Taking the Skill Bias out of Global Migration*

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Abstract

Global migration is heavily skill-biased, with tertiary-educated workers being four times more likely to migrate than workers with a lower education. In this paper, we quantify the global impact of this skill bias in migration. Based on a quantitative multi-country model with trade, remittances and human capital externalities, we compare the current world to a counterfactual with the same number of migrants, where all migrants are neutrally selected from their countries of origin. The skill bias in migration increases welfare in virtually all OECD countries, while the effects on non-OECD countries are more subtle. They are negative in many countries but positive in countries where migration-based externalities are strong. We find the global effect of the skill-bias to be unambiguously positive.

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1 Introduction

Policymakers' concerns about migration are as much about the skills of migrants — "who migrates?" — as they are about the scale of migration — "how many migrate?" Many migrant-sending countries worry that the emigration of high-skilled workers negatively affects economic development, whereas most receiving countries seek to attract high-skilled while restricting access for low-skilled immigrants. Indeed, the data point to a heavy skill bias in global migration. From most sending countries, high-skilled people are three to four times more likely to emigrate than low-skilled people, such that the skill selection from most sending countries is positive. From the perspective of the receiving countries, a similar pattern can be observed. In the UK and Canada, for example, the current share of tertiary-educated workers among immigrants is three times as large as it would be if all immigrants were drawn at random from the population of their country of origin.

Separate literatures have emerged for the sending and receiving countries, approaching the implications of the skill bias in migration from fundamentally different angles. The literature on the sending countries — often summarized by the buzzword *Brain Drain* — takes a macro perspective, thereby analyzing the impact of the skill bias in migration on economic growth as well as the channels through which this effect operates (Docquier & Rapoport, 2012). In contrast, much of the literature on the receiving countries approaches the skill bias from a micro perspective by analyzing the self-selection of migrants from the population of the sending country. Most papers study if and why a country's immigrants have been selected from the top or bottom of the skill distribution in the sending country.[1] These literatures leave two important gaps that we aim to fill. First, despite ample evidence that migrants are self-selected from their country of origin, it is unclear whether the resulting skill bias in migration has economic consequences for the receiving countries. The key question here is whether natives would be better or worse off if immigrants were selected differently from the country of origin. Second, it is unclear whether the skill bias in migration yields global efficiency gains, i.e. whether global welfare is higher if migrants are positively self-selected from their countries of origin, and if so, how big these gains are.

In this paper, we jointly quantify the importance of the skill bias in migration for the welfare of never-migrants — people who are non-migrants today as well as in our counterfactual of skill-neutral selection — in the sending and receiving countries. We consider South-North migration from 111 countries to the OECD, as well North-North migration between OECD countries. Our central contribution is to provide an order of magnitude of the extent to which the skill composition of migrants affects the welfare of people in 146 countries as well as globally. If the skill bias in migration leads to global efficiency gains because high-skilled workers are going to places where they are most productive, our estimate can inform policymakers about the welfare costs of restricting high-skilled emigration from poor countries through taxes (Bhagwati

[1] See Biavaschi & Elsner (2013) for a literature review. The skill bias in migration also feeds into the literature on the labor market effects of migration (see Kerr & Kerr, 2011 for a summary), but this literature is mostly about changes in the scale of migration.

& Hamada, 1974) or emigration restrictions (Collier, 2013).

To assess the global welfare implications of the skill bias in migration, we develop a quantitative model of the world economy in which countries are linked through trade in differentiated goods and remittances. Within the model, a change in the skill distribution of migrants simultaneously alters the skill composition of the workforce in the sending and receiving countries, which in turn affects the welfare of never-migrants through changes in market size, wage ratios and trade flows. In addition, we incorporate the most important migration-driven externalities that have been highlighted in the literature, such as a brain gain mechanism (Beine *et al.*, 2008), a TFP externality (Lucas, 1988), and a network externality in trade (Rapoport, 2018). We calibrate the model to match key features of the global economy, namely bilateral trade and remittance flows, cross-country differences in GDP per capita as well as wage premia for different skill groups within countries. We then use this model to simulate the impact of a change in the skill composition of migrants on the welfare of never-migrants in the sending and receiving countries.

The analysis aims to answer the question '*how important is the skill bias in migration in today's world?*'. Consequently, in our simulations we construct a counterfactual that eliminates the skill bias in global migration. We isolate the impact of the skill bias by holding bilateral migrant stocks constant while changing the skill composition of migrants, thereby assuming that migrants are neutrally selected from their countries of origin. Take as an example migration from India to the US, which is heavily skill biased: the share of tertiary educated people born in India is close to 10%, while among Indian migrants going to the US, this share stands at almost 80%. In our counterfactual, we assume that the number of Indians living in the US remains the same but only 10% have a tertiary education. In this scenario, a larger number of high-skilled workers stay in India and fewer high-skilled Indians live and work in the US. Such a counterfactual may not be congruent with actual migration policies — hardly any country wants to replace high-skilled with low-skilled immigrants — but it serves to estimate the magnitude by which the skill bias contributes to global welfare in the current world.

Our analysis yields five main results. First, when we simulate the counterfactual in our baseline model, the skill bias in migration has a positive effect on most receiving countries, while the effect on the sending countries is positive in some countries and negative in others. The analysis yields welfare effects in the OECD countries ranging between -0.5 and 4.6%. On the contrary, almost three quarters of the non-OECD countries face average welfare losses from skill-biased migration of about 2.8%. In a couple of sending countries, these losses amount to over 20%, although in other non-OECD countries — importantly China and India, which jointly represent one third of the world population — we find a welfare gain of around 0.5%-0.6%.

Second, the global welfare impact of the skill bias in migration is positive but small. Weighted by population, welfare increases by 1% in the OECD and decreases by 0.1% in the non-OECD countries. Taken together, this results in a global welfare gain of 0.6%. This result suggests that high-skilled workers tend to move to places where they are most productive, which is globally welfare improving.

Third, the skill bias in migration has a different effect on high- versus low-skilled workers. In our counterfactual world without the skill bias in migration, receiving countries would have fewer high-skilled and more low-skilled workers than in today's world. Most sending countries, on the other hand, would have more high-skilled and fewer low-skilled workers. In the receiving countries, this leads to lower wages for high-skilled and higher wages for low-skilled workers, while the opposite is true in the sending countries.

Fourth, when comparing the effect of the skill bias in migration to the total welfare effect of migration — that is, the difference between a world with the current migration stocks and one without any migration — we find that the skill bias is much more important in the OECD than in the non-OECD countries. In the OECD, the skill bias accounts for 16% of the total welfare effect of migration. In contrast, in the non-OECD countries, the total effect of migration is positive while the effect of the skill bias is negative. This suggests that emigration from non-OECD countries has a positive effect overall, which is dampened by the fact that emigrants are positively selected. We find the dampening effect of the skill bias to be around one third of the total effect of migration on the sending countries.

Fifth, the welfare effect of the skill bias is mainly driven by the market size effect and the human capital externality in TFP. Other channels that have been highlighted in the literature, namely remittances, network effects in trade, or changes in nominal wages, only play a minor role. This does not mean that these channels are unimportant in global migration, but they make little difference when the number of migrants in the baseline and counterfactual remains constant. An increase in the volume of remittances or trade mainly occurs if the number of migrants increases, whereas both are virtually unaffected when the composition of migrants changes.

With this paper, we contribute to two large strands of literature. First, by focusing on the skill composition of global migration, the paper complements prior research seeking to estimate the global welfare effects of migration. The main margin analyzed in this literature is a change in the number of migrants. Some studies estimate the contribution of current migration to global welfare by simulating a counterfactual world in autarky, i.e. without any migration (di Giovanni *et al.*, 2015, Aubry *et al.*, 2016), while others take the current number and skill composition of migrants as benchmark and estimate the welfare effect of having more migrants, a scenario that would occur if some or all migration restrictions were lifted.[2] These quantitative studies have highlighted the importance of migration for global welfare and the global distribution of income. The central contribution of this paper is to explicitly isolate the global impact of the skill bias in migration, i.e. isolating "*who migrates*" from "*how many migrate*". Given that many policymakers are concerned with the skills of migrants, we believe it is important to provide an estimate of the quantitative importance of the skills alone, and to assess which externalities matter and which do not.

A second strand of literature this paper contributes to is on the self-selection of migrants. Be-

[2] See, for example, Hamilton & Whalley (1984), Felbermayr & Kohler (2007), Klein & Ventura (2007, 2009), Iranzo & Peri (2009), Docquier *et al.* (2015), Kennan (2013), Battisti *et al.* (2018), Delogu *et al.* (2018), Docquier & Machado (2015), Clemens & Pritchett (2016).

ginning with the theoretical work of Borjas (1987), many economists have been interested in the determinants of who migrates and why.[3] The fact that some immigrant groups are selected from the lower part of the skill distribution of their country of origin while other groups are selected from the upper part has been put forward as a main explanation why some immigrant groups fare so much better than others. However, to assess whether the self-selection is economically important for the receiving country, it is crucial to estimate its impact on never-migrants. If it turns out that never-migrants are unaffected by the skill composition of their fellow migrants, then the economic impact of migrant self-selection would be limited. In this paper, we provide a quantitative assessment of migrant self-selection on a global scale. Our findings show that migrant self-selection — which is positive for most bilateral migration stocks and flows — has positive effects on never-migrants in the receiving countries. At the same time, it has negative effects on welfare in many sending countries.

The remainder of the paper unfolds as follows. Section 2 establishes the stylized facts about skill-biased migration from the perspective of the sending and receiving countries. Section 3 presents the main features of the theoretical model and explains the channels through which skill-biased migration affects welfare. The calibration of the model is explained in Section 4. Section 5 presents the main simulation results of the welfare impact of the skill bias in migration. Section 6 concludes.

2 The skill bias in global migration: stylized facts

We begin by presenting stylized facts about the skill bias in global migration. We speak of a skill bias if the skill distribution of emigrants differs from that of the total population in the sending country. The total population comprises every person born in a given country, that is, non-migrants and emigrants. In most sending countries, the skill distribution of emigrants is heavily skewed towards high-skilled workers, i.e. the share of high-skilled workers among emigrants is often a multiple of the share of high-skilled workers in the total population. In the descriptive analysis that follows, we define high-skilled workers as those with at least some tertiary education.

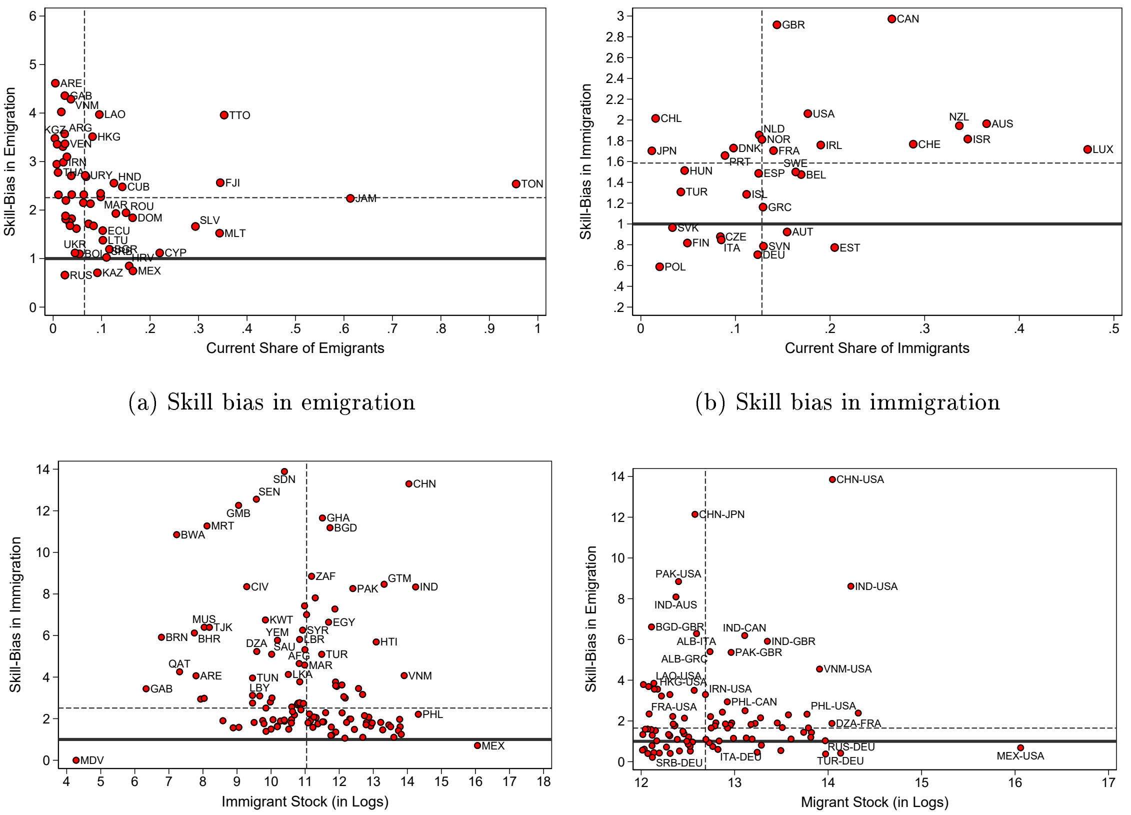
In the sending countries, we measure the skill bias in emigration as the share of high-skilled workers among emigrants divided by the share of high-skilled workers in the total population,

$$\text{skill bias}=\frac{\text{Share of high-skilled among emigrants}}{\text{Share of high-skilled in the total population}}.$$

If this ratio equals 2, then the share of high-skilled workers is twice as high among emigrants compared to the total population. Figure 1(a) illustrates the extent of the skill bias for selected non-OECD countries plus Mexico in 2010. The vertical axis displays the skill bias, while the

[3] The most frequently studied flow is Mexican migration to the US, for which Chiquiar & Hanson (2005) find a neutral selection on education levels, whereas Fernández-Huertas Moraga (2011, 2013), Ambrosini & Peri (2012) and Burzyński & Gola (2018) find negative selection based on pre-migration wages. For many other migration flows in the world, the selection seems to be positive. See Biavaschi & Elsner (2013) for a literature review.

horizontal axis displays the share of emigrants in the total population. The dashed lines represent the median of each axis. At a value of one on the vertical axis, indicated by the thick line, the selection of emigrants from a particular country would be skill-neutral, whereby the share of high-skilled workers among emigrants equals the share of high-skilled persons in the total population.



(a) Skill bias in emigration

(b) Skill bias in immigration

(c) Skill bias in immigration, US

(d) Skill bias in emigration, top 100 Corridors

Figure 1: The skill bias in immigration and emigration

Source:. Own calculations from OECD-DIOC.

Notes: These graphs plot the skill bias in migration (vertical axis) against the share of emigrants and immigrants, respectively (horizontal axis), for the main sending countries (Panel (a)) and the OECD countries (Panel (b)). Panel (c) plots the skill-bias among immigrants to the US against the total number of immigrants (in logs). Panel (d) plots the skill bias in the 100 largest bilateral corridors in the world against the stock of migrants (in logs). For expositional reasons we only display countries with a skill-bias smaller than 14. In all four panels, a value of 1 on the vertical axis indicates the absence of a skill bias. The dashed lines represent the median of both axes. See text for the calculation of the skill bias. See Appendix G for the list of abbreviations.

For the vast majority of sending countries, the skill bias in emigration is positive. At the median of the countries displayed here, the skill bias is 2. For expositional reasons, we only display here countries with a maximum skill bias of 5. However, some countries in the sample — for example, Mali — have a skill bias greater than 30. The literature suggests that the observed positive skill bias is mainly driven by two factors. One factor is the self-selection of migrants. In most corridors, migration is much more beneficial for high-skilled than for low-skilled workers (Borjas, 1987). A second factor is migration policies in the receiving countries, which tend to favor high-skilled over low-skilled workers.

In Figure 1(b), we consider the perspective of the OECD countries. Here, the skill bias is calculated differently. The numerator is the share of high-skilled workers among immigrants in the current world with skill bias. The denominator is the share of high-skilled workers among immigrants under neutral selection, i.e. in the counterfactual world in which every migrant is randomly drawn from his/her respective country of origin. For instance, if the skill bias in a receiving country is 2, then the share of high-skilled workers among immigrants is currently twice as large as it would be in a world in which all migrants are neutrally selected from their home countries. The higher the skill bias, the more positive the selection of migrants hosted in a particular OECD country. As shown in Figure 1(b), most OECD countries attract a positive selection of immigrants. The skill bias is particularly large in countries with selective migration policies, such as Canada, the UK, the US, New Zealand and Australia. For instance, in Canada, the share of high-skilled immigrants is three times as large as it would be under skill-neutral migration. In some prominent immigration destinations — notably Germany, Italy and Austria — migrants are negatively selected, whereby their migrant stock would have higher skills under neutral selection from the country of origin.

While Panels (a) and (b) show the average skill bias in a given sending or receiving country, Figure 1(c) provides an example for the skill bias among immigrants to a single receiving country, namely the US. It shows that the average skill bias of 2 seen in Panel (b) masks substantial variation by country of origin: the share of high-skilled among migrants from China to the US is 13 times larger than it would be with neutral selection, while the share of high-skilled among emigrants from Mexico is slightly smaller.

In the analysis to follow, we quantify the welfare impact of the skill bias in migration by comparing the current world — in which migration is heavily skill-biased — to a world in which all migrants are neutrally selected from their country of origin. In our counterfactual, the number of migrants remains the same *within each migration corridor*, although the skill distribution of migrants is now the same as the one of the population in the sending country. Figure 1(d) illustrates the skill bias in migration for the 100 largest bilateral corridors. In our counterfactual, we keep every corridor at the same value on the horizontal axis, but change the skill distribution such that the skill bias equals one and all points lie on the solid horizontal line. For most corridors, this means that receiving country gets a lower share of high skilled migrants while the sending country retains a higher share of skilled workers. However, for some corridors, notably Mexico-USA and Turkey-Germany, the opposite is true.

We expect the skill bias to have the largest impact in countries in the northeastern corners of Figures 1(a) - (d), namely those with both a high skill bias and a high share of migrants. The size of the effect will depend on many factors, such as the stage of a country's economic development, the skill structure of the labor market and trade flows.

3 Theoretical framework

To quantify the global welfare impact of the skill bias in migration, we develop an integrated multi-country general equilibrium model that allows us to perform counterfactual simulations whereby we exogenously change the skill composition of migrants.

The basic setup of the model is in the spirit of Krugman (1980).[4] We consider a world with J countries, indexed by $i = 1, \ldots, J$. In each country, the economy comprises two broad sectors: a traditional sector producing a homogeneous good T, and a horizontally differentiated manufacturing sector. The manufacturing sector comprises two sub-sectors, one producing a tradable differentiated good X, and one producing a non-tradable differentiated good Y. The market for manufactured goods X and Y is monopolistically competitive. Firms can freely enter the market, although they pay a sunk entry cost. Good T is consumed domestically and not traded across countries, while the markets for the tradable differentiated good X are separated by asymmetric iceberg trade costs. The real wage of workers is expressed in US dollars adjusted for cross-country purchasing power parities, which serve as the numeraire. Countries differ in terms of worker productivity. The workforce in each country comprises three education levels (low-, medium- and high-skilled workers). Moreover, in the receiving countries, immigrants and natives are imperfect substitutes in production.

As one key innovation, our model includes non-homothetic preferences over basic goods versus differentiated goods. This is in contrast to most standard trade models, which assume that the share of expenditure on food and other goods remains constant irrespective of income. We choose this alternative preference structure to account for shifts in spending patterns as people's income changes. With higher income, people tend to spend a higher share of their income on the differentiated good and less on the traditional good. Non-homothetic preferences are particularly relevant in developing countries, where spending patterns tend to strongly react to income changes.

The model includes trade in differentiated goods, which ensures that an expansion in market size in one country is passed on to its trading partners. It also incorporates several adjustment channels and migration-driven externalities that have been highlighted in the literature, such as remittances, incentives to invest in education, TFP externalities or trade creation through ethnic networks.

In the remainder of this section, we provide a description of the main building blocks of the model as well as a critical discussion of its main mechanisms. For the core of the model — the part describing preference and technology structures — we provide full microfoundations. To keep the model tractable, we include the migration-driven externalities as reduced-form relationships without microfoundations. Further details about the model can be found in Appendix A. Later in the analysis, we assess the sensitivity of the results to most modeling assumptions, both in

[4] In line with Aubry *et al.* (2016) and Iranzo & Peri (2009), we abstract here from firm heterogeneity within sectors in the spirit of Melitz (2003) and in contrast to the approach applied to migration by di Giovanni *et al.* (2015). As argued by di Giovanni *et al.* (2015), the main source of the market size effect is the change in the *number* of firms, rather than the changes in the distribution of technology within sectors due to the entry-and-exit process at the margin of the productivity distribution.

terms of functional form as well as parameter values.

3.1 Preferences and welfare

Consumers have non-homothetic preferences; they always demand a certain amount of the traditional good T independent of income.

A consumer in country $i = 1, \dots, I$ with income $\hat{w}_i$ maximizes utility

$$\begin{aligned} \max_{\{T_i, x_{ij}(k), y_i(k)\}} & \beta^T (T_i)^\mu + \left(1 - \beta^T\right) \left[(1-\beta)(Y_i)^{\frac{\theta-1}{\theta}} + \beta (X_i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \\ \text{subject to: } & P_i^T T_i + P_i^Y Y_i + P_i^X X_i = \hat{w}_i, \end{aligned} \tag{1}$$

where β is the relative preference for the tradable differentiated goods, β^T is a preference parameter for the traditional good, and θ is the elasticity of substitution between tradable and non-tradable goods X and Y. The consumption of traditional goods is subject to decreasing marginal utility, such that $\mu < 1$. Y_i and X_i are CES composites of different varieties k produced in the manufacturing sector,

$$X_i = \left[\sum_{j=1}^{J} \int_0^{N_j^X} (x_{ij}(k))^{\frac{\varepsilon-1}{\varepsilon}} \, dk\right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad Y_i = \left[\int_0^{N_i^Y} (y_i(k))^{\frac{\varepsilon-1}{\varepsilon}} \, dk\right]^{\frac{\varepsilon}{\varepsilon-1}}. \tag{2}$$

N_i^X and N_i^Y are the numbers of varieties of goods X_i and Y_i available in country i. Varieties of the composite tradable good X_i are either domestically produced, $x_{ii}(k)$, or imported from other countries $x_{ij}(k), j \neq i$, while all varieties of Y_i, $y_i(k)$, are domestically produced. The parameter ε is the elasticity of substitution between any two varieties within a sub-sector, with $\varepsilon > \theta > 1$. Therefore, consumer preferences exhibit love of variety, which means that consumers gain utility when the number of available varieties increases. This translates into a 'market size effect' similar to the one obtained by Iranzo & Peri (2009) and di Giovanni *et al.* (2015) in a two-sector model and Aubry *et al.* (2016) in a one-sector model.

We measure the welfare of a country's population or sub-population as the average indirect utility, which is derived from the base consumption of good T_i, and the utility-maximizing consumption of varieties of the differentiated goods X_i and Y_i. Thus, indirect utility equals the weighted average of the utility from consuming the traditional good, and the utility from consuming manufactured goods divided by the price index in country i,

$$U_i = \beta^T \left(\frac{\beta^T \mu}{1-\beta^T} \frac{P_i}{P_i^T}\right)^{\frac{\mu}{1-\mu}} + (1-\beta^T) \frac{\hat{w}_i - T_i}{P_i}. \tag{3}$$

where P_i is the ideal price index in country i,

$$P_i = \left[(1-\beta)^{\theta} \left(P_i^Y\right)^{1-\theta} + \beta^{\theta} \left(P_i^X\right)^{1-\theta} \right]^{\frac{1}{1-\theta}},$$

$$\text{with: } P_i^X = \left[\sum_{j=1}^{J} \int_0^{N_j^X} (p_{ij}(k))^{1-\varepsilon} dk \right]^{\frac{1}{1-\varepsilon}}, \text{ and } P_i^Y = \left[\int_0^{N_i^Y} (p_i(k))^{1-\varepsilon} dk \right]^{\frac{1}{1-\varepsilon}}. \quad (4)$$

A change in the selection of migrants affects welfare through the overall prive level P_i and incomes $\hat{w}_i$, which include labor income, w_i, remittances sent or received, as well as the overall price level P_i. Both can be affected directly, for example through competition on the labor market, complementarities between workers of different skill levels, TFP externalities, and indirectly through changes in market size or changes in trade costs and patterns, which are detailed below.

3.2 Labor force composition and production

Basic production function. In the model, labor is the only production factor. Countries have different levels of TFP in the traditional and manufacturing sector. Labor markets are assumed to be perfectly competitive. Workers sort into whichever sector pays the highest wage given their skill level. The traditional sector only produces with low-skilled workers,[5]

$$Q_i^T = A_i^T L_i^T, \quad (5)$$

where L_i^T is the supply of low-skilled labor employed in the traditional sector, and A_i^T is the productivity residual, which equals the price-adjusted wage of low-skilled workers: $A_i^T = W_i^L / P_i^T$.[6]

The manufacturing sector employs workers from all three skill levels and produces with a constant-elasticity-of-substitution (CES) technology. Workers with different skills are imperfect substitutes in production. The production function of the manufacturing sector is given by

$$Q_i^M = A_i^M L_i^M = A_i^M \left[\alpha_i^L (L_i)^{\frac{\sigma_s-1}{\sigma_s}} + (1-\alpha_i^L-\alpha_i^H)(M_i)^{\frac{\sigma_s-1}{\sigma_s}} + \alpha_i^H (H_i)^{\frac{\sigma_s-1}{\sigma_s}} \right]^{\frac{\sigma_s}{\sigma_s-1}}. \quad (6)$$

In Equation (6), L_i, M_i and H_i represent the supplies of low-, medium- and high-skilled workers. L_i is the number of low-skilled workers not working in the traditional sector. α_i^L and α_i^H are the country-specific efficiency weights of low- and high-skilled workers.

The choice of three skill groups is the result of a trade-off between providing fine-grained

[5] We exclude medium and high-skilled workers from sector T, as this is a low-productivity sector; in addition, wage equalization across sectors would imply that only a very small number of medium- and high-skilled workers could actually work in this sector. However, both migrants and natives are employed in this sector.

[6] This condition results from the profit maximization problem of firms operating on a perfectly competitive traditional sector. They set prices equal to the marginal cost of production, such that: $P_i^T = W_i^L / A_i^T$. Furthermore, wages of low-skilled workers are equal across sectors. Therefore, any low-skilled worker in sector T has no incentive to move to sectors X and Y. Note that the linear production function implies that the marginal productivity of low-skilled workers is constant in the traditional sector. In a set of sensitivity checks, we confirm that using a non-linear production function of the form $Y_T = A_T L_T^{\alpha}$ with α=0.5 or 0.8 has no impact on the results. These results are available on request.

results across skill levels and using data on as many countries as possible. Capturing the selectivity of migration in the best possible way would require a continuum of skill types or a large number of skill types. However, consistent migration data by education level is only available for three skill groups, which constrains the number of skill groups we can use in the quantitative analysis.

The production function in Equation (6) assumes that all three skill levels are equally substitutable. In light of the US-based evidence suggesting that some skill groups are more substitutable than others (Goldin & Katz, 2007, Card, 2009, Ottaviano & Peri, 2012), we relax this assumption in Appendix F.2 by adding additional nests to the production function.

Human capital externality. We assume TFP to be an increasing function of the average level of human capital in a country. Following Lucas (1988), the idea behind this externality is that a more skilled workforce increases efficiency. TFP in the manufacturing sector is modelled as

$$A_i^M = \bar{A}_i^M \left(\frac{H_i}{L_i + M_i + H_i} \right)^{\sigma_a}, \tag{7}$$

whereby the elasticity σ_a governs the response of TFP to changes in the share of high-skilled workers in the population. The scaling parameter $\bar{A}_i^M$ is a country-specific productivity residual.

Natives and immigrants in production. In the receiving countries, each skill group comprises natives (labeled with superscript N) and immigrants (with superscript F), which are imperfect substitutes with a constant elasticity of substitution $\sigma_n > 1$. For example, the CES aggregate for high-skilled workers is given by

$$H_i = \left[(1 - \alpha_i^F)(H_i^N)^{\frac{\sigma_n - 1}{\sigma_n}} + \alpha_i^F (H_i^F)^{\frac{\sigma_n - 1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n - 1}}, \tag{8}$$

and likewise for medium- and low-skilled workers. Two important assumptions underlie Equation (8). First, skills are transferable across countries. This assumption implies that a worker who is high-skilled in the sending country works in a high-skilled occupation in the receiving country. This, however, does not imply that immigrants and natives with the same skill level are equally productive and earn the same wage. The parameter α_i^F governs the relative efficiency of immigrants versus natives of a given skill level, and allows for differences in productivity and wages. We allow α_i^F to vary across countries, but assume that it is the same across skill groups within a country. In Appendix E, we relax the assumption of skill transferability and allow for down-skilling — the fact that high-skilled immigrants tend to work in occupations with a lower skill requirement (Mattoo *et al.*, 2008). The second assumption is that all immigrants in country i with the same skill level are perfect substitutes regardless of their country of origin. This implies that for any $s \in \{L, M, H\}$: $s_i^F = \sum_{j \neq i} s_{ij}$.

Market structure. The manufacturing sector is monopolistically competitive, such that firms have some price-setting power. Each firm produces one variety of a differentiated good.

Firms can freely enter the manufacturing sector, but incur a sunk entry cost of f_i^Y and f_i^X units of efficient labor in the respective sector. Sub-sectors Y and X both use identical production technologies. Firms within a country are homogeneous and set prices as a constant mark-up over the marginal cost of production,

$$p_i(k) = p_i = \frac{\varepsilon}{\varepsilon - 1} c_i, \tag{9}$$

where the $c_i = \frac{W_i}{A_i^M}$ is the marginal cost of production, and W_i is the overall wage index of the manufacturing sector, given by

$$W_i = \left[(\alpha_i^L)^{\sigma_s}(W_i^L)^{1-\sigma_s} + (1 - \alpha_i^L - \alpha_i^H)^{\sigma_s}(W_i^M)^{1-\sigma_s} + (\alpha_i^H)^{\sigma_s}(W_i^H)^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}}. \tag{10}$$

Education externality. Our model further includes a 'brain gain' mechanism, which is a dynamic feedback effect of emigrants' skill selection on the population of their origin country. The opportunity to emigrate raises returns to skills and induces people to invest more in their education. However, because not all people who invested in education also emigrate, the country may end up with a higher level of human capital than in the absence of migration. While earlier work has pointed to this mechanism as a theoretical possibility (Mountford, 1997, Stark *et al.*, 1997, Beine *et al.*, 2001, 2008), recent micro studies from several developing countries suggest that this mechanism is quantitatively important (Chand & Clemens, 2008, Batista *et al.*, 2011, Shrestha, 2015, Dinkelman & Mariotti, 2016). Formally, we allow the share of high-skilled workers in the origin country i to depend on the share of high-skilled emigrants from the country (following Beine *et al.*, 2008):

$$\widehat{sh_i^P} = sh_i^P \left(\frac{\widehat{sh_i^E}}{sh_i^E}\right)^{\sigma_b}, \tag{11}$$

where $sh_i^P = \left(H_i^N + H_i^E\right) / \left(H_i^N + M_i^N + L_i^N + H_i^E + M_i^E + L_i^E\right)$ is the share of high-skilled in the native population of country i, while $sh_i^E = H_i^E / \left(H_i^E + M_i^E + L_i^E\right)$, defines the respective share of emigrants from i. The variables $\widehat{sh_i^P}$ and $\widehat{sh_i^E}$ indicate the corresponding shares under the counterfactual. The elasticity σ_b describes the strength of the brain gain mechanism. If $\sigma_b = 0$, there is no additional investment in education, whereas if σ_b is positive, the share of high-skilled natives becomes an increasing function in the share of high-skilled emigrants.

3.3 Market size, International Trade and Remittances

Market Size. Market size is a central adjustment channel in the model. A change in the selection of migrants affects the number of varieties produced, which in turn has an effect on utility due to consumers' love of variety. The empirical literature shows that the market size effect is quantitatively important in both trade (Broda & Weinstein, 2006) and migration (Iranzo & Peri, 2009, di Giovanni *et al.*, 2015, Aubry *et al.*, 2016).

Each firm produces a single variety of a differentiated good. In equilibrium, firms make zero profits and all goods markets clear. These conditions — together with the optimal pricing rule

(9) — pin down the optimal number of varieties, N_i^X and N_i^Y:

$$N_i^X = \frac{sh_i^X L_i^M}{\varepsilon f_i^X}, \quad N_i^Y = \frac{sh_i^Y L_i^M}{\varepsilon f_i^Y}. \tag{12}$$

The optimal number of firms in sectors X and Y, operating in country i is proportional to the efficient labor supplies employed in these sectors and inversely proportional to the fixed costs of entry.[7]

Trade. Varieties of the manufactured good X are traded between countries such that an expansion in market size in one country is passed on to its trading partners. The volume of trade depends on trade costs, as well as differences in consumer demand and price levels. Exports from country i to country j, denoted by X_{ji}, are subject to iceberg trade costs $\tau_{ji} > 1$. Trade costs are asymmetric, such that $\tau_{ji} \neq \tau_{ij}$, for different i and j. X_{ji} is given by

$$X_{ji} = \int_{k \in N_i^X} x_{ji}(k) p_{ji}(k) dk = N_i^X GDP_j^X \left[\frac{P_j^X}{\tau_{ji} p_i} \right]^{\varepsilon - 1}. \tag{13}$$

where p_{ji} and x_{ji} are the price and quantity of a variety produced in country i, consumed in country j. Given that $\varepsilon > 1$, trade negatively depends on import prices and trade costs, $\tau_{ji} p_i$, and positively on the domestic price level. The total value-added in sector X in country i is computed as the sum of all trade flows to country i, including domestic consumption X_{ii}.

Bilateral trade costs are endogenous and depend on the share of high-skilled immigrants from origin i in destination j. A growing literature highlights the presence of diaspora externalities in international migration. Existing migrant networks maintain close ties to their origin countries, which affect trade, foreign direct investment, technology diffusion, or the transfer of social norms (Rapoport, 2018). A particularly important dimension of diaspora externalities is trade creation. A growing literature documents that immigrants foster trade with their home countries by reducing trade costs and demanding home-country-specific goods (Gould, 1994, Rauch & Trindade, 2002, Felbermayr & Toubal, 2012, Egger *et al.*, 2012, Parsons & Vézina, 2018). To incorporate this mechanism, we assume that trade costs respond to changes in migrants' skill composition,

$$\tau_{ji} = \bar{\tau}_{ji} \left(\frac{H_{ji}}{L_{ji} + M_{ji} + H_{ji}} \right)^{\sigma_t}, \tag{14}$$

with σ_t being the elasticity of bilateral trade cost with respect to the skill share in the bilateral immigration inflow and $\bar{\tau}_{ji}$ being a country-pair-specific scaling parameter.

[7] Thus, the sector-specific barriers to enter production (captured by the fixed cost of entry) are the main driving forces of the market size effect. Calibrating different entry costs for tradable and non-tradable sectors separately allows us to introduce both the selection mechanism in firms' trade choices (represented by uneven market size effects in tradable/non-tradable sectors) as well as changing terms of trade (the movement of relative prices of traded and non-traded bundles of varieties) within a Krugman (1980)-type model. A change in the skill distribution affects the number of varieties produced and consumed in the destination countries, and, consequently, has an indirect impact on the welfare of native citizens.

Remittances. Finally, our model includes remittances between the destination and origin countries. Remittances are among the most important financial flows to developing countries (Yang, 2011). Whether remittances are affected by the selection of migrants depends on the migrants' remitting behavior. Selection has no effect on remittances if each migrant sends the same absolute amount independent of income. However, it does affect remittances if migrants remit a share of their income. In that case, if the population of migrants becomes less skilled and earns less, the amount of remittances decreases. We model remittances in a way that incorporates both polar cases — remittances are a fixed amount or proportional to earnings — and a weighted average of both. Assume that the amount of remittances sent per emigrant of skill type $s \in \{L, M, H\}$ from country j living in country i is given by:

$$R^s_{ji} = \eta_{ij}(w^{sF}_i)^\gamma, \tag{15}$$

where γ is the elasticity of remittances with respect to income and η_{ij} can be interpreted as a fixed amount of remittances when $\gamma = 0$. The income after remittances of an emigrant of skill s from country j living in country i becomes $\hat{w}^{sF}_i = w^{sF}_i - \eta_{ij}(w^{sF}_i)^\gamma$. Assuming that the total amount of remittances is split equally among stayers, the budget of a never-migrant in country j is $\hat{w}^{sN}_j = w^{sN}_j + \bar{R}_j$, where $\bar{R}_j = \sum_{i \neq j} \sum_{s \in \{L,M,H\}} s_{ij}\eta_{ij}(w^{sF}_i)^\gamma / \sum_{s \in \{L,M,H\}} s^N_j$.

In Equilibrium, trade is unbalanced due to the presence of remittances. The balance of payments identity implies that the value of exports plus inflowing remittances equals the value of imports plus outflowing remittances, $\sum_{j=1}^J X_{ji} + \sum_{j=1}^J R_{ij} = \sum_{j=1}^J X_{ij} + \sum_{j=1}^J R_{ji}$, where $R_{ji} = \sum_{s \in \{L,M,H\}} s_{ij}\eta_{ij}(w^{sF}_i)^\gamma$.

3.4 Definition of equilibrium

We provide here a concise definition of the equilibrium. A more comprehensive definition, with references to model equations, can be found in Appendix A.7.

Definition 1 *For a set* $\{\beta, \beta^T, \theta, \mu, \varepsilon, \sigma_s, \sigma_n, \sigma_a, \sigma_t, \sigma_b, \gamma, \}$ *of structural parameters, a set* $\{A^T_i, \bar{A}^M_i, \alpha^F_i, \alpha^H_i, \ \alpha^L_i, L^{T,N}_i, L^{T,F}_i, L^N_i, L^F_i, M^N_i, M^F_i, H^N_i, H^F_i, f^X_i, f^Y_i\}_{\forall i}$ *of exogenous country-specific institutional, demographic and technological characteristics, a set* $\{\bar{\tau}_{ji}\}_{\forall i,j}$ *of bilateral trade cost residuals and a set of bilateral remittances residuals* $\{\eta_{ij}\}_{\forall i,j}$

- *consumption of the three types of goods* $\left\{x^s_{ij}, y^s_i, T^s_i\right\}$ *maximizes an agent's utility subject to the budget constraint,*
- *assuming full employment and cost-minimizing behavior of firms, the labor market clearing conditions equalize the wage rates to marginal productivities, and determine the nominal wages for all types of workers:* $\{w^{LN}_i, w^{LF}_i, w^{MN}_i, w^{MF}_i, w^{HN}_i, w^{HF}_i\}$
- *the price of one variety,* $p_i(k)$*, maximizes firm's profits given the demand that it faces,*
- *the price of a unit of the traditional good,* P^T_i*, equals the marginal productivity of a low-skilled worker,*

- *the number of varieties in sector X and Y, N_i^X and N_i^Y, is such that the zero-profit conditions hold,*
- *the value-added in sector X equals the aggregated value of production in sector X,*
- *the net trade balance equals the negative value of the balance in remittances.*

3.5 First- and Second-Order Mechanisms

Within the model, a change in the skill distribution of migrants affects welfare through several channels. We use as an example a receiving country that switches to a more highly-skilled migrant population, such that the number of low-skilled migrants L_i^F decreases while the number of high-skilled migrants H_i^F increases by the same amount, $-\Delta L_i^F = \Delta H_i^F$. For simplicity, we assume here that the number of medium-skilled migrants M_i^F remains constant.

This change in the skill composition of migrants has a first-order effect on welfare through its impact on nominal wages and market size. Due to a change in skill-specific labor supply, nominal wages of high-skilled workers decrease while those of low-skilled workers increase. However, the change in the nominal wage structure affects wage inequality more than it affects welfare. A more important channel for welfare is market size, i.e. the number of available varieties. A workforce with a higher skill level is more productive, such that any good can be produced at a lower unit cost. Lower unit costs, in turn, induce more firms to enter the market and increase the number of varieties. As shown in Equation (4), a higher number of varieties reduces the price index, thus increasing welfare. This reflects consumers' love of variety, whereby their utility increases in the number of available varieties even if their income remains constant. The market size effect is propagated to other countries through trade linkages, which dampen the positive welfare effect at home while increasing the welfare of all trading partners.

In addition to the first-order effects, welfare is affected by four externalities. First, a larger number of high-skilled immigrants reduces bilateral trade costs vis-a-vis the countries of origin. This may increase trade flows and, in turn, increase welfare. Second, the model includes a Lucas (1988)-type externality, such that a higher average skill level raises TFP, which amplifies the first-order effects. Third, a higher share of high-skilled migrants potentially leads to higher amounts of remittances, which benefits never-migrants in the sending countries. Finally, due to the education externality, a higher share of high-skilled emigrants leads to higher investment in education in the sending countries. The latter two externalities, namely investment in education and remittances, mainly affect the sending countries, while having little effect on the receiving countries. Because all these externalities interplay with first-order effects, the overall net effect of a more positive selection of migrants is predominantly positive in the receiving countries, but the sign is ambiguous in the sending countries.

4 Data and Calibration

We calibrate our model such that it replicates the most important features of the world economy in 2010, namely bilateral migrant stocks, bilateral trade flows, differences in GDP per capita and skill premia. In terms of migration flows, we consider South-North migration from 111 countries to the OECD, as well as migration among the 34 OECD countries, thereby accounting for the majority of global migration.[8] For South-South migration, we assume that all bilateral stocks remain constant in terms of scale and skill composition in both the baseline and counterfactual.

4.1 Data

The calibration requires several types of country-specific and country-pair-specific macro variables for the reference year 2010. The sample consists of 34 OECD countries and 111 non-OECD countries. Non-OECD countries for which data is not available are lumped together in the Rest of the World (ROW). The list of countries and their abbreviations are available in Appendix G.

Migration and population data. Calibration requires data on the size and skill distribution of the migrant and never-migrant population of each country. Our main dataset is the 2010 DIOC database, which provides data on bilateral stocks by education level of migrants who went from 111 sending countries to the OECD and migrants who moved between all 34 OECD countries, as well as the population size and skill distribution of natives in the 34 OECD countries. The definition of the three education levels is as follows: low-skilled individuals are those who achieved up to lower secondary education or the second stage of basic education; medium-skilled individuals obtained up to some post-secondary non-tertiary education; while high-skilled individuals have at least some tertiary education. To obtain the number and skill distribution of never-migrants for the non-OECD countries, we use data from Barro & Lee (2010). For the Rest of the World, we apply the average skill distribution of the available non-OECD countries. For more details on the aggregation of skill groups in both datasets, see Appendix B.1.

GDP, remittances trade and fixed costs of entry. We take GDP per capita in current international dollars from the World Development Indicators (WDI) database of the World Bank. The WDI database also provides the share of workers employed in agriculture and the shares in total GDP of traded and non-traded manufacturing goods. For the global flows of remittances, we use bilateral data on the volume of monetary transfers from the World Bank (2015). To compute the trade costs, we require a bilateral matrix of trade in value-added, which we construct by combining gross trade flows in 2010 from the UN Comtrade database and the share of value-added in trade from the OECD TiVA database. We impute missing trade flows based on an estimated gravity equation, details of which can be found in Appendix B.2. To obtain the fixed cost of entry in the tradable sector, f_i^X, we follow di Giovanni *et al.* (2015)

[8] This means that most OECD countries are both sending and receiving countries at the same time. As of December 2017, South-North and North-North migration accounted for 60% of all international migrants. Source: Population Facts No. 2017/5, December 2017, United Nations. Retrieved on March 24, 2018.

and use a component of the World Bank Ease-of-Doing-Business indicator, which measures the number of days necessary to open a business. The longer it takes to open a business, the more difficult it is to enter a market and the higher the fixed costs of entering. We normalize the fixed costs for the US to 1 and compute the fixed costs relative to the US for all other countries.

Wage ratios. To calibrate the efficiency parameters for high- and low-skilled workers (α_H and α_L), we require country-specific wage ratios for high- vs. medium-skill, W_i^H/W_i^M, and medium- to low-skill workers, W_i^M/W_i^L. For the OECD countries, we compute these ratios from the "Education at a Glance" report 2010 (OECD, 2010). For the non-OECD countries, we take data from the Wageindicator Foundation, which runs online-based surveys about wages in 80 countries. For the non-OECD countries, Wageindicator provides information on 38 high- vs. medium-skill, and 27 medium- vs. low-skill wage ratios.[9] For the remaining countries, we impute the wage ratios based on the returns to education in similar countries. A more detailed description of the imputation procedure can be found in Appendix B.3.

4.2 Calibration of technology and preference parameters

We calibrate the model such that the generated data matches country-specific (i.e. GDP, population and wage structure) and bilateral (i.e. migration and trade) moments for the 146 countries in our sample (145 countries and ROW).

Through the parameterization of the aggregate production function, we take into account four important differences in the economic structure between all 146 countries in our sample. First, countries differ in their productivity and consequently in their GDP per capita. The GDP per capita in Luxembourg — the OECD's richest country — is five times larger than in Mexico, the OECD's poorest country. Moreover, in poorer countries the agricultural sector contributes a larger share to aggregate production. The productivity parameters A_i^T and $\bar{A}_i^M$ account for the differences in aggregate productivity across — as well as differences in — the sectoral productivity within countries. Second, as shown by Trefler (1993), countries considerably differ in their endowment of effective labor. For instance, the same high-skilled worker is more productive in the US than in Mexico. We account for these differences through country-specific efficiency parameters for high- and low-skilled workers, α_i^L, α_i^H. Third, within a country, workers with similar skills are closer substitutes in production than workers with different skills (Card & Lemieux, 2001). We account for this imperfect substitutability by modeling the production function of the manufacturing sector with a CES structure. Fourth, as shown by Ottaviano & Peri (2012) and Peri & Sparber (2009), migrants and natives are imperfect substitutes even when they have the same level of education, which we account for in Equation (8) with an elasticity of substitution between immigrants and natives $\sigma_n < \infty$ and country-specific efficiency parameters α_i^F.

To calibrate the most important structural parameters — preference parameters and elasticities of substitution between segments of the workforce — we use estimates from empirical

[9] See wageindicator.org for more information. A table with all wage ratios is available upon request.

studies where available, and set the values of the remaining parameters similar to those found in other quantitative studies. To ensure that the choice of parameters does not fundamentally change the results, we conduct a series of sensitivity checks that are presented in the appendix. Table 1 summarizes the calibrated parameters.

Table 1: Values of structural parameters

Parameter	Value	Source
Preference parameters		
β	0.5	exogenous
β^T	0.139	calibrated (match consumption to production)
θ	3	exogenous
μ	0.5	exogenous
ε	4	Simonovska & Waugh (2014)
σ_s	5	Docquier *et al.* (2014)
σ_n	20	Ottaviano & Peri (2012)
Worker efficiency parameters		
a_i^F	0.478	calibrated to match OECD average
a_i^L	0.12-0.40	calibrated from FOC of cost minimization
a_i^H	0.24-0.60	calibrated from FOC of cost minimization
Parameters of Migration-Driven Externalities		
σ_a	0.05	Acemoglu & Angrist (2000)
σ_t	-0.02	Parsons & Vézina (2018)
σ_b	0.048	Beine *et al.* (2008)
γ	0.5	exogenous

Note: This table summarizes the calibration of the structural parameters in the model. A more detailed description of the procedures can be found in the text of Section 4.2 and in Appendix B.

The non-homothetic utility function ensures that the expenditure share of the traditional good decreases with income. This allows us to account for the higher fraction of income spent on traditional (i.e. agricultural) goods in developing countries, a standard observation in household datasets.[10] Setting $\mu = 0.5$ implies that the expenditure share on the traditional good decreases with income and increases with the price level P_i.[11]

We set the relative preference for the tradable differentiated good, β, to 0.5, such that individuals have the same preference for the traded and non-traded manufacturing goods.[12] For

10 As shown by the US Department of Agriculture, consumers in the US spent 6.8% of their total expenditure on food in 2011, whereas the expenditure shares in developing countries are considerably higher, for example 36.2% in Vietnam and 57.1% in Nigeria. http://www.ers.usda.gov/data-products/food-expenditures.aspx (viewed 19 Feb 2016).

11 Our model imposes that $0 < \mu < 1$ to ensure a negative impact of the price level on the expenditure for the traditional good. The results prove robust to a wide range of values for this parameter.

12 Note that real demand will also depend on prices, such that the quantities demanded for each good are not necessarily equal. A robustness analysis on this parameter shows that the results are not affected by this choice.

the elasticity of substitution between tradable and non-tradable goods, θ, we choose a value of 3. Following Simonovska & Waugh (2014), we set ε, the elasticity between any two varieties within a sector, to a value of 4.[13]

The share of output produced by foreign workers (a_i^F) is calibrated to match the education-specific wage premia for natives over immigrants, which is 5% in OECD countries. For non-OECD countries, we use the average value obtained in OECD countries ($a_i^F = 0.478$) as we cannot assess country-specific values due to the lack of immigration data. The production function includes three types of workers. To calibrate its structural parameters, we use parameter values obtained by Ottaviano & Peri (2012). To account for imperfect substitution between the three education groups, the elasticity of substitution, σ_s, is set to 5. We further allow for imperfect substitution between immigrant and native workers within each skill group. The value of the elasticity of substitution, σ_n, is set to 20, and is identical among the three skill groups. As we show in Appendix F.2, all results are robust to changes in these parameters.

We subsequently calibrate the country-specific efficiency parameters for high- and low-skilled workers, a_i^H and a_i^L, to perfectly match the high- vs. medium- and high- vs. low-skilled wage ratios within countries. We first use the market clearing condition for the manufacturing sector with data on GDP and the number of domestic and foreign workers per skill group to obtain the wage index for the manufacturing sector, W_i. The efficiency parameters are then obtained by inserting this information into the first-order conditions of a manufacturing firm's cost-minimization problem. With these parameters and the efficiency parameter of foreign workers, α_i^F, we compute the skill-specific wage aggregates, W_i^L, W_i^M, and W_i^H. Based on the wage aggregates and α_i^F, we compute the wages for all six types of workers.

4.3 Calibration of migration-driven mechanisms

We mainly follow the literature in setting the reference values for the parameters defining the externalities. For the Lucas externality, we set $\sigma_a = 0.05$ following Acemoglu & Angrist (2000), who find a weak positive impact of the share of high-skilled workers on the TFP. Based on the estimates by Parsons & Vézina (2018), we set the parameter of the trade externality, σ_t, to -0.02. The magnitude of brain gain effect is governed by σ_b, which we set equal to 0.048, the estimate reported by Beine *et al.* (2008). Finally, we calibrate the residual variables for the remittances, trade costs and TFP, such that the cross-country TFP differences, remittances and trade flows closely match their empirical counterparts in the data. Based on these, we are able to compute all equilibrium prices and quantities, as well as the equilibrium number of firms. In Appendix B, we provide a more detailed description of the calibration procedure. In Section 5.3 we show the robustness of our results to the exclusion of the migration-driven mechanisms and

[13] As we show in Appendix F.1, the simulation results are robust to a wide range of parameters, ranging from $\theta = 0.5$ to $\theta = 3.9$. For ε, a value slightly higher is obtained by Parro (2013), who uses a tariff-based approach to estimate an aggregate trade elasticity for traded goods. Estimation of the shape parameter of the productivity distribution based on firm-level sales data provides values in the range of 3.6 to 4.8 (Bernard *et al.*, 2003, Eaton *et al.*, 2011). As we show in Appendix F.1, the simulation results are robust to changing the parameter values to $\varepsilon = 3$ and $\varepsilon = 5$.

to a scenario where the externality parameters are set to higher values.

5 The importance of the skill bias in global migration

We now use the calibrated model to run counterfactual simulations based on which we estimate the welfare contribution of the skill bias in migration in the current world. The central question we aim to answer here is '*how quantitatively important is the skill bias in migration?*'.

In this section, we first describe the counterfactual that allows us to answer this question and define the population whose welfare we are analyzing in Section 5.1. We then present the three results related to this research question. In Section 5.3, we assess the welfare impact of the skill bias in migration in the sending and receiving countries in our calibrated baseline model. In Section 5.4, we put these effects into perspective by showing how they compare to the total welfare contribution of migration. In Section 5.5, we assess the impact of the skill bias in migration on the income distribution *within* countries.

5.1 Defining the counterfactual

To assess the welfare contribution of the skill bias in migration in the current world, we construct a counterfactual that eliminates the skill bias while holding all other aspects of the global economy constant. Specifically, we hold the bilateral stocks of migrants constant, but assume that all migrants have been neutrally selected from the population of the sending country. This is the case if the shares of high-, medium- and low-skilled workers among emigrants are the same as in the total population, whereby the total population is defined as all people born in a sending country — current non-migrants as well as emigrants. In other words, our counterfactual is a world in which a receiving country 'imports' migrants that are randomly drawn from the skill distribution of all people born in a given country of origin, rather than being positively or negatively selected.[14] For people who are emigrants under the baseline but not in the counterfactual, we assume that they work in the country of origin in a job that is adequate for their education level.

In this analysis, we remain agnostic as to why the observed selection pattern came about in the first place. The literature offers several explanations: differences in returns to skill make migration more beneficial for some groups than for others (Borjas, 1987); if migration costs are the same for all workers, migration is more beneficial for high-skilled workers (Chiswick, 1999); moreover, receiving countries may actively seek to attract high-skilled while restricting access for low-skilled migrants. In our counterfactual, we undo the selection pattern that was created by these forces, and exogenously change the skill composition of migrants.[15]

[14] Given data limitations, we focus here on selection on observable characteristics. It is possible that migrants are differently selected on unobservable characteristics. However, detecting selection on unobservable characteristics would require data on wages before migration. See, for example, Fernández-Huertas Moraga (2013) or Borjas *et al.* (2018).

[15] Critical readers might be concerned that our counterfactual is not the result of optimal migration decisions of all potential migrants in the sending countries. Nonetheless, the goal here is to provide a positive analysis

5.2 Measuring welfare

Before turning to the welfare effects, we need to define the population whose welfare we analyze. In our preferred analysis, our population of interest are never-migrants, i.e. people who are neither migrants under the baseline nor under the counterfactual.

An alternative measure would be welfare per capita, i.e. the average indirect utility of all individuals living in a particular sending or receiving country. However, while this measure is easy to understand and compute, it holds limited value because the skill composition of the underlying population differs between the baseline and the counterfactual. In the language of program evaluation, the difference in welfare per capita is a combination of a *treatment effect* — the causal impact of a change in migrant selectivity on the welfare of never-migrants — and a *composition effect*, namely the result of replacing high-earning with low-earning migrants. In our analysis, we are interested in the treatment effect, i.e. the impact of the skill bias in migration on the welfare of people who live in a given sending country under both the baseline and the counterfactual.

To isolate the pure treatment effect of the skill bias, we base our welfare calculation on the population of *never-migrants*. Constructing the skill distribution of this group is challenging because some people who are migrants in the current world would live in their country of origin under the counterfactual, and vice versa. This difference in the composition of the population would mechanically lead to a difference in welfare between the baseline and the counterfactual. We avoid this problem by considering only the welfare of groups that are never-migrants in both scenarios. We construct these as the minimum number of workers in a given skill group between the baseline and the counterfactual. For instance, the number of high-skilled never-migrants is $H_{NM} = \min(H_{baseline}, H_{counterfactual})$. In Appendix C, we provide a graphical intuition for the construction of the population of never-migrants.

5.3 Baseline results

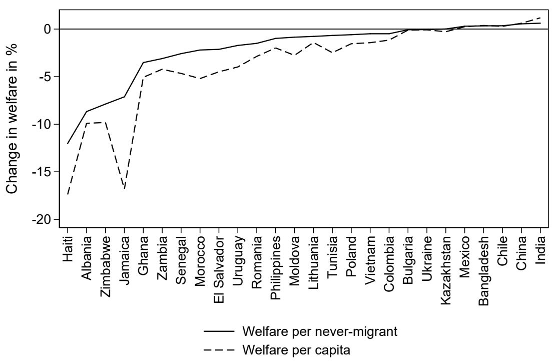
We begin by analyzing the impact of skill-biased migration on the average individual's welfare. Using the model outlined in Section 3 and the baseline calibration in Section 4, we simulate a counterfactual in which migration is skill-neutral. We measure the change in welfare as the percentage difference in indirect utility,

$$\frac{\Delta U}{U} = \frac{U_{skill-bias} - U_{skill-neutral}}{U_{skill-neutral}}.$$

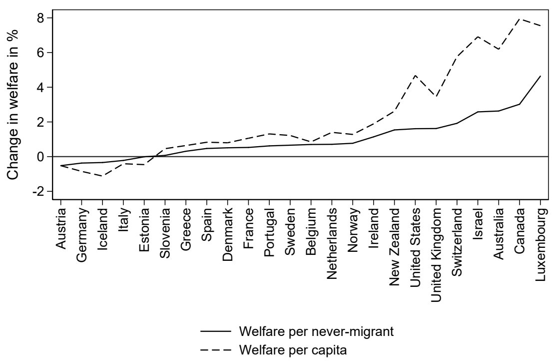
Figure 2 displays the simulation results for selected receiving and sending countries, while Appendix G reports the full set of results. The countries are ordered from left to right by welfare effect per never-migrant, from smallest to highest. All effects represent the difference in welfare under skill-biased versus skill-neutral migration. A positive effect means that the average

and assess the quantitative importance of the skill bias in migration for the welfare of never-migrants. If one wanted to extend the model to study alternative migration policies, a microfoundation of the migration decisions would be necessary.

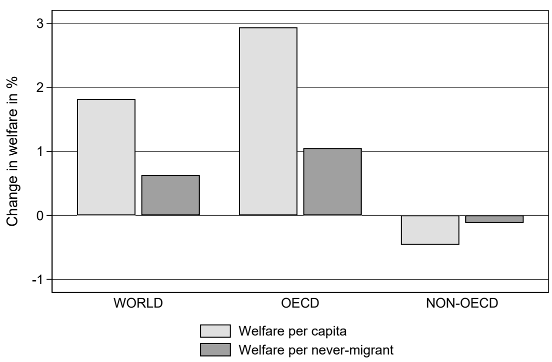
person living in a given country is better off under skill-biased migration. The dotted line represents the effect on welfare per capita, while the solid line represents the effect on welfare per never-migrant.



(a) Welfare effects in the sending countries



(b) Welfare effects in the receiving countries



(c) Welfare effects in OECD and non-OECD countries, and in the world

Figure 2: Main results: welfare effects per capita and per never-migrant

Source: Own calculations.

Notes: This graph displays the impact of the skill bias in migration on welfare in selected countries. The calculation is based on the model described in Section 3 and the calibration summarized in Table 1. The dashed line represents the effect on welfare per capita, while the solid line represents the effect on welfare per never-migrant. The countries on the horizontal axis are ordered by the welfare impact per never-migrant. The vertical axis shows welfare differences in percent. Panel 2(a) focuses on selected sending countries, while Panel 2(b) focuses on selected receiving countries. Panel 2(c) shows the population-weighted average effect in all non-OECD and OECD countries as well as across the whole world.

Figure 2(a) shows the effects for selected sending countries. These correspond to the welfare effects of high-skilled emigration that have been estimated in the previous literature (Beine *et al.*, 2008). The effects on welfare are negative for about three quarters of the countries and are particularly large for Jamaica and Haiti, both of which have large shares of emigrants who are predominantly high-skilled. Depending on the welfare measure, the brain drain lowers the welfare in these two countries by 7-17%, while in most other countries the welfare effects are more modest and range between -3% and 0.6%. Similar to Beine *et al.* (2008), in some cases we find small, positive welfare effects for high-skilled emigration, notably in large countries such as China or India. This result is explained by the positive effect of the human capital externalities, which counteract the negative market size effect. The difference in the effect under both welfare measures underlines the importance of choosing the right base population. The effects are considerably larger when we consider welfare per capita, suggesting that much of the effect on welfare per capita is driven by compositional changes. When we use welfare per never-migrant, these compositional changes are eliminated. Figure 2(c) suggests that the population-weighted welfare per never-migrant across all non-OECD countries is -0.1%. This average, however, masks a large degree of heterogeneity. In a few highly populated countries, the skill bias in migration leads to welfare gains, whereas in many smaller developing countries it leads to welfare losses.

Figure 2(b) displays the welfare effect of the skill bias in the receiving countries. Given the stylized fact that the skill bias is positive for most receiving countries, we would expect positive welfare effects in most countries. With the exceptions of a handful of countries, this is indeed the case. The effects are particularly large in Canada, Australia, Israel, the US and Luxembourg, all of which combine high immigration rates with a high degree of selectivity. In the receiving countries, the difference in the effect on both welfare measures is more pronounced than in the sending countries. The impact on welfare per never-migrant is considerably smaller than the impact on welfare per capita. Nonetheless, the effect on welfare per never-migrant is positive for most countries, and lies between -0.5% and 4%. As shown in Figure 2(c), the population-weighted welfare per never-migrant for the OECD is about 1% higher due to the skill bias in migration.

When we take the average effects across all countries weighted by population, we find the global welfare effect to be 0.6%. This means that because most migrants are positively selected, the average never-migrant in the world is better off than in the counterfactual of neutral selection. The skill bias in migration is globally welfare improving because a larger number of high-skilled workers are in high-productivity countries relative to the counterfactual.

Relative importance of channels. The welfare effect presented above results from the interplay of several economic forces, namely trade, wages, market size, as well as several migration-driven externalities. To assess the quantitