second, relative wages are also increasing in relative employment rates according to the matching function (15). Matching frictions imply that firms need to pay greater wages as the number of employed increases (the more so the greater $\alpha$ is), because labor market tightness increases. Thus, we can state the following proposition.

**Proposition 1.** *With endogenous technologies, an increase in the relative number of skilled results in an increase in their wage and employment rate relative to unskilled, if* $2 < \epsilon < 2 + \alpha$*, and in a decrease otherwise.*

Let us now examine more closely the labor market effects of an increase in the relative supply of skilled, H/L. Consider first the case where $\epsilon < 2$. In this case the labor demand curve is downward-sloping and an increase in $H/L$ shifts it down, so the situation is the same as in Figure 5: both the skill premium and the relative employment rate of the skilled decrease.

Now consider the more interesting case where $\epsilon > 2$. In this case the labor demand curve is upward-sloping and an increase in $H/L$ shifts it up. The overall effect on relative wages and employment rates depends on whether wages increase more strongly with employment according to relative matching (15) or labor demand (25): whether the relative wage curve (15) crosses relative labor demand (25) from below (Figure 6, panel a) or above (Figure 6, panel b). In the first case where $\epsilon < 2 + \alpha$ (labor demand is relatively elastic compared to the wage curve[8]), relative wages and employment of the skilled increase. In contrast, in the second case where $\epsilon > 2 + \alpha$ (labor demand is relatively inelastic), relative wages and employment of skilled decrease. The intuition is that when $\alpha$ is small compared to $\epsilon$, so that labor markets have small matching frictions and an increase in the relative labor market tightness does not affect wages much, while the labor demand curve is relatively steep, so that a given change in the wage premium does not affect relative employment much, the following situation arises: The additional workers are very efficiently channeled to employment, but labor demand does not react sufficiently strongly to absorb the increased supply. Thus, the skill premium needs to drop, reducing the relative employment rate of the skilled. Moreover, since the relative number of employed decreases, technology adjusts away from skilled towards unskilled workers. Note that the conditions for the skill premium to be increasing in the skill ratio are more stringent here than in models of directed technological change without unemployment (e.g., Acemoglu (1998, 2002)), where $\epsilon > 2$ is the only relevant condition.

Finally, note that the relative size of the wage and employment response also depends on the

[8]The elasticity of labor demand is given by $\frac{1}{\epsilon - 2}$ according to (25) and the elasticity of the wage curve is given by $\frac{1}{\alpha}$ according to (15).

elasticities of the wage curve and labor demand. When $\alpha$ tends to infinity (very inelastic labor supply), the wage curve becomes vertical and all the adjustment in response to a greater skill supply happens through the skill premium, which increases, whereas employment rates are unaffected. In this case, the model is equivalent to the one with exogenous labor supply (Acemoglu (1998, 2002)). Differently, when $\alpha$ tends to zero (very elastic labor supply), the wage curve becomes horizontal and all the adjustment happens via the relative employment rate, which decreases, with no effect on the skill premium.

## 2.5 Labor Market Institutions

We now introduce unemployment benefits and firing costs in the model. Again, we follow Helpman and Itskhoki (2007) in modeling labor market frictions. For simplicity, we assume that unemployment benefits and firing costs are the same for skilled and unskilled workers. Let $b_u$ denote unemployment benefits, which is the income of workers who do not find a job, and let $b_f$ be firing costs, which is a transfer to workers who get matched and are then fired. We assume that workers who get matched are unsuitable for the job with probability $\delta$, in which case they are fired. Thus, a firm that wants to have $j$ employees needs to recruit $j/(1-\delta)$ workers, and bears a search cost of $a_j x_j^{\alpha} j/(1-\delta)$. In addition, since it fires a fraction $\delta$ of hired workers, it faces a firing cost of $b_f \delta j/(1-\delta)$.

We consider a firm in sector $j$ that has $j$ employees after recruiting and firing. Its revenue is given by equation (8). We assume that a worker who loses his job gets unemployment benefits $b_u$. Again, we follow Stole and Zwiebel (1996a,b) and assume that marginal surplus of each worker is equally divided between the worker and the firm. If $w_j(j)$ is the equilibrium wage rate as a function of employment, this implies the following split of revenues:

$$\frac{\partial}{\partial j}\left[Y_j^{1/\sigma}(Zj)^{\frac{\sigma-1}{\sigma}}P_j E_j - w_j(j)j\right] = w_j(j) - b_u \tag{29}$$

The left-hand side is the marginal gain of the firm from employing an additional worker, taking into account that his departure will impact on the wage rate of the remaining workers. The right-hand side is the marginal gain of the worker of being employed, which is given by the difference between the wage rate and the unemployment benefit. This condition leads to a differential equation with the following solution:[9]

$$w_j(j) = \frac{\sigma-1}{2\sigma-1}\frac{Y_j^{1/\sigma}(Zj)^{\frac{\sigma-1}{\sigma}}P_j E_j}{j} + \frac{1}{2}b_u \tag{30}$$

Hence, wages equal a fraction $\frac{\sigma-1}{2\sigma-1}$ of revenues divided by the number of employees plus half of

[9] This can be verified by substituting (30) into (29).

the outside option. This implies that the firm gets the remaining share $\frac{\sigma}{2\sigma-1}$ of revenues minus half of the workers' total unemployment benefits. The firm then chooses employment to maximize profits, given by

$$\max_j \frac{\sigma}{2\sigma-1} Y_j^{1/\sigma} (Zj)^{\frac{\sigma-1}{\sigma}} P_j E_j - b_j j - \mu. \tag{31}$$

where the hiring costs per worker now equal $b_j = \frac{1}{2}b_u + b_f\delta/(1-\delta) + a_j x_j^{\alpha}/(1-\delta)$.

The first-order condition of this problem can be solved for optimal employment, which is given by $j = \left[\frac{\sigma-1}{2\sigma-1} Z^{\frac{\sigma-1}{\sigma}} P_j E_j (b_j)^{-1}\right]^{\sigma} Y_j$. Employment of each firm is increasing in the sectoral price index $P_j$ and sector size $Y_j$, while it is decreasing in hiring costs $b_j$. Moreover, optimal prices are given by $p_j = \frac{2\sigma-1}{\sigma-1}\frac{b_j}{Z}$. Finally, the expression for optimal employment implies that $w_j = b_j + \frac{1}{2}b_u$.

From the expression for hiring costs, $b_j$, and the relation between wages and hiring costs, we again derive the relative matching function (wage curve):

$$\frac{w_H - \frac{1}{2}b_u}{w_L - \frac{1}{2}b_u} = \frac{\frac{a_H\left(\frac{H_E}{H}\right)^{\alpha} + \delta b_f}{1-\delta} + \frac{1}{2}b_u}{\frac{a_L\left(\frac{L_E}{L}\right)^{\alpha} + \delta b_f}{1-\delta} + \frac{1}{2}b_u} \tag{32}$$

Further, using relative demand for the sectoral aggregate goods, (17), the fact that $p_j = P_j A_j$, the relation between relative technologies from the free entry conditions, (24), the expression for optimal prices, and the relation between wages and hiring costs, we derive the relative inverse demand for skilled workers:

$$\frac{w_H - \frac{1}{2}b_u}{w_L - \frac{1}{2}b_u} = Z^{\epsilon-2}\left(\frac{H_E}{L_E}\right)^{\epsilon-2} \tag{33}$$

We can use the free entry conditions to derive expressions for $H_E$ and $L_E$ as functions of relative employment rates: in the skilled sector, the condition $\Pi_H = 0$ implies that $\frac{1}{2\sigma-1} Z P_H H_E - \mu = 0$, which can be solved for $H_E = (2\sigma-1)\mu Z^{-1}\left[1 + \left(\frac{P_H}{P_L}\right)^{\epsilon-1}\right]^{\frac{-1}{\epsilon-1}} = (2\sigma-1)\mu Z^{-1}\left[1 + \left(\frac{Zx_H}{x_L}\right)^{1-\epsilon}\left(\frac{H}{L}\right)^{1-\epsilon}\right]^{\frac{-1}{\epsilon-1}}$. Similarly, $L_E = (2\sigma-1)\mu\left[1 + \left(\frac{Zx_H}{x_L}\right)^{\epsilon-1}\left(\frac{H}{L}\right)^{\epsilon-1}\right]^{\frac{-1}{\epsilon-1}}$. Then, combining equations (32) and (33) using the above expressions for $H_E$ and $L_E$, we can derive an implicit equation for the equilibrium relative employment rate of the skilled:

$$Z^{\epsilon-1}\left[\frac{1 + \left(\frac{Zx_H}{x_L}\right)^{1-\epsilon}\left(\frac{H}{L}\right)^{1-\epsilon}}{1 + \left(\frac{Zx_H}{x_L}\right)^{1-\epsilon}\left(\frac{H}{L}\right)^{1-\epsilon}}\right]^{\frac{\epsilon-2}{1-\epsilon}} = \frac{\frac{a_H H^{-\alpha}\left[(2\sigma-1)\mu Z^{-1}\left[1+\left(\frac{Zx_H}{x_L}\right)^{1-\epsilon}\left(\frac{H}{L}\right)^{1-\epsilon}\right]^{\frac{-1}{\epsilon-1}}\right]^{\alpha} + \delta b_f}{1-\delta} + \frac{1}{2}b_u}{\frac{a_L L^{-\alpha}\left[(2\sigma-1)\mu\left[1+\left(\frac{Zx_H}{x_L}\right)^{\epsilon-1}\left(\frac{H}{L}\right)^{\epsilon-1}\right]^{\frac{-1}{\epsilon-1}}\right]^{\alpha} + \delta b_f}{1-\delta} + \frac{1}{2}b_u} \tag{34}$$

As this equation cannot be solved analytically, we have to rely on simulations for the comparative statics effects of an increase in the skill ratio. In Figure 7 we plot the relative employment rate of skilled workers $x_H/x_L$, the skill premium, $w_H/w_L$, and the relative productivity of skill, $A_H/A_L$, as a function of the skill ratio for different levels of unemployment benefits for the case where $2 < \epsilon < 2 + \alpha$.[10] We consider $\epsilon = 2.25$ and $\alpha = 1.17$[11] and three levels of unemployment benefits: $b_u \in \{0, 0.2, 0.25\}$. We can see that when unemployment benefits are zero (solid line), relative employment rates, skill premia and relative productivity unambiguously increase in the skill ratio. However, for positive unemployment benefits ($b_u = 0.2$: dashed line, $b_u = 0.25$: dashed-dotted line), the relation is non-monotonic: relative employment rates, skill premia and relative productivity increase in the skill ratio for low levels of the skill ratio up to a threshold, where things turn around and relative employment rates, the skill premium and relative productivity start to decline in the skill ratio. Note also that the threshold level of the skill ratio is decreasing in the unemployment benefit. Thus, the decrease starts sooner the higher the unemployment benefit. We thus expect that when unemployment benefits are low, an increase in the skill ratio increases the relative employment rate of skilled, but when unemployment benefits are sufficiently high, it has the opposite effect.

What is the reason for the non-monotonic relationship between relative employment rates, wage premia, technology and the skill ratio in the presence of unemployment benefits? Initially, as the skill ratio rises, wages and employment rates of skilled workers rise, as technology adjusts endogenously, increasing the relative productivity of skilled workers, while wages and employment of unskilled workers fall with the decline in their relative productivity. At some point, however, unskilled wages are very close to the unemployment benefit and thus cannot fall further, since wages equal half of the unemployment benefit plus the expression related to labor market tightness (see above). Moreover, any reduction in employment or exit of firms from the unskilled sector would reduce profits[12] and, therefore, wages.[13] Thus, as wages and profits in the unskilled sector cannot fall further, an increase in $H$ at this point needs to be associated with an increase in employment in the unskilled sector. This induces an endogenous adjustment of technology towards increasing the productivity of the unskilled, which in turn increases unskilled wages and employment rates via higher demand for unskilled workers.

The impact of firing costs is qualitatively the same as the one of unemployment benefits, as we verify in unreported simulations. This can be seen from equation (34), where up to a scaling factor, firing costs and unemployment benefits enter in the same way. Thus, changes in the unemployment benefit and the firing cost can change the relation between the the skill ratio and the direction of

[10]For $\epsilon < 2$ or $\epsilon > 2 + \alpha$ the qualitative implications of the model are not affected by the introduction of labor market regulations.

[11]For the choice of parameter values see section 3.1 on calibration.

[12]Since profits in the unskilled sector equal $\Pi_L = P_L L_E - \mu$ and the market size effect is stronger than the price effect whenever $\epsilon > 1$.

[13]Since profits are proportional to revenue and wages are a fraction of revenue plus one half the unemployment benefit.

technological change, relative employment rates and skill premia. In countries with very regulated labor markets an increase in the skill ratio may not trigger skill-biased technological change and therefore not increase the skill premium and the relative employment rate of skilled workers.

### 2.6 Migration

In this section, we augment our model with endogenous migration, which provides us with further predictions that we can use to test models of directed technological change. Regarding the labor market, we use the basic model without unemployment benefits and firing costs for ease of exposition.

Let utility for individual $k$ of skill type $j$ associated with migration to the Organisation for Economic Co-operation and Development (OECD) countries be given by

$$U_j^M(k) = w_j^{OECD} x_j^{OECD} - c_j - \varepsilon(k), \quad j \in H, L$$

where $w_j^{OECD} x_j^{OECD}$ is the expected wage in the OECD, $c_j$ is a deterministic skill-specific cost of migration to the OECD in terms of utility and $\varepsilon(k)$ is a stochastic migration cost that is individual-specific, and let utility associated with staying in the country of origin be given by

$$U_j^S = w_j x_j. \quad j \in H, L$$

Then, the probability of emigration for a skilled (unskilled) worker can be written as the probability that the stochastic migration cost is sufficiently low, so that the expected wage in the OECD – adjusted for the deterministic part of migration costs – is larger than the expected wage in the country of origin:

$$Prob(U_j^M(k) > U_j^S) = Prob(\varepsilon < w_j^{OECD} x_j^{OECD} - w_j x_j - c_j), \quad j \in H, L$$

Assuming that migration costs are logistically distributed with mean zero and variance unity, the migration rate for skill type $j$ is:

$$s_j = Prob(U_j^M(k) > U_j^S) = \frac{1}{1 + e^{-(w_j^{OECD} x_j^{OECD} - w_j x_j - c_j)}}, \quad j \in H, L \tag{35}$$

In the case of endogenous technology, we substitute for expected wages $w_H x_H$ and $w_L x_L$ as functions of $s_H$ and $s_L$ as follows. According to the matching function (14), wages of the skilled and unskilled workers can be expressed as

$$w_H = a_H \left[\frac{H_E}{(1-s_H)H}\right]^\alpha \qquad w_L = a_L \left[\frac{L_E}{(1-s_L)L}\right]^\alpha$$

We can substitute for $H_E$ and $L_E$ using the free entry conditions (13)

$$\pi_H = \left(\frac{1}{2\sigma-1}\right) Z P_H H_E - \mu = 0 \qquad \pi_L = \left(\frac{1}{2\sigma-1}\right) P_L L_E - \mu = 0$$

where we substituted for $p_H y_H$ and $p_L y_L$ by first using the intermediate production functions $y_H = Zh$ and $y_L = l$ and then using the fact that $p_H h = \frac{P_H Y_H}{Z A_H} = P_H H_E$ and $p_L l = \frac{P_L Y_L}{A_L} = P_L L_E$.

Next, we use the optimal price index (5) to substitute for $P_H = \left[1 + \left(\frac{P_H}{P_L}\right)^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}$ and, analogously, for $P_L$. We further substitute for the sectoral relative price $P_H/P_L$ using (17) together with relative technologies (24) and for relative employment (26).

As a result, we can re-write wages $w_H$ and $w_L$ and employment rates $x_H$ and $x_L$ to express expected wages as functions of emigration rates $s_H$ and $s_L$:[14]

$$w_H x_H = a_H \left[\frac{\mu(2\sigma-1)}{(1-s_H)HZ}\left(1 + Z^{\frac{(\alpha+1)(\epsilon-1)}{\epsilon-2-\alpha}}\left[\frac{a_L}{a_H}\left(\frac{(1-s_H)H}{(1-s_L)L}\right)^\alpha\right]^{\frac{\epsilon-1}{\epsilon-2-\alpha}}\right)^{\frac{1}{1-\epsilon}}\right]^{1+\alpha} \tag{36}$$

$$w_L x_L = a_L \left[\frac{\mu(2\sigma-1)}{(1-s_L)L}\left(1 + Z^{\frac{(\alpha+1)(1-\epsilon)}{\epsilon-2-\alpha}}\left[\frac{a_H}{a_L}\left(\frac{(1-s_L)L}{(1-s_H)H}\right)^\alpha\right]^{\frac{\epsilon-1}{\epsilon-2-\alpha}}\right)^{\frac{1}{1-\epsilon}}\right]^{1+\alpha} \tag{37}$$

Substituting (36) and (37) into the migration equations (35), we obtain two equations in $s_H$ and $s_L$. Even though these equations cannot be solved analytically, some intuition can be gained from them. Suppose the skilled migration rate increases above its equilibrium value. This, on the one hand, reduces expected wages because a decrease in skill endowments leads to an endogenous adjustment of technology and, thus, demand for skills and further increases incentives for emigration (term in inner square brackets). On the other hand, an increase in skilled migration increases expected wages because of the increase in labor market tightness (first term in outer square brackets). Overall, this second effect becomes dominating whenever the skilled migration rate is too far above its equilibrium value. While the first effect reinforces migration incentives and suggests multiplicity of equilibria as found in Grossmann and Stadelmann (2011) and De la Croix and Docquier (2010),

[14]Note that $x_H = \left[\frac{\mu(2\sigma-1)}{(1-s_H)HZ}\left(1 + Z^{\frac{(\alpha+1)(\epsilon-1)}{\epsilon-2-\alpha}}\left[\frac{a_L}{a_H}\left(\frac{(1-s_H)H}{(1-s_L)L}\right)^\alpha\right]^{\frac{\epsilon-1}{\epsilon-2-\alpha}}\right)^{\frac{1}{1-\epsilon}}\right]$, $w_H = a_H x_H^\alpha$ and $x_L = \left[\frac{\mu(2\sigma-1)}{(1-s_L)L}\left(1 + Z^{\frac{(\alpha+1)(1-\epsilon)}{\epsilon-2-\alpha}}\left[\frac{a_H}{a_L}\left(\frac{(1-s_L)L}{(1-s_H)H}\right)^\alpha\right]^{\frac{\epsilon-1}{\epsilon-2-\alpha}}\right)^{\frac{1}{1-\epsilon}}\right]$, $w_L = a_L x_L^\alpha$.

the second effect guarantees that the equilibrium is unique, as is confirmed by our simulations as follows.

# 3 Simulation of Unemployment Rates and Brain Drain

## 3.1 Calibration

We now describe the choice of parameter values that we use to simulate the model with migration. A key parameter in our model is the elasticity of substitution between skilled and unskilled workers, $\epsilon$. Gancia, Müller and Zilibotti (2011) calibrate $\epsilon$ simultaneously together with $Z$, the factor determining the exogenous difference in the relative productivity of skilled workers. They use a version of equation (25) without unemployment to fit the evolution of the US skill premium, defined as the relative wage of college graduates over non-college graduates between 1970 and 2000 and calibrate $\epsilon = 2.25$ and $Z = 1.96$. Thus, in our baseline calibration we set $\epsilon$=2.25. Note that this value is somewhat larger than the value of the short-run elasticity between skilled and unskilled labor found by other studies (e.g., Ciccone and Peri (2006) provide estimates for this parameter in the interval [1.4,2]).[15] We therefore also consider alternative values for $\epsilon \in \{1.75, 2, 2.5\}$ in robustness checks. We set $Z = 1.96$ throughout our simulations.

Another important parameter is $\alpha$, the elasticity of the matching function.This parameter is related to the elasticity of the standard Cobb-Douglas matching function with respect to vacancies, for which many estimates are available, via the relation $\alpha = (1 - \eta)/\eta$.[16] The estimates for this parameter differ substantially across studies (see Petrongolo and Pissarides (2001) for a survey) and range from 0.1 to around 0.9, with most of the estimates lying somewhere between 0.3 and 0.5. Among the more recent estimates, Shimer (2005) finds $\eta$ to equal 0.27 for the US and Mortensen and Nagypal (2007) provide a point estimate of 0.54 for the same parameter. When addressing problems with both approaches, Brügemann (2008) reports $\alpha$ to lie in the interval [0.37, 0.46]. We thus consider values of $\eta$ equal to 0.27, 0.46 and 0.54 for our calibration exercise, which implies values for $\alpha$ of 2.7, 1.17. Note that all the estimates for $\alpha$ (including the highest available estimate $\eta = 0.54$, which corresponds to $\alpha = 0.85$) satisfy the condition $\epsilon < 2+\alpha$. Therefore, for illustration purposes we also choose an unrealistically low value of $\alpha$ equal to 0.1 ($\eta = 0.9$) such that $\epsilon > 2+\alpha$. In sum, we consider the values $\alpha \in \{0.1, 0.85, 1.17, 2.7\}$.

[15] Also note, however, that the elasticity of substitution between skilled and unskilled workers may be smaller in developed than in developing countries, for which no comparable estimates exist.

[16] Let the matching function be $M = a_1 V^\eta N^{1-\eta}$, where $V$ is the number of vacancies and $N$ is the number of unemployed. Remember that $x = M/N$ is the probability for a worker to find a job. The probability for a firm to find a worker can then be written as $M/V = a_1^{1/\eta} x^{(\eta-1)/\eta}$. As a consequence, a firm that wants to hire $m$ workers has to post $v = a_1^{-1/\eta} x^{(1-\eta)/\eta} m$ vacancies. Assume that posting $v$ vacancies costs $a_2 v$ in terms of the final good. Then a firm that wants to hire $m$ workers has to bear a hiring cost of $a x^\alpha m$, where $a = a_2/a_1^{1/\eta}$ and $\alpha = (1-\eta)/\eta > 0$.

To calibrate the other parameters of the matching functions, $a_H$ and $a_L$, we use the matching function (14) together with the fact that $b_j = w_j$ and data on employment-weighted averages of wage rates and employment rates of the developing countries in our sample (the set of non-OECD countries in our data). Note that since these parameters measure the efficiency of labor market institutions, assuming them to be the same for all countries is a constraint imposed by the availability of data.

Consistently with the consensus in the international trade literature, we set the elasticity between varieties, $\sigma$, equal to 4. This is the mean value of the substitution elasticity estimates from Broda and Weinstein (2006), who use trade data to estimate this parameter. Similarly, Bernard, Eaton, Jensen and Kortum (2003) find an estimate of 3.8 when fitting US plant and macro data.

Moreover, we need parameter values for the OECD employment rates and wages. According to our data, the employment-weighted average of OECD employment rates is 0.96 for skilled and 0.95 for unskilled workers. Similarly, average yearly OECD wages in constant PPPs are around US$ 37,000 for skilled and US$ 15,000 for unskilled workers. We therefore set $w_H^{\text{OECD}} = 0.37$ and $w_L^{\text{OECD}} = 0.15$, $x_H^{\text{OECD}} = 0.96$ and $x_L^{\text{OECD}} = 0.95$.

To calibrate the fixed cost, $\mu$, we use the equation for expected wages of skilled workers (36) to solve for $\mu$, taking as given employment-weighted averages of unskilled wages, employment rates and migration rates of developing countries.

Finally, to obtain estimates of the average migration costs of skilled and unskilled workers, we calibrate $c_H$ and $c_L$ using the equations for the migration rates (35) to match migration rates of skilled and unskilled workers for the average developing country in our sample exactly, given the average developing-country skill ratio $H/L = 0.05$ and average working-age population of L=10.

We summarize the calibrated parameter values in Table 1.

### 3.2 The Impact of the Elasticity of Substitution

According to our model, the effects of changes in the skill ratio on expected wages and emigration rates crucially depend on the elasticity of substitution between skilled and unskilled workers. Note that, given that employment rates are a positive monotonous transformation of wages, the pattern for expected wages is very much alike that for each wages and employment rates separately. We therefore show only expected wages for space considerations in the following but keep in mind that arguments concerning the skill ratio effects run analogously for wages and employment rates. Figure 8 (panel a) shows the expected wage of skilled relative to unskilled workers as a function of the skill ratio for different values of $\epsilon$. As predicted by the closed economy model in Proposition 1, also with endogenous migration rates the skill premium and the relative employment rate of the skilled are increasing in the skill ratio as long as $\epsilon \in (2, 2+\alpha)$, i.e. for $\epsilon \in \{2.25, 2.5\}$. In contrast, skill premia and relative employment rates are constant, if $\epsilon = 2$, and they are decreasing in the skill ratio for $\epsilon = 1.75$. The positive relative wage and employment effects are greater for $\epsilon = 2.5$ compared to $\epsilon = 2.25$, as the negative supply effect becomes weaker compared to the positive technology effect. Panel b shows how the change in expected relative wages translates into changes in the equilibrium relative emigration rates of skilled and unskilled workers, the so-called brain drain. For $\epsilon = 2.25$ and $\epsilon = 2.5$, the relative emigration rate of skilled workers decreases in the skill ratio. Overall, the quantitative effects are most pronounced for small skill ratios (below 0.2), while they become less important for greater skill ratios. We thus expect a larger impact of skill accumulation for relatively skill-scarce developing countries. For $\epsilon$ equal to 1.75 the brain drain increases in the skill ratio: as relative expected wages of the skilled decrease, skilled workers' incentives to emigrate decrease and their emigration rate increases relative to those of unskilled workers. For $\epsilon = 2$, while the skill premium does not change (as the technology and the supply effects of a greater ratio of skilled employed exactly cancel each other), the brain drain increases slightly because the difference in absolute expected wages between skilled and unskilled decreases. Panel c shows the effect of the skill ratio on the skill bias in technology for the different elasticities of substitution. While the skill-bias is positive for all values $\epsilon > 1$, its increase is greater for greater $\epsilon$.

### 3.3 The Impact of the Elasticity of the Wage Curve

Apart from the elasticity of substitution between skilled and unskilled workers, $\epsilon$, the sign and size of effects of the skill ratio on the labor market and emigration crucially depends on the elasticity of the wage curve, $\alpha$. Figure 9 shows relative expected wages and emigration rates as well as the skill bias in technology for three different values of $\alpha \in \{0.1, 1.17, 2.7\}$ corresponding to the baseline specification (1.17) and a value smaller and greater than that. As we now keep $\epsilon$ constant at 2.25, curves for $\alpha = 1.17$ in this figure are exactly the same as those for $\epsilon = 2.25$ in the previous figure. Again, for $\epsilon \in (2, 2+\alpha)$ – for example when $\alpha$ equal to 1.17 and 2.7 – relative wages and employment rates of the skilled increase and, correspondingly, the relative emigration rate of the skilled decreases. In turn, for $\epsilon > 2+\alpha$ – for example when $\alpha = 0.1$ – a greater skill ratio decreases relative expected skilled wages and increases the brain drain. This is because when labor market frictions are low enough for the elasticity of the wage curve to exceed the elasticity of labor demand, an increase in the supply of skilled workers cannot be accommodated by firms. Instead, the relative number of skilled employed decreases, which decreases relative employment rates and wages of the skilled. We can also see that, in this case, the technological bias is actually directed towards the unskilled – even though labor demand is upward-slowing ($\epsilon > 2$) - as a greater skill ratio does not translate into a greater but a smaller ratio of skilled *employed*.

### 3.4 The Impact of Skill-Biased Technological Change

The relation between skill endowments and the brain drain according to our model is very different depending on whether we assume technology to be exogenous or endogenous. In this exercise we use our preferred calibration for $\epsilon = 2.25$ and $\alpha = 1.17$ and again choose migration costs to match observed migration rates for an average developing country with a skill ratio of 0.1. Table 2 shows emigration rates that correspond to progressively increasing levels of the skill ratio with exogenous and endogenous technology. In the former case, technology parameter values $A_H$ and $A_L$ were chosen such that emigration rates are exactly the same as in the case of endogenous technology for a skill ratio of 0.05. Consistent with Remark 1 and Proposition 1, an increase in the skill ratio results in an increase in brain drain in the case where technology is assumed to remain constant but results in an decrease in the brain drain when technology can adjust endogenously to changes in the skill ratio. The intuition is pretty straightforward: with endogenous technology and $\epsilon \in (2, 2+\alpha)$ the relative demand curve for skilled workers is upward-sloping and sufficiently elastic such that an increase in skill endowments leads to an increase in the relative employment rate of skilled workers and an increase in their relative expected wage. As a result, their relative emigration rate drops. In contrast, with exogenous technology the relative demand curve for skilled workers is downward sloping. Thus, an increase in the skill ratio increases the unemployment rate of skilled workers, reduces their expected wage and increases their emigration rate.

## 4 Empirical evidence

In this section we provide empirical evidence on the relations between the skill ratio and the skill premium, relative productivity, unemployment and brain drain that are predicted by our theoretical model. We first briefly discuss the data and then turn to the regression results. We conclude with a quantitative simulation exercise where we try to replicate correlations between variables of interest observed in the data using our theoretical model.

Throughout, we define skilled workers as those with at least some tertiary education, while we consider all other workers as unskilled. Data on emigration to the OECD by skill level are from Beine, Docquier and Rapoport (2008). Data on human capital come from Barro and Lee (2000, 2011) and De La Fuente and Domenech (2002). Data on wages by skill category are constructed using the occupational wages around the world data set collected by Freeman and Oostendorp (2000), considering a fixed number of skilled and unskilled occupations. Unfortunately, we do not have wages by educational attainment, but we choose occupations so that they roughly correspond to our skill categories. Information on unemployment rates by educational attainment are constructed from the ILO Key Indicators of the Labour Market Database (2009). We also employ data on labor market regulation from the IMF labor market regulation database (Aleksynska and Schindler (2011)) to obtain information on replacement rates, minimum wages and firing costs, and from the Fraser Institute Freedom of the World 2011 Database (Gwartney et al. (2011)), from which we obtain an overall labor market regulation index. Migration data are available for a balanced panel of countries for 1990 and 2000, while for the other data we have an unbalanced panel in five-year intervals from 1985 to 2000 (wage data) and from 1980-2005 (unemployment data). A more detailed discussion of the data and the list of countries used in the regressions can be found in the Appendix.

## 4.1 Skill Ratio, Wages and Technology

We first test the predictions of our model with respect to the effect of skill ratios on the skill premium and the relative productivity of skilled. In the absence of skill-biased technological change, we should observe a strong negative correlation between the skill ratio and the skill premium. Differently, when technological change is directed, we expect a very low negative or even a positive correlation between the skill ratio and the skill premium, as the demand for skill increases with skill supply.

To see this, consider again the expression for the skill premium (18) from our model, reproduced here for convenience:

$$\frac{w_H}{w_L} \equiv \omega = \left[\frac{ZA_H}{A_L}\right]^{1-\frac{1}{\epsilon}} \left[\frac{H_E}{L_E}\right]^{\frac{-1}{\epsilon}} \tag{38}$$

Thus, when there is no connection between skill ratios and the relative productivity of skilled workers, the model predicts a log-linear relation between the skill premium and the skill ratio, with a constant $\alpha \equiv \left(1-\frac{1}{\epsilon}\right)\log(\frac{ZA_H}{A_L})$ and slope $\beta \equiv -\frac{1}{\epsilon}$. Taking logs of equation (38) and proxying for $H_E/L_E$ using $H/L$,[17] we thus obtain

$$\log\left(\frac{w_{Hit}}{w_{Lit}}\right) = \alpha + \beta\log(H/L)_{it} + \gamma\log(X)_{it} + \mu_t + u_i + \nu_{it}, \tag{39}$$

where $\log(w_{Hit}/w_{Lit})$ is the (log) skill premium in country $i$ in period $t$, $\log(X)_{it}$ is a vector of country controls, which includes the level of real per capita GDP in purchasing power parities (PPP), the real growth rate of GDP in PPP and openness. $\mu_t$ is a time dummy, $u_i$ is an unobserved country-specific effect and $\nu_{it}$ is an error term. We include openness[18] to control for potential omitted variable bias, since it is likely to be correlated with the skill ratio and may also affect the relative demand for skilled workers (e.g. through a skill-biased scale effect, see Epifani and Gancia (2008)). For similar reasons, we also include per capita GDP as a control.

[17] Skill-specific unemployment rates and wage data are jointly available only for a very limited number of countries.

[18] Defined as (exports+imports)/GDP.

We run this regression on an unbalanced panel of developing and developed countries in five-year intervals from 1985 to 2000. Results are presented in columns (1)-(6) of Table 3. Columns (1) to (3) present results from the pooled cross-section regression, controlling for time dummies, which squeezes out the pure cross-section variation. In column (1), where we include no further controls, the coefficient for the skill ratio is -0.214 and strongly significant. Thus, in the cross section, a one percent higher skill ratio is associated with a 0.2 percent lower skill premium. However, when adding further controls, which may serve as proxies for differences in the relative productivity of skilled workers, in column (2), the coefficient of skill ratio drops to -0.1 and becomes insignificant. Since one may be concerned that skill ratios are endogenous to the skill premium because higher skill premia may induce people to acquire more education, in the next specification we instrument the skill ratio with public education expenditure and with 5-year lagged values of the skill ratio. Public education expenditure is arguably an exogenous determinant of the skill ratio, being independent of the skill premium. Whether lagged values of the skill ratio are a valid instrument is less clear ex ante, but we can test this. In column (3) we present the IV estimate, obtaining a marginally significant coefficient of -0.15. Note that the instruments are valid: according to the F-statistic of 312 the instruments are strongly correlated with the endogenous variable, while the P-value of 0.8 for the Sargan test does not allow to reject the null hypothesis that the instruments are uncorrelated with the error term.[19] In columns (4)-(6), we use a fixed effects panel estimator to control for unobserved country-specific effects, thus relying on the within-country variation of our data. In column (4) we just use skill ratio as a control and obtain an insignificant coefficient of -0.02. The coefficient remains insignificant, when adding further controls in column (5), or when employing an instrumental variable strategy (estimated in first differences since the fixed effects IV-estimator is inconsistent when using lagged values as an instrument) in column (6).

The finding that an accumulation of skilled workers does not lead to a drop in the relative price of skilled workers suggests that the relative demand for skill increases with relative supply. In fact, even the negative effect of -0.2 found in the cross-section is not consistent with a story of exogenous relative demand for skills. This estimate implies an elasticity of substitution between skilled and unskilled workers equal to 5, which is far larger than the respective consensus estimates, which range from 1.4 to around 2.5. (see, e.g. Ciccone and Peri (2006), Gancia et al. (2011)).[20] Note that while our model does not only predict a weak negative but in fact a positive relation between skill premia and skill ratios when $2 < \epsilon < 2 + \alpha$ (see equation (28)), this relation may be weak when $\alpha$

[19] In unreported regressions, we obtain very similar point estimates for the just identified case, using only public education expenditure as an instrument.

[20] The fact that the relation between wage premia and skill ratios that is found in the data is much weaker than expected is also observed in Caselli and Coleman (2006). As prominently argued in their paper, a relative productivity of skilled workers that is higher in more skill-abundant countries would serve to reconcile expected and observed relations.

is small (labor markets are relatively flexible) and may thus be impossible to detect.[21]

We can take equation (38) a bit further and use it to back out the implied relative productivity of skill, $A_H/A_L$, given an estimate of $\epsilon$.[22] Using our baseline calibration, we set $\epsilon = 2.25$, which is close to the upper end of existing estimates for this parameter and thus minimizes the chance that we find a (positive) relation between the relative productivity of skill and the skill ratio, as it implies a relative demand curve that is rather flat. In columns (7)-(12) of Table 3 we present results from regressing the so obtained relative productivities on skill ratios, using the specification

$$\log(A_H/A_L)_{it} = \alpha + \beta \log(H/L)_{it} + \gamma \log(X)_{it} + \mu_t + u_i + \nu_{it}. \tag{40}$$

In columns (7)-(9) we pool the data and control for time dummies. In column (7) we use the log skill ratio as the sole control, in column (8) we add GDP per capita, GDP growth and openness as controls and in column (9) we instrument for skill ratios with lagged values and public education expenditure. In all specifications, we obtain similar results: the coefficient of the skill ratio is positive (between 0.415 and 0.595) and strongly significant. Moreover, the instruments are strong and valid (the first-stage F-statistic is 308, the P-value for the overidentifying restrictions is 0.78).[23] Thus, a one percent increase in the skill ratio is associated with a 0.4 to 0.6 percent increase in the relative productivity of the skilled. In columns (10)-(12), we repeat the same specifications using a fixed effects panel estimator. We now obtain somewhat larger and again very significant estimates for the coefficient of interest, ranging from 0.572 (for the IV estimate implemented in first differences) to 0.754. We conclude that there is evidence for the relative productivity of skilled workers to respond endogenously to the skill ratio.

### 4.2 Skill Ratio and Unemployment

We now test our model's prediction regarding the effect of the skill ratio on the relative unemployment rate of skilled workers. According to equation (27), for $0 < \epsilon < 2 + \alpha$, the relative unemployment rate of skilled should be negatively related to the skill ratio. To test this prediction,

[21] Finally, we expect measurement error to be considerable for wages, in particular for developing countries. Since ILO only collects wages for workers in the formal sector, measured unskilled wages are probably upward-biased in developing countries, implying that the true skill premia in skill-scarce countries are higher than in our data. Thus, the measurement error for wages is likely to be negatively correlated with the skill ratio, leading to an attenuation bias of the coefficient of the latter.

[22] Alternatively, we could also use equation (28), which requires a choice of $\alpha$ but gives similar results for the values of $\alpha$ derived from the literature.

[23] Again, using only public education expenditure as an instrument gives very similar but less precise estimates.

we use the following econometric specification:[24]

$$\log(u_{Hit}/u_{Lit}) = \alpha + \beta \log(H/L)_{it} + \gamma \log(X)_{it} + \mu_t + u_i + \nu_{it}, \tag{41}$$

where $\log(u_{Hit}/u_{Lit})$ is the (log) relative unemployment rate of skilled in country $i$ in period $t$ and $\log(X)_{it}$ is the usual vector of country controls. In this regression, to maximize the number of observations, we use an unbalanced panel in five year intervals from 1980-2005. In columns (1)-(3) of Table 4 we report results of the pooled regression, controlling for time dummies. In column (1) the skill ratio is the only other control. The coefficient of interest is -0.457 and significant at the one percent level. Thus, a one percent increase in the skill ratio implies a 0.457 percent reduction in the relative unemployment rate of skilled. In column (2) where add the other controls the coefficient of the skill ratio increases slightly in magnitude and remains strongly significant. To address potential endogeneity of the skill ratio with respect to unemployment (higher relative unemployment may induce lower skill ratios), in column (3) we instrument for the skill ratio using lagged values of the same variable and public education expenditure as instruments. The coefficient of the skill ratio is unaffected and remains strongly significant, while the instruments are valid.[25] Finally, in columns (4)-(6) we repeat the same specifications, controlling also for country fixed effects. The results are similar to the ones of the pooled regressions and remain significant, except for the last column, where we present IV estimates implemented in first differences, using lagged skill ratio and public education expenditure as instruments. Here, the coefficient of the skill ratio is also significantly larger. However, the first-stage F-statistic is only 6.15, indicating that the instrument is rather weak, which may result in biased and less precise estimates. Still, overall these results are consistent with the predictions of our model: an increase in the skill ratio reduces the relative unemployment rate of skilled workers.[26]

Our extended model predicts that the impact of the skill ratio on the relative unemployment rate should also depend on the level of unemployment benefits and firing costs. In particular, our model suggests a negative relation between the skill ratio and relative unemployment rates for low levels of unemployment benefits and firing costs, and a positive relation for sufficiently high levels of

[24]We use unemployment rates instead of employment rates because it is a more standard measure of labor market outcomes. Using employment rates instead, we obtain similar results.

[25]The first-stage F-statistic of 413 implies that the instruments are very strongly correlated with the potentially endogenous variable and the P-value of 0.98 of the Sargan test implies that the overidentifying restrictions are valid. Again, we obtain similar, but less precise, point estimates using only education expenditure as an instrument.

[26]Ideally, we would like to control a for measure of relative productivity in the regressions. In this case, we would expect the coefficient of the skill ratio to become negative. Unfortunately, we are unable to do this because the sample overlap for unemployment and wage data is small. However, we do perform this exercise in the brain drain regressions, where we find evidence in line with this prediction.

these variables (see section 2.5). To test for this prediction, we run the following regression:

$$\log(u_{Hit}/u_{Lit}) = \alpha + \beta_1 \log(H/L)_{it} + \beta_2 LMRig_{it} + \beta_3 \log(H/L)_{it} * LMRig_{it} + \gamma \log(X)_{it} + \mu_t + u_i + \nu_{it}, \tag{42}$$

where $LMRig_{it}$ is a measure of labor market rigidity. Thus, the elasticity of relative unemployment with respect to the skill ratio is now: $\frac{\partial \log(u_{Hit}/u_{Lit})}{\partial \log(H_{it}/L_{it})} = \beta_1 + \beta_3 LMRig_{it}$. From our model we expect $\beta_1$ to be negative and $\beta_3$ to be positive. The vector $X_{it}$ includes our usual controls (GDP per capita, GDP growth, openness). As measures of labor market rigidity, we alternatively use the replacement rate, the ratio of minimum to median wages, a measure of firing costs from the IMF labor market institutions database (Aleksynska and Schindler (2011)) and the labor market regulation index from the Fraser Institute Freedom of the World 2011 Database. Again, we use an unbalanced panel in five-year intervals from 1980-2005. We present the results for these regressions in Table 5. In columns (1) to (4) we report results of the pooled regression, controlling for time dummies. We find $\beta_1$, the impact of the skill ratio when labor market rigidity is zero, to be negative and significant for three out of four of our measures of labor market regulation. Furthermore, we find $\beta_3$, the coefficient of the interaction term, to be positive and significant in all cases except for firing costs. The direct impact of labor market regulation on the relative unemployment rate of skilled is always positive and significant. In columns (4)-(8), we account for potential endogeneity of the skill ratio and the interaction term, by instrumenting them with the lagged skill ratio, public education expenditure, and their interactions with the different measures of labor market rigidity. The results for the direct effect of the skill ratio and the interaction term continue to hold. With regard to the validity of the employed instruments, the F-statistics are always very large, so we can exclude weak instrument problems and the null hypothesis that the instruments are uncorrelated with the error term can never be rejected. Finally, in columns (9)-(12) we report results for the fixed effects specifications. Again, the coefficient of the skill ratio is negative and significant in all specifications except for the last one (labor market regulation index) and the coefficient of the interaction term is always positive and significant except for the last specification. Summing up, in line with our theoretical prediction, we find strong evidence for rigid labor market institutions to reduce the negative effect of the skill ratio on relative unemployment rates of skilled workers.

### 4.3 Skill Ratio, Migration Rates and Brain Drain

The last prediction derived from our model relates to the impact of the skill ratio on brain drain (the relative emigration rate of skilled workers). According to the model and given plausible parameter values, an increase in the skill ratio should reduce the relative emigration rate of skilled workers. Note that the logistic migration equations (35) imply that the logistic transformation of migration rates is linear: $log(s_j/(1-s_j)) = w_j^{OECD} x_j^{OECD} - w_j x_j - c_j$. Thus, the brain drain $\log(s_H/s_L) \approx$

$\log(s_H/(1-s_H)) - \log(s_L/(1-s_L)) = (w_H^{OECD}x_H^{OECD} - w_L^{OECD}x_L^{OECD}) - (w_Hx_H - w_Lx_L) - (c_H - c_L)$. We proxy for the difference in expected wages using a function of the skill ratio and other controls, specifying $w_Hx_H - w_Lx_L = \beta\log(H/L) + \gamma_1\log(X_{1it}) + \mu_t + u_i + \nu_{it}$, and we model the deterministic migration cost as $c_H - c_L = \gamma_2 log(X_{2it})$. We thus employ the following empirical specification:

$$\log(s_H/s_L)_{it} = \alpha + \beta\log(H/L)_{it} + \gamma\log(X)_{it} + \mu_t + u_i + \nu_{it} \tag{43}$$

We test the model's prediction using a panel of countries for the years 1990 and 2000. The vector of country control variables includes again the level of GDP per capita, the growth rate of real GDP and openness. In some specifications, we also proxy for the relative migration cost to the OECD using distance to the OECD, a dummy for the country having been a colony of an OECD country after 1945, and dummies for English and French as official languages. In columns (1)-(3) of Table 6 we pool the observations and control for time dummies. In columns (1) and (2) we use ten-year-lagged skill ratios as the main variable of interest.[27] The coefficient of the skill ratio in column (1) is strongly significant and implies that a one percent increase in the skill ratio reduces the brain drain by around 0.76 percent. When adding further controls in column (2), the magnitude of the coefficient of interest drops slightly, but remains very significant. In column (3) we use contemporaneous skill ratios as the explanatory variable and instrument it using the lagged skill ratio and public education expenditure as instruments. The coefficient on the skill ratio remains similar (-0.66) and strongly significant, while the instruments are valid. In columns (4)-(6) we repeat the same specifications using a fixed effects estimator. In columns (4) and (5) the magnitude of the coefficient of the lagged skill ratio is somewhat reduced (to around -0.28 to -0.35) but remains significant. The IV estimate in column (6) is considerably larger (-1.8) but the first-stage F-statistic is only 2.4, indicating a weak instrument problem. Finally, in columns (7) and (8), we add measures of the relative productivity of skilled workers as a control. Conditional on technology, which should reduce brain drain, a higher skill ratio is now expected to increase the brain drain. This is precisely what we find: the coefficient on relative productivity of skilled is negative and significant, while the coefficient of the lagged skill ratio now turns positive. Thus, the prediction regarding the effect of the skill ratio on brain drain is also supported by the data.

## 4.4 Predicted and Actual Correlations

For the last both qualitative and quantitative test of our model, we check if we can use it to replicate a number of relations that we observe in the data. To this end, we proceed as follows.

[27] We do this since migration rates are measured as stocks and the emigration of skilled workers may occur with a lag after education has been acquired. Therefore, an increase in the skill ratio would mechanically reduce the migration rate and could lead to a spurious negative correlation between the two. Moreover, contemporaneous skill ratios may also be subject to reverse causality.

First, in order to be able to test the model, we calibrate all parameters using data from outside the model, as explained in the section on calibration. Moreover, we use estimated migration costs for each country.[28] Thus, we do not match any data moments by construction. We take the OECD as a single destination and take OECD wages and employment rates as exogenous. For the set of countries used in the migration regressions (see data appendix for the list of countries), we take endowments of skilled and unskilled workers for 1990 and 2000 and simulate the model for both years.

To assess model fit, we pool data for 1990 and 2000 and regress variables of interest on each other. We then compare the so obtained regression coefficients with the ones that we get from running the same regressions on our simulated data. We compare coefficients from the following regressions (all in logs): 1) the regression of the relative unemployment rate of skilled workers on the skill ratio, 2) the regression of brain drain on the skill ratio, 3) the regression of the skill premium on the skill ratio, 4) the regression of brain drain on the relative unemployment rate, 5) the regression of changes in the brain drain between 1990 and 2000 on changes in the skill ratio, and 6) the regression of relative productivity of skilled workers on the skill ratio.[29] Our baseline calibration is again $\epsilon = 2.25$ and $\alpha = 1.17$, but we also report results for $\epsilon \in \{1.75, 2, 2.5\}$ and $\alpha \in \{0.85, 2.7\}$.

The results of this exercise are presented in Table 7. In the first row, we present the regression coefficients that were obtained with the data. In the rows below we report regression coefficients computed with the simulated data for different parameter values. Turning first to our baseline calibration with $\epsilon = 2.25$ and $\alpha = 1.17$ (in bold in row 7), the model is able to replicate the signs and the approximate magnitudes of almost all coefficients. Despite our parsimonious calibration, the model fits quite well the coefficient of the regression of relative unemployment rates on skill ratios (-0.26, compared to -0.21 in the data), the one of brain drain and skill ratios (-0.43 compared to -0.82 in the data), the one between brain drain and relative unemployment rates (0.15 compared to 0.26 in the data), between changes in the brain drain and changes in the skill ratio (-0.2 compared to -0.55 in the data) and between relative productivities and skill ratio (0.3 compared to 0.42 in the data). There is just one coefficient that our model cannot replicate: the one from the regression of the skill premium on skill ratios (0.32 compared to -0.16 in the data). This, however, is not surprising, since our model with labor market frictions always predicts the same sign for the relation between wages and the skill ratio as for the one between employment rates and the skill ratio.

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[28] We regress the logistic transformation of migration rates, on the skill ratio and migration cost controls, instrumenting for the skill ratio with public education expenditure.

$$\log(s_j/(1-s_j))_{it} = \alpha + \beta \log(H/L)_{it} + \gamma \log(c)_{ij} + \mu_t + u_i + \nu_{it}, \tag{44}$$

Then the predicted migration costs are given by $\hat{c}_{iH} = -0.25^{(*)} \log(distance) - 0.08 Colony + 1.01^{(***)} English - 0.11 French$ and $\hat{c}_{iL} = -0.66^{(***)} \log(distance) - 0.54 Colony + 0.72^{(***)} English - 0.18 French$.

[29] Data on $A_H/A_L$ are constructed using equation (18).

We now briefly discuss results for different values of $\epsilon$ and $\alpha$. For $\epsilon = 1.75$ and any value of $\alpha$ the regression coefficients mostly have the wrong signs. The only improvement is the coefficient of the regression of the wage premium on the skill ratio, which now turns negative. Intuitively, when $\epsilon < 2$ the relative employment rate and the skill premium is decreasing in the skill ratio, because the market size effect is not strong enough. For $\epsilon = 2$, which is the case when relative productivity is independent of the skill ratio (see equation (24)), the regression coefficients are in general too small and often insignificant. Next, for $\epsilon = 2.5$ the signs of the coefficients are the same ones as for $\epsilon = 2.25$ but the magnitude of the coefficients in general corresponds less well the data. Turning to changes in $\alpha$ for $\epsilon = 2.25$, we can observe that our results are not very sensitive to the value of this parameter (as long as the condition $\epsilon < 2 + \alpha$ is satisfied). Both for high and low values of $\alpha$ the signs of the regression coefficients are maintained, though the magnitudes mostly correspond less well the data.

We thus conclude that a very simple model of migration with endogenously directed technology and $\epsilon > 2$ performs reasonably well in terms of replicating the correlations between skill-specific labor market outcomes and migration rates in the data. In contrast, the same model with $\epsilon < 2$ – which implies a downward-sloping relative demand curve for skilled labor – cannot replicate the salient features of the data. We take this as support for the mechanisms emphasized in our model.

# 5 Conclusion

In this paper, we have developed a model of directed technological change, frictional unemployment and migration to examine the effects of a change in skill endowments on wages, employment rates and emigration rates of skilled and unskilled workers. We found that for plausible values of the elasticity of substitution between skilled and unskilled workers and the elasticity of matching workers to jobs, returns to skill were an increasing function of skill ratios in the presence of endogenous skill-biased technological change: an increase in the relative stock of skilled workers lead to lower relative unemployment rates and higher skill premia. In consequence, the relative expected wage rate of skilled workers increased, resulting in a lower relative emigration rate (brain drain). We have provided empirical estimates and simulations of wages, employment rates and emigration rates to confirm that increases in the skill ratio have empirically relevant and sizeable effects on these outcomes. Moreover, we have shown that labor market institutions, such as unemployment benefits and firing costs, interact with skill ratios in determining the reaction of technological change. An increase in the skill ratio triggered skill-biased technological change provided that labor markets were sufficiently flexible but may cause unskill-biased technological change when labor market frictions are large. Our findings also fit the stylized facts on educational upgrading in developing countries during the 1980s and the subsequent decrease in the brain drain during the 1990s. They suggest that education policies can contribute significantly to a slow down in brain drain and, therefore, improve long-run perspectives for prosperity and growth in emigration countries.

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# 7 Appendix

## 7.1 Data

**Wages**

We construct wages for skilled and unskilled workers from the Occupational Wages around the World (OWW) dataset that has been compiled by Freeman and Oostendorp (2000) from ILO data. This data set covers the period 1983-2001 and contains wages by occupation for a large sample of countries. Wages are reported as the average monthly wage rate of male workers in constant dollars, which we convert into yearly PPP-adjusted wages using price indices from the Penn World Tables 6.2. Instead, we need to aggregate occupational wages into series of skilled and unskilled wages under the constraint that the number of occupations for which wage data are available differ across countries for a given time period and for a given country across time. We follow the procedure suggested by Chor (2001) to construct the two wage series, taking a fixed set of seven skilled and seven unskilled occupations.[30] For skilled and unskilled occupations we separately perform the following procedure.[31] We regress wages for occupation $o$ in country $c$ in period $t$, $w_{cto}$ on the wages of all the other occupations in separate regressions to squeeze out the common trend for these occupations for a given country: $w_{cto} = \beta_1 w_{cto'} + \delta_{co} + u_{ct0}$, and we obtain predicted values as $\hat{\beta}_1 w_{cto'} + \hat{\delta}_{co}$. Subsequently, we average the predicted values of all regressions to obtain an estimate of the wage series. Finally, we take averages of the data using one year windows around 1985, 1990, 1995 and 2000 to maximize data availability.

**Human capital stocks**

Data on educational attainment of the population come from Barro and Lee (2000, 2011), supplemented with data by De la Fuente and Domenech (2002) for OECD countries. These data-sources are the ones that have been used by Beine, Docquier and Rapoport (2008) to construct migration rates by skill. Skilled workers are those with tertiary education (13 years and above), while all

[30]The 7 unskilled occupations selected were: thread and yarn spinners in the textiles industry (#25); sewing machine operators in the manufacture of wearing apparel excluding footwear (#30); laborers in printing, publishing and allied industries (#51); laborers in the manufacture of industrial chemicals and other chemical products (#56/#59)13; laborers in the manufacture of machinery except electrical (#70); laborers in electric light and power (#80); and laborers in construction (#90).14 These choices satisfied three criteria. First, the job scopes did not require higher education. Second, the industries picked were found in most economies, ensuring wide geographical coverage. These 7 occupations lie on the low end of the wage spectrum in the OWW: In countries that listed wages for at least 80 of the 159 occupations during 1983-1998, the 7 occupations were in the lower one-third of the distribution of reported wages in at least 75% of country-year pairs, with one exception (#80). For skilled labor, the 7 occupations were: chemical engineers in the manufacture of industrial chemicals (#52); power distribution and transmission engineers (#76); bank accountants (#129); computer programmers in the insurance industry (#133); government executive officials in public administration (#139); mathematics teachers at the third (tertiary) level (#145); and general physicians (#152). The skilled workers we focus on are professionals. The 'skilled' wage is thus a wage return to technical expertise that would require at least a secondary level of schooling. Certainly, these 7 occupations lie above the 75th percentile of the wage distribution for country-year pairs reporting at least 80 occupations during 1983-1998.

[31]For a more detailed explanation see Chor (2001).

other workers are considered as unskilled for our purposes. This is the standard definition of skilled workers in the brain drain literature and matches our definition of skilled wages quite closely. These data are available in 5 year intervals and we use those for 1980, 1985, 1990, 1995, 2000 and 2005.

**Migration rates**

The source of the migration data by skill level is Beine, Docquier and Rapoport's (2008) database on migration to the OECD countries by sending country and skill level for the years 1990 and 2000. They construct migration rates by sending country by combining information on migrant stocks in OECD countries by skill with data on educational attainment of the sending countries' labor force.[32] Migrants are defined as all working-age (25 and over) foreign-born individuals living in an OECD country. Skilled migrants are those who have at least tertiary educational attainment that has been acquired in their home countries. Migration rates are measured as stock variables. Denoting $H_{it}$ ($L_{it}$) as the stock of skilled (unskilled) residents and $H_{mit}$ ($L_{mit}$) as the stock of skilled (unskilled) migrants age 25 or over from country i at time t, emigration rates of the skilled and unskilled are defined as $s_{Hit} = \frac{H_{mit}}{H_{it}+H_{mit}}$ and $s_{Lit} = \frac{L_{mit}}{L_{it}+L_{mit}}$. More precisely, $s_{jit}$ measures the fraction of agents of skill $j \in \{H, L\}$ born in country i and living in an OECD country at time $t$. Brain drain is the relative migration rate of skilled workers, defined as brain drain$_{it} = s_{Hit}/s_{Lit}$.

**Unemployment rates**

Unemployment rates for skilled and unskilled workers have been constructed from the ILO Key Indicators of the Labour Market database. This database provides information on employment by educational attainment for a (strongly unbalanced) panel of countries. We have combined this information with the data on the number of workers by educational attainment from Barro and Lee (2000, 2011) and De la Fuente and Domenech (2002) to construct unemployment rates for skilled and unskilled workers for 1980, 1985, 1990, 1995, 2000 and 2005.

**Labor market institutions**

Data on labor market institutions are from Aleksynska and Schindler (2011) and from the Fraser Institute Freedom of the World, 2011 Database (Gwartney et al. (2011)). Aleksynska and Schindler (2011) have constructed a database of labor market regulations during 1980-2005 for 91 countries that contains information on unemployment insurance systems, minimum wages and employment protection legislation using a common methodology. This data set is the most complete cross-country panel of labor market institutions available. We use the variable 'replacement rate', defined as the gross replacement rate in the first year of unemployment, 'minimum wage' defined as the ratio of the minimum to the median wage, and 'firing cost', which is an indicator that includes both advance notice requirements and severance pay. As a robustness check, we also use the labor market

[32] Since most migration is to OECD countries, this is a good proxy for total migration rates.

regulation index from the Fraser Institute Freedom of the World, 2011 Database. We multiply the index with minus one, so that higher values correspond to more regulated labor markets.

**Other data**

We use additional control variables such as real PPP-GDP per capita levels, real PPP GDP growth and openness, defined as (exports+imports)/GDP, from the Penn World Tables 6.2. We also use educational spending as a fraction of GDP from the Word Development Indicators 2000 and 2011 and a number of country-specific variables from Beine et al. (2008), such as distance from the OECD, an indicator of whether a country has been a colony of an OECD country after 1945, and an indicator of whether a country has English or French as an official language.

**List of countries used in wage regressions (Table 3)**

ARG (1995-1995), AUS (1985-2000), AUT (1985-2000), BDI (1990), BEN (1985, 1990), BGD (1990, 1995), BGR (1990), BOL (1990-2000), BRB (1985-1995), BWA (1985), CAF (1990, 1995), CAN (1985), CHL (1985), CHN (1990, 1995), COL (1990), CRI (1995, 2000), CYP (1985-2000), CZE (1995,2000), DNK (1990), DOM (1995), DZA (1985, 1990), FIN (1985-1995), FJI (1985), GBR (1990, 1995), GUY (2000), HND (1985-1995), HRV (1995), HUN (1995, 2000), IND (1990-2000), ITA (1985-2000), JPN (1985), KOR (1985-2000), LKA (2000), MEX (1985, 2000), MLI (1985, 1990), MOZ (1990), MUS (1985-2000), MWI (2000), NIC (1995, 2000), NZL (1985, 1990), PER (1985, 1995, 2000), PHL (1990, 1995), PNG (1995), POL (1995, 2000), PRT (1995, 2000), ROM (1985-2000), RUS (1995, 2000), RWA (1985, 1990), SDN (1990), SGP (1985-2000), SLE (1995), SVK (1995, 2000), SVN (1990, 1995), SWE (1985-1995), THA (1985-1995), TTO (1995-1995), TUN (1985, 1995), URY (1985), USA (1990-2000), VEN (1985, 1990), ZMB (1990, 1995).

**List of countries used in unemployment regressions (Tables 4, 5)**

ARE (1995, 2005), ARG (1995-2005), ARM (1995-2005), AUS (1990-2005), AUT (1985-2005), BEL (1995-2005), BGD (2000,2005), BGR (2000, 2005), BHR (2000, 2005), BLZ (1995, 2005), BOL (2000), BRA (2005), BRB (1995, 2000), CAF (1990,1995), CAN (1980-2005), CHE (1995-2005), CHL (2000, 2005), CRI (1990-2005), CUB (1990-2005), CYP (1985-1995, 2005), CZE (1995-2005), DNK (1995-2005), DZA (1995), ESP (1980-2005), EST (1995-2005), FIN (1995-2005), FJI (2005), FRA (2005), GBR (1990-2005), GER (2000, 2005), GRC (1995-2005), HRV (2000, 2005), HUN (1995-2005), IDN (1985-2005), IND (1990-2005), IRL (1990, 1995, 2005), ISL (1995, 2000), ITA (1995-2005), JPN (1990-2000), KGZ (1995-2005), KWT (1995-2005), LTU (1995-2005), LUX (2000, 2005), LVA (2005), MAR (1990-2005), MEX (1995-2005), MLT (1995, 2005), MNG (2000), MUS (2005), MYS (1995-2005), NIC (1995-2005), NLD (1995-2005), NOR (2000, 2005), NZL (1990-2005), PAK (1995-2005), PAN (1985, 2005), PER (2005), PHL (2000, 2005), POL (1995-2005), PRT (1995-2005), ROU (1995-2005), RUS (1995-2005), RWA (2000), SAU (2000), SGP (1985-1995), SVK (1995-2005), SVN (1995-2005), SWE (1990, 2005), TJK (1990-2005), TTO (1995, 2000), TUN (2000, 2005), TUR (1995-2005), UKR (1995-2005), URY (2005), ZAF (2000, 2005).

**List of countries used in migration regressions (1990, 2000), (Table 6)**

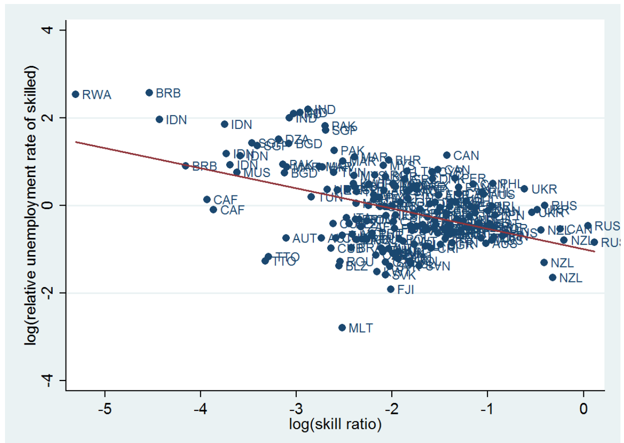
ARG, AUS, AUT, BEL, BGD, BGR, BOL, BRA, BRB, CAN, CHE, CHL, CHN, CMR, COG, COL, CRI, CUB, CYP, DNK, DOM, DZA, ECU, EGY, ESP, FIN, FJI, FRA, GBR, GHA, GRC, GTM, GUY, HKG, HND, HTI, HUN, IDN, IND, IRN, IRQ, ISL, ISR, ITA, JAM, JOR, JPN, KEN, KOR, KWT, LBR, LKA, LSO, MEX, MLI, MLT, MWI, MYS, NER, NIC, NLD, NOR, NZL, PAK, PAN, PER, PHL, PNG, POL, PRT, PRY, ROM, SDN, SEN, SGP, SLE, SLV, SWE, SYR, TGO, THA, TTO, TUN, TUR, TWN, UGA, URY, USA, VEN, ZAF, ZAR, ZMB.

**List of countries used in model simulations (1990, 2000), (Table 7)**

Same as in migration regressions.

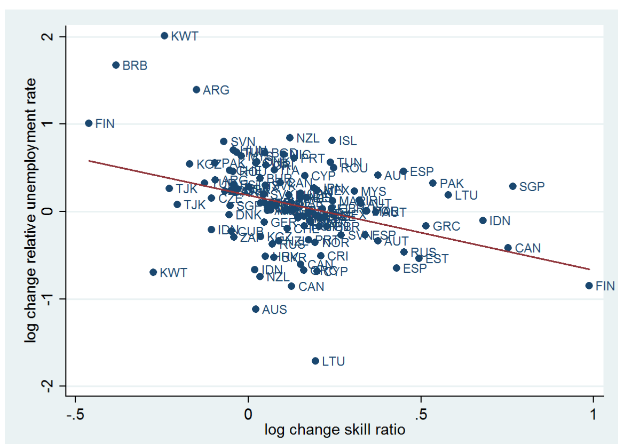
# Tables and Figures

Figure 1: Skill ratio and relative unemployment.



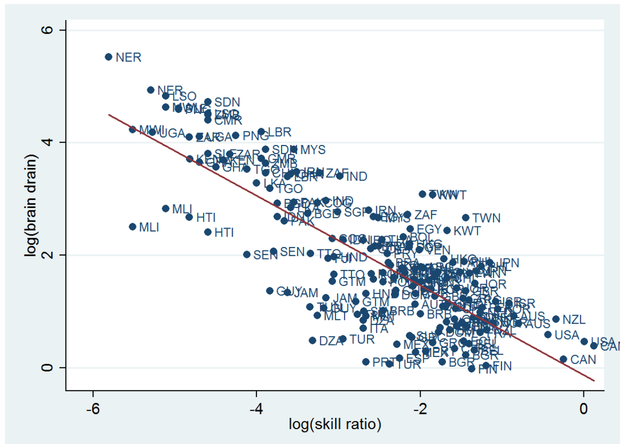

Note: The figure shows the simple correlation between the log relative unemployment rate of skilled and the log skill ratio. The regression coefficient of log skill ratio is -0.46 (robust SE: 0.10), with R-squared of 0.20. Data are for an unbalanced panel of 75 countries in 5-year intervals from 1980-2005.

Figure 2: Change in skill ratio and change in relative unemployment.



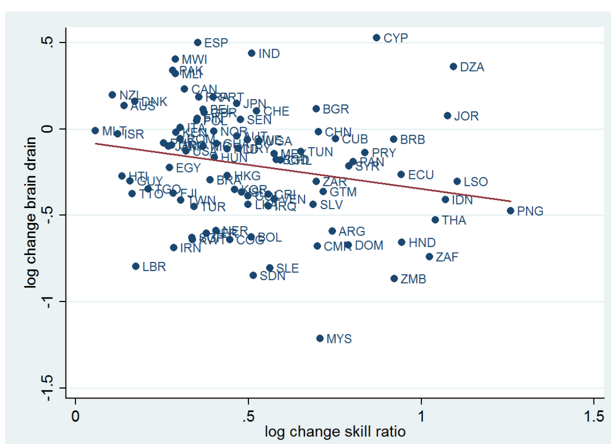

Note: The figure shows the simple correlation between the log change of relative unemployment rate of skilled and the log change of skill ratio. The regression coefficient of log skill ratio is -0.86 (robust SE: 0.20), with R-squared of 0.13. Data are for an unbalanced panel of 75 countries in 5-year intervals from 1980-2005.

Figure 3: Skill ratio and brain drain.



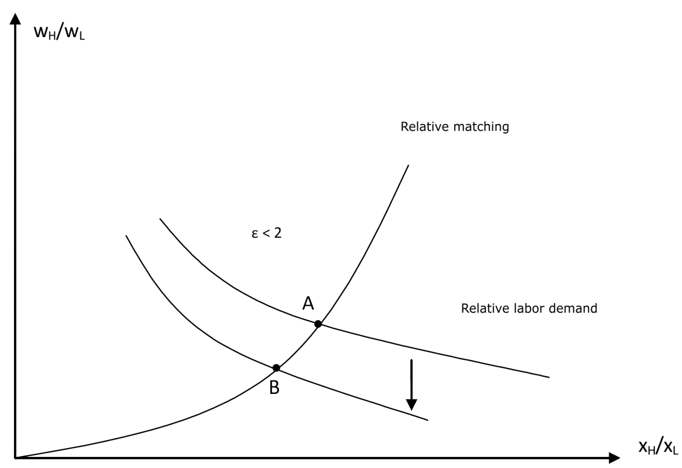

Note: The figure shows the simple correlation between the log relative migration rate of skilled (brain drain) and the log skill ratio. The regression coefficient of log skill ratio is -0.796, (robust SE: 0.06), with R-squared of 0.63. Data are for a sample of 92 countries for 1990 and 2000.

Figure 4: Change in skill ratio and change in brain drain.



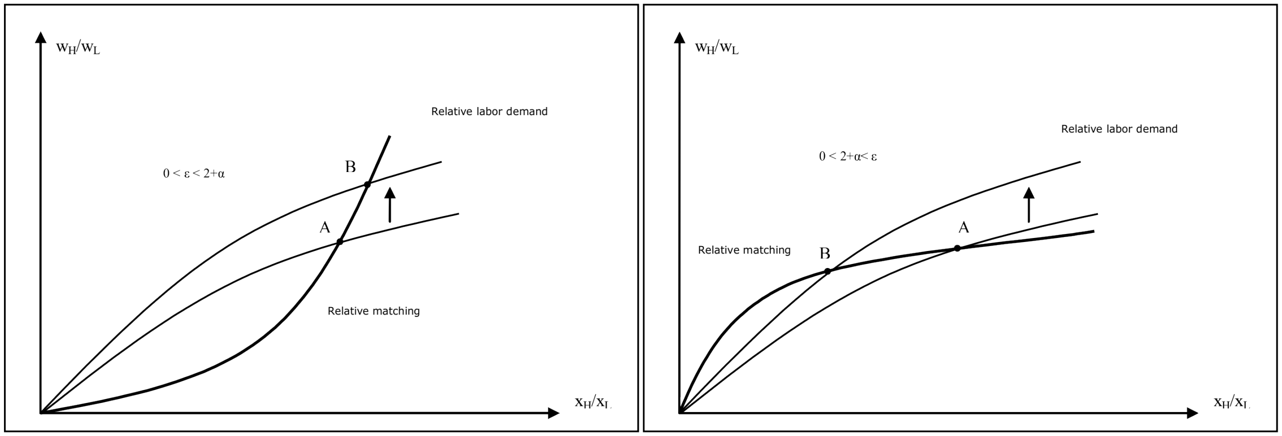

Note: The figure shows the simple correlation between the log change of the relative migration rate of skilled (brain drain) and the log change of skill ratio. The regression coefficient of log skill ratio is -0.28, (robust SE: 0.13), with R-squared of 0.04. Data are for a sample of 92 countries for 1990 and 2000.

Figure 5: Labor market, exogenous technology



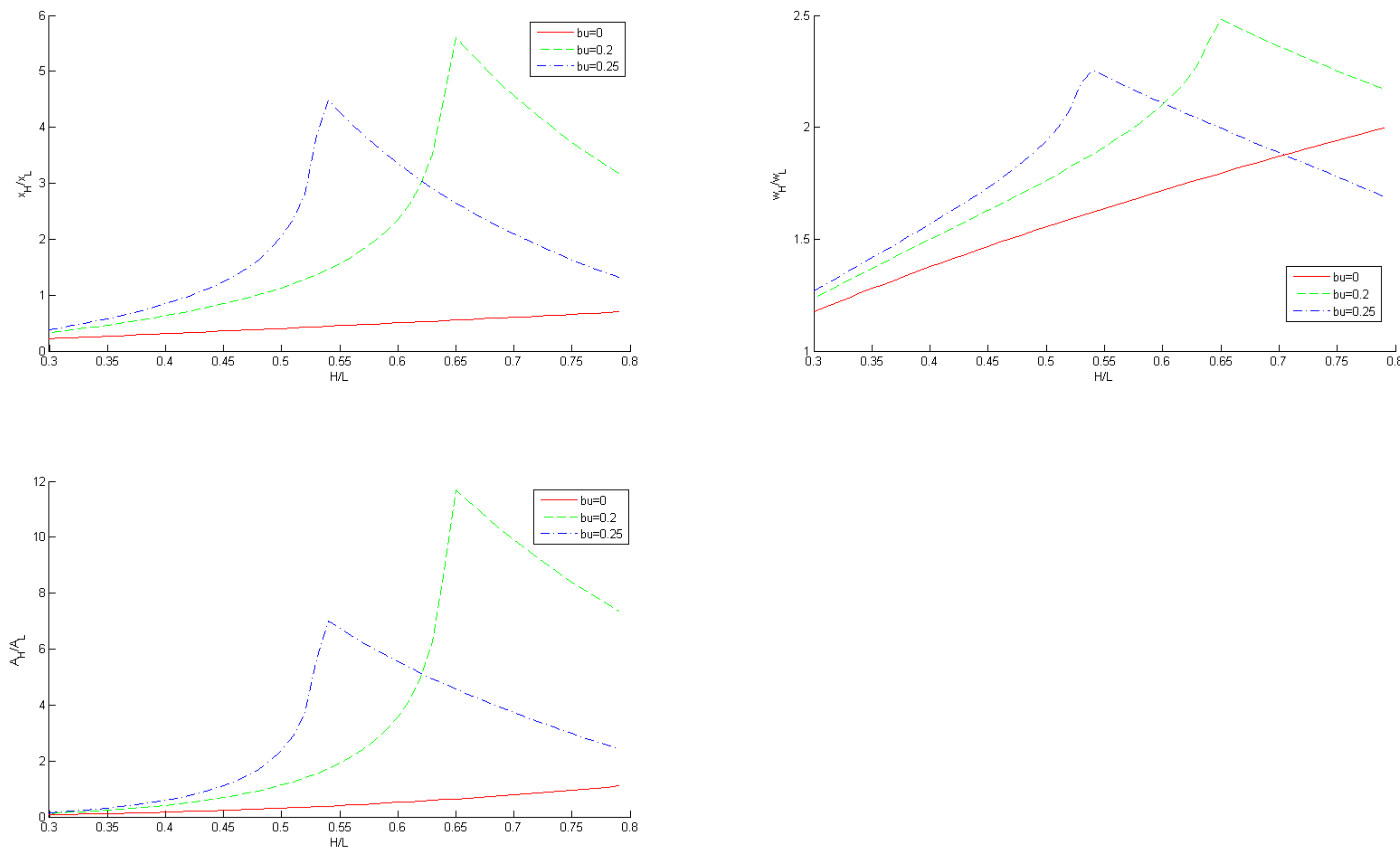

Note: The figure depicts the relationship between the skill premium $w_H/w_L$ and the relative employment rate $x_H/x_L$ according to 1) relative matching and 2) relative labor demand. If technology is exogenous (or, if technology is skill-biased but $\epsilon < 2$), then the labor demand curve is downward-sloping. Then, an increase in the skill ratio H/L leads to an increase in the relative employment of skilled, $H_E/L_E$ - compare (19) - but a decrease in the relative employment rate and the skill premium via a downward-shift of the labor demand curve (movement from point A to point B) - compare (20) and (21).

Figure 6: Labor market, endogenous technology



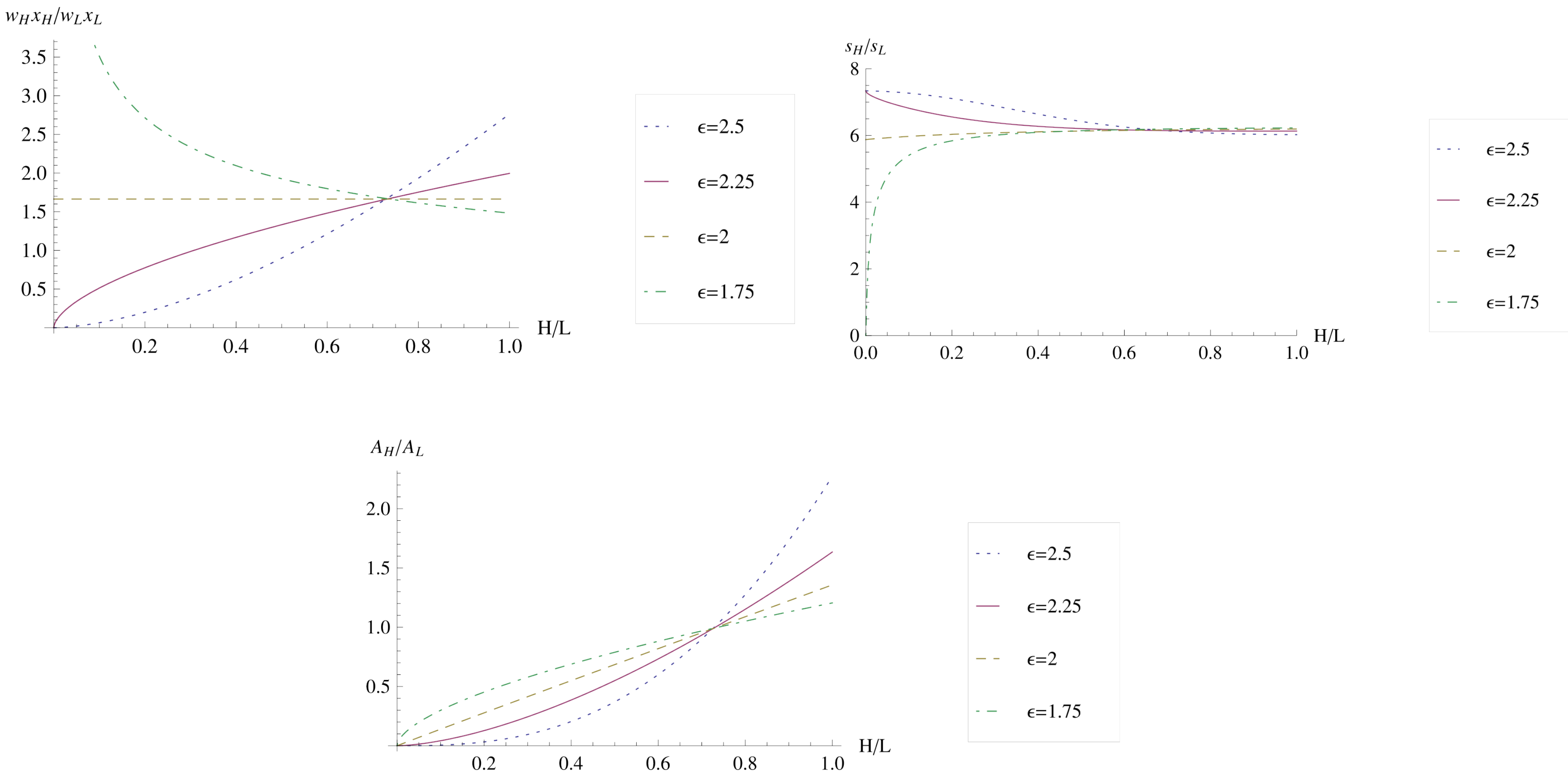

Note: The above figure represents the same relations as Figure 5. However, the relative labor demand curve is now upward-sloping, which is the case, if technology is skill-biased and $\epsilon > 2$. Now, the effect of an increase in the skill ratio H/L depends on the elasticity of matching, $1/\alpha$, relative to the elasticity of labor demand, $1/(\epsilon$-2). If the matching elasticity is relatively low (panel a), we expect an increase in the skill ratio of employed, the relative employment rate of skilled and the skill premium via an upward-shift of the labor demand curve (movement from point A to point B). If the matching elasticity is relatively high (panel b), we expect a decrease in the skill ratio of employed, the relative employment rate of skilled and the skill premium. Compare (26)-(28). Note that in this graph, the labor demand function is concave (convex), if $\epsilon$>3 ($\epsilon$<3) and the matching function is concave (convex), if $\alpha$<1 ($\alpha$>1).

Figure 7: Unemployment benefits



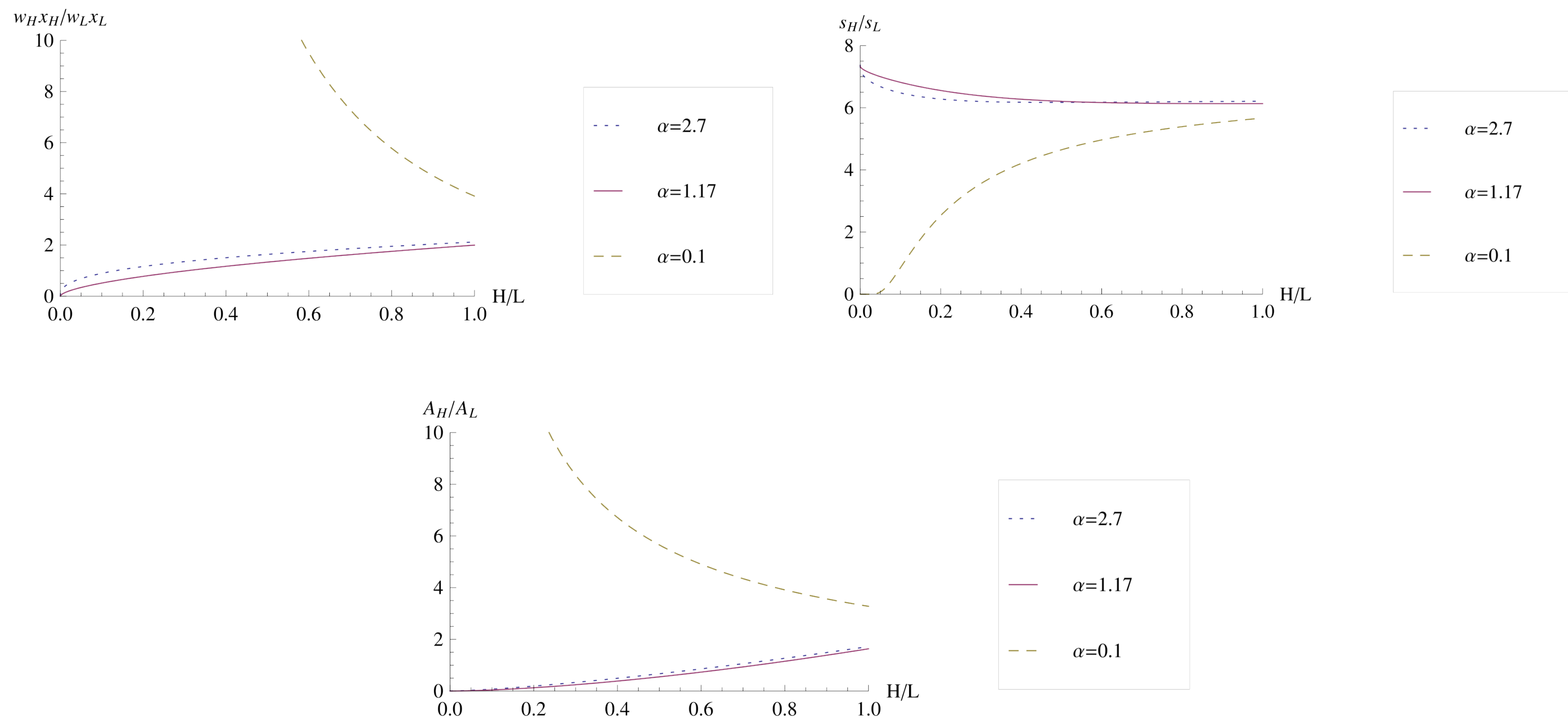

Note: Parameter values are chosen according to the baseline calibration (see section 3.1): The elasticity of substitution $\epsilon$ is 2.25, the elasticity of the matching function $\alpha$ is 1.17.

Figure 8: Relative Wages, Migration Rates and Technology for Skilled and Unskilled in General Equilibrium - The Impact of the Elasticity of Substitution ($\epsilon$)




Note: Skill-specific migration costs $c_H$ and $c_L$ are chosen to match average migration rates of skilled and unskilled workers exactly given an average skill ratio H/L of 0.05 and an unskilled working population normalized to 2. The elasticity of matching is kept constant at $\alpha$=1.17.

Figure 9: Relative Wages, Migration Rates and Technology for Skilled and Unskilled in General Equilibrium - The Impact of the Elasticity of Matching ($\alpha$))




Note: Skill-specific migration costs $c_H$ and $c_L$ are chosen to match average migration rates of skilled and unskilled workers exactly given an average skill ratio H/L of 0.05 and an unskilled working population normalized to 2. The elasticity of substitution $\epsilon$ is kept constant at 2.25.

Table 1: Baseline choice of parameters

| Parameter | $w_H^{\text{OECD}}$ | $w_L^{\text{OECD}}$ | $x_H^{\text{OECD}}$ | $x_H^{\text{OECD}}$ | $a_H$ | $a_L$ | $\mu$ |
|---|---|---|---|---|---|---|---|
| Value | 0.37 | 0.15 | 0.96 | 0.95 | 0.38 | 0.16 | 1.41 |
| Parameter | Z | L | $\alpha$ | $\sigma$ | $c_H$ | $c_L$ | $\epsilon$ |
| Value | 1.96 | 10 | 1.17 | 4 | 1.62 | 3.45 | 2.25 |

Note: The baseline parameters are taken from the literature as described in section 3.1. Migration costs are chosen to match observed migration rates for the average developing country in our sample.

Table 2: Simulation of the brain drain ($s_H/s_L$) depending on the skill ratio

| H/L | 0.01 | 0.05 | 0.10 | 0.20 | 0.50 | 1 |
|---|---|---|---|---|---|---|
| Exogenous technology | 6.53 | 7 | 7.11 | 7.18 | 7.26 | 7.3 |
| Endogenous technology | 7.21 | 7 | 6.81 | 6.55 | 6.2 | 6.13 |

Note: In the case of exogenous technology, $A_H$ and $A_L$ were chosen such that for H/L=0.05 emigration rates ($s_H$, $s_L$) are exactly the same as in the case of endogenous technology.

Table 3: Skill ratio and skill premia/relative technology

| | Dependent variable: skill premium | | | | | | Dependent Variable: $A_H/A_L$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Skill ratio | -0.214*** | -0.104 | -0.143* | -0.055 | -0.0219 | -0.1246 | 0.415*** | 0.595*** | 0.541*** | 0.701*** | 0.754*** | 0.572*** |
| | (0.039) | (0.066) | (0.077) | (0.083) | (0.071) | (0.148) | (0.071) | (0.118) | (0.140) | (0.150) | (0.133) | (0.248) |
| GDP per capita | | -0.159* | -0.0977 | | -0.178* | 0.0382 | | -0.289** | | | -0.322* | 0.014 |
| | | (0.080) | (0.088) | | (0.094) | (0.0960) | | (0.143) | | | (0.169) | (0.142) |
| GDP growth | | 0.77 | 1.227 | | -0.263 | -0.089 | | 0.152 | 0.336 | | -0.212 | 0.115 |
| | | (1.505) | (1.623) | | (0.877) | ( 1.379) | | (0.529) | (0.529) | | (0.281) | (0.446) |
| Openness | | 0.111 | 0.119 | | 0.256 | 0.146 | | 0.186 | 0.21 | | 0.491* | 0.249 |
| | | (0.095) | (0.092) | | (0.155) | (0.102) | | (0.173) | (0.169) | | (0.276) | (0.193) |
| Time Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Fixed Effects | NO | NO | NO | YES | YES | YES | NO | NO | NO | YES | YES | YES |
| Cluster | Country | Country | Country | Country | Country | Country | Country | Country | Country | Country | Country | Country |
| Estimator | OLS | OLS | IV | OLS | OLS | IV | OLS | OLS | IV | OLS | OLS | IV |
| F-statistic first stage | | | 312.604 | | | 15.266 | | | 308.719 | | | 15.474 |
| Sargan J-statistic (P-Value) | | | 0.796 | | | 0.533 | | | 0.778 | | | 0.513 |
| Observations | 133 | 132 | 98 | 133 | 132 | 43 | 133 | 132 | 98 | 133 | 132 | 43 |
| Countries | 62 | 62 | 54 | 62 | 62 | 28 | 62 | 62 | 54 | 62 | 62 | 22 |
| R-squared | 0.356 | 0.389 | 0.341 | 0.06 | 0.173 | 0.079 | 0.44 | 0.48 | 0.465 | 0.526 | 0.589 | 0.381 |

Note: Dependent variable is the (log) relative wage of skilled workers (columns (1)-(6)) and the relative productivity of skilled workers (columns (7)-(12)). Explanatory variables are in logs and include levels of skill ratios, the level of GDP per capita, the growth rate of GDP and openness. In columns (3),(6),(9) and (12) we instrument for skill ratios using 5-year-lagged skill ratios, and public education expenditure as instruments. In columns (6) and (12) the regression is estimated in first differences. The column 'F-statistic' refers to the Kleibergen-Paap test for weak instruments. In the column 'Sargan J-statistic', we report the P-Value of the Sargan test for the validity of the overidentifying restrictions. The skill premium, defined as the log relative wage of skilled workers is constructed from the Occupational Wages around the World dataset (Freeman and Oostendorp (2000)) by considering a fixed set of occupations, which are divided into skilled and unskilled activities (see data appendix for details). The relative productivity of skilled workers, $A_H/A_L$ is computed from equation (48), using data on skill premia and skill ratios for $\epsilon = 2.25$. Skill ratios are constructed from Barro and Lee (2000) and are defined as the fraction of people with tertiary education in the working-age population over 25 years. Other data are from Penn World Tables, except public education expenditure, which comes from the World Development Indicators. The data set is an unbalanced panel in 5-year-intervals from 1985-2000. All standard errors are clustered at the country level.

Table 4: Skill ratio and relative unemployment rates

| | Dependent variable: relative unemployment rate | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Skill ratio | -0.457*** | -0.472*** | -0.470*** | -0.691*** | -0.487* | -2.709 |
| | (0.107) | (0.132) | (0.149) | (0.234) | (0.278) | ( 1.815) |
| GDP per capita | | -0.154 | -0.195 | | -0.975 | 1.337 |
| | | (0.120) | (0.122) | | (0.929) | ( 1.849) |
| GDP growth | | -0.126 | -0.142 | | 1.249 | -3.616 |
| | | (0.719) | (0.761) | | (0.949) | (2.303) |
| Openness | | -0.188 | -0.16 | | 0.346 | -1.064 |
| | | (0.207) | (0.231) | | (0.279) | (1.367) |
| Time Fixed Effects | YES | YES | YES | YES | YES | YES |
| Country Fixed Effects | NO | NO | NO | YES | YES | YES |
| Cluster | Country | Country | Country | Country | Country | Country |
| Estimator | OLS | OLS | IV | OLS | OLS | IV |
| F-statistic first stage | | | 413.140 | | | 6.145 |
| Sargan J-statistic (P-Value) | | | 0.9795 | | | 0.767 |
| Observations | 200 | 117 | 103 | 200 | 117 | 50 |
| Countries | 75 | 58 | 54 | 75 | 58 | 37 |
| R-squared | 0.252 | 0.399 | 0.375 | 0.224 | 0.438 | 0.114 |

Note: Dependent variable is the (log) relative unemployment rate of skilled workers. Explanatory variables are in logs and include levels of skill ratios, the level of GDP per capita, the growth rate of GDP and openness. In columns (3) and (6), we instrument for skill ratios using 5-year-lagged skill ratios, and public education expenditure as instruments. In column (6) the regression is estimated in first differences. The column 'F-statistic' refers to the Kleibergen-Paap test for weak instruments. In the column 'Sargan J-statistic', we report the P-Value of the Sargan test for the validity of the over-identifying restrictions. Unemployment rates by educational attainment are constructed using data from ILO and Barro and Lee (2000, 2011). Skill ratios are constructed from Barro and Lee (2000, 2011) and are defined as the fraction of people with tertiary education in the working-age population over 25 years. Other data are from Penn World Tables, except public education expenditure, which comes from the World Development Indicators. The data set is an unbalanced panel in 5-year-intervals from 1980-2005. All standard errors are clustered at the country level.

Table 5: Skill ratio, relative unemployment rates and labor market institutions

| | Dependent variable: relative unemployment rate | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Skill ratio | -0.693*** | -2.030** | -0.615*** | 0.526 | -0.711*** | -0.864 | -0.609*** | 1.059* | -2.657*** | -2.718*** | -1.348*** | -0.175 |
| | (0.196) | (0.680) | (0.180) | (0.396) | (0.265) | (0.996) | (0.193) | (0.563) | (0.973) | (0.886) | (0.467) | (0.429) |
| Replacement rate | 1.969** | | | | 2.210** | | | | 3.132 | | | |
| | (0.732) | | | | (0.976) | | | | (2.139) | | | |
| Replacement rate | 1.131** | | | | 1.225* | | | | 4.582*** | | | |
| x Skill ratio | (0.477) | | | | (0.650) | | | | (1.554) | | | |
| Minimum Wage | | 0.171 | | | | 3.058 | | | | 9.831* | | |
| | | (1.396) | | | | (2.498) | | | | (4.787) | | |
| Minimum Wage | | 3.685** | | | | 1.047 | | | | 4.835* | | |
| x Skill Ratio | | (1.397) | | | | (2.304) | | | | (2.464) | | |
| Firing Cost | | | 0.0670** | | | | 0.0727** | | | | 0.202** | |
| | | | (0.033) | | | | (0.033) | | | | (0.094) | |
| Firing Cost | | | 0.0289 | | | | 0.0318* | | | | 0.0865** | |
| x Skill Ratio | | | (0.019) | | | | (0.019) | | | | (0.037) | |
| LM Regulation | | | | 0.203* | | | | 0.374** | | | | 0.117 |
| | | | | (0.121) | | | | (0.181) | | | | (0.117) |
| LM Regulation | | | | 0.170** | | | | 0.264*** | | | | 0.0919 |
| x Skill ratio | | | | (0.067) | | | | (0.099) | | | | (0.057) |
| GDP per capita | -0.208 | 1.241*** | -0.276** | -0.258*** | -0.226 | 1.120*** | -0.287** | -0.256*** | -0.274 | 1.97 | 0.864 | 0.258 |
| | (0.154) | (0.331) | (0.121) | (0.088) | (0.148) | -0.227 | (0.115) | (0.095) | (1.724) | (1.267) | (1.871) | (0.887) |
| GDP growth | -0.286 | 0.693 | -0.153 | -0.488 | -0.119 | 0.304 | 0.00694 | -0.334 | -0.425 | -1.394 | -1.695 | -0.232 |
| | (0.840) | (0.716) | (0.742) | (0.629) | (0.883) | (0.806) | (0.790) | (0.639) | (1.218) | (1.477) | (1.831) | (0.684) |
| Openness | -0.3 | 0.0431 | -0.253 | -0.202 | -0.278 | -0.0152 | -0.216 | -0.252 | -0.655 | 0.329 | -0.683 | 0.116 |
| | (0.216) | (0.147) | (0.282) | (0.190) | (0.211) | (0.124) | (0.292) | (0.200) | (0.609) | (1.345) | (1.033) | (0.328) |
| Time Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Fixed Effects | NO | NO | NO | NO | NO | NO | NO | NO | YES | YES | YES | YES |
| Cluster | Country | Country | Country | Country | Country | Country | Country | Country | Country | Country | Country | Country |
| Estimator | OLS | OLS | OLS | OLS | IV | IV | IV | IV | OLS | OLS | OLS | OLS |
| F-statistic first stage | | | | | 180.647 | 38.393 | 144.904 | 141.078 | | | | |
| Sargan J-statistic (P-Value) | | | | | 0.8276 | - | 0.9404 | 0.173 | | | | |
| Observations | 98 | 37 | 102 | 100 | 91 | 29 | 91 | 90 | 98 | 37 | 102 | 100 |
| Countries | 44 | 15 | 46 | 53 | 44 | 12 | 44 | 48 | 44 | 15 | 46 | 53 |
| R-squared | 0.429 | 0.786 | 0.422 | 0.464 | 0.398 | 0.791 | 0.383 | 0.457 | 0.526 | 0.722 | 0.156 | 0.424 |

Note: Dependent variable is the (log) relative unemployment rate of skilled workers. Explanatory variables are in logs and include levels of skill ratios, the interaction of skill ratio with different measures of labor market institutions, the level of GDP per capita, the growth rate of GDP and openness. In columns (4) -(8), we instrument for skill ratios and interaction terms using 5-year-lagged skill ratios, public education expenditure and their interactions with labor market institutions as instruments. The column 'F-statistic' refers to the Kleibergen-Paap test for weak instruments. In the column 'Sargan J-statistic', we report the P-Value of the Sargan test for the validity of the over-identifying restrictions. Unemployment rates by educational attainment are constructed using data from ILO and Barro and Lee (2000, 2011). Skill ratios are constructed from Barro and Lee (2000, 2011) and are defined as the fraction of people with tertiary education in the working-age population over 25 years. Data on labor market institutions are from Aleksynska and Schindler (2011) (Replacement rate, Minimum wage, Firing cost) and from the Fraser institute Freedom of the World 2011 Database (LM regulation).'Replacement rate' is defined as the gross replacement rate in the first year of unemployment, 'Minimum Wage' is the ratio of the minimum to the median wage, 'Firing cost' is an indicator that includes both advance notice requirements and severance pay.'LM regulation' is the labor market regulation index from the Freedom of the world database. Other data are from Penn World Tables, except public education expenditure, which comes from the World Development Indicators. The data set is an unbalanced panel in 5-year-intervals from 1980-2005. All standard errors are clustered at the country level.

Table 6: Skill ratio and brain drain

| | Dependent variable: brain drain | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged Skill ratio | -0.764*** | -0.564*** | | -0.279** | -0.345* | | 0.268 | 0.262 |
| | (0.056) | (0.101) | | (0.136) | (0.186) | | (0.389) | (0.478) |
| Skill Ratio | | | -0.662*** | | | -1.799** | | |
| | | | (0.108) | | | (0.869) | | |
| $A_H/A_L$ | | | | | | | -0.344** | -0.263* |
| | | | | | | | (0.154) | (0.155) |
| GDP per capita | | -0.0419 | 0.00131 | | 0.436* | 0.473* | | -0.0406 |
| | | (0.140) | (0.156) | | (0.232) | (0.255) | | (0.249) |
| GDP growth | | -0.212 | -0.365 | | -0.459*** | -0.616*** | | -0.153 |
| | | (0.335) | (0.370) | | (0.123) | (0.191) | | (0.251) |
| Openness | | -0.244* | -0.228* | | 0.0763 | -0.154 | | 0.421 |
| | | (0.133) | (0.123) | | (0.133) | (0.169) | | (0.312) |
| Time Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Fixed Effects | NO | NO | NO | YES | YES | YES | YES | YES |
| Migration Cost Controls | NO | YES | YES | NO | NO | NO | NO | NO |
| Cluster | Country | Country | Country | Country | Country | Country | Country | Country |
| Estimator | OLS | OLS | IV | OLS | OLS | IV | OLS | OLS |
| F-statistic first stage | | | 405.155 | | | 2.407 | | |
| Sargan J-statistic (P-Value) | | | 0.2806 | | | 0.8056 | | |
| Observations | 184 | 142 | 119 | 184 | 142 | 53 | 67 | 67 |
| Countries | 92 | 71 | 59 | 92 | 71 | 53 | 48 | 48 |
| R-squared | 0.625 | 0.715 | 0.758 | 0.311 | 0.412 | | 0.383 | 0.496 |

Note: Dependent variable is the (log) skilled relative to unskilled migration rate from the source country to the OECD. Explanatory variables are in logs and include levels of skill ratios or 10-year-lagged skill ratios, the level of GDP per capita, the growth rate of GDP and openness. Columns (2) and (3) include migration cost proxies – distance to the OECD, dummies for colony of the OECD, English and French as official languages (coefficient not reported). In columns (3) and (6), we instrument for skill ratios using 10-year-lagged skill ratios, and public education expenditure as instruments. In column (6) the regression is estimated in first differences. The column 'F-statistic' refers to the Kleibergen-Paap test for weak instruments. In the column 'Sargan J-statistic', we report the P-Value of the Sargan test for the validity of the over-identifying restrictions. In columns (7) and (8), we control for the relative productivity of skill, $A_H/A_L$, constructed from equation (48), assuming $\epsilon = 2.25$. Migration data for 1990 and 2000 are from Beine et al. (2008), skill ratios are constructed from Barro and Lee (2000, 2011) and are defined as the fraction of people with tertiary education in the working-age population over 25 years. Other data are from Penn World Tables, except migration cost proxies, which come from Beine et al. (2008), and public education expenditure, which comes from the World Development Indicators. All standard errors are clustered at the country level.

Table 7: Model simulations versus data

| | Coefficient from regression of, on | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $u_H/u_L, H/L$ | $s_H/s_L, H/L$ | $w_H/w_L, H/L$ | $s_H/s_L, u_H/u_L$ | $\Delta(s_H/s_L), \Delta(H/L)$ | $A_H/A_L, H/L$, $\epsilon = 1.75$ | $A_H/A_L, H/L$, $\epsilon = 2$ | $A_H/A_L, H/L$, $\epsilon = 2.25$ | $A_H/A_L, H/L$, $\epsilon = 2.5$ |
| **Data** | **-0.212*** ** | **-0.819*** ** | **-0.163*** ** | **0.262*** ** | **-0.546*** ** | **0.988*** ** | **0.700*** ** | **0.415*** ** | **0.413*** ** |
| $\epsilon = 1.75, \alpha = 2.7$ | -0.129 | -0.141* | -0.228** | -0.053 | -0.051 | -0.217*** | | | |
| $\epsilon = 2, \alpha = 2.7$ | -0.167* | -0.247*** | 0 | 0.243 | -0.097 | | 0 | | |
| $\epsilon = 2.25, \alpha = 2.7$ | -0.173 | -0.344*** | 0.276*** | 0.656*** | -0.057 | | | 0.257*** | |
| $\epsilon = 2.5, \alpha = 2.7$ | -0.273*** | -0.488*** | 0.615*** | 0.593*** | -0.271 | | | | 0.566*** |
| $\epsilon = 1.75, \alpha = 1.17$ | 0.107*** | '-0.279*** | -0.206*** | -0.096** | 0.523*** | -0.212*** | | | |
| $\epsilon = 2, \alpha = 1.17$ | -0.041 | -0.359*** | 0 | 0.093 | 0.013 | | 0 | | |
| $\epsilon = 2.25, \alpha = 1.17$ | **-0.260** ** | **-0.428*** ** | **0.319*** ** | **0.148** | **-0.200** ** | | | **0.304*** ** | |
| $\epsilon = 2.5, \alpha = 1.17$ | -0.675*** | -0.609*** | 0.874*** | 0.083 | 0.010 | | | | 0.793*** |
| $\epsilon = 1.75, \alpha = 0.85$ | 0.157*** | -0.326*** | -0.194*** | -0.269*** | 0.196* ** | -0.202*** | | | |
| $\epsilon = 2, \alpha = 0.85$ | -0.018 | -0.355*** | 0 | 0.006 | 0.003 | | 0 | | |
| $\epsilon = 2.25, \alpha = 0.85$ | -0.364*** | -0.382*** | 0.355*** | 0.169 | -0.070 | | | 0.339*** | |
| $\epsilon = 2.5, \alpha = 0.85$ | -0.831*** | -0.670*** | 1.215*** | -0.005 | -0.310 | | | | 1.043*** |

Note: The table shows regression coefficients of regressing the first variable in the column header on the second one. The first row presents the regression coefficients obtained from the data. Rows (2)-(13) present regression coefficients obtained from regressions using data generated by the model for different values of the elasticity of substitution between skilled and unskilled workers ($\epsilon$) and matching elasticities ($\alpha$). Row (8) is our baseline calibration. Simulations for countries for which migration data are available. Simulations are for the years 1990 and 2000. $\Delta$ refers to changes between 1990 and 2000. *** denotes significance at the one percent level.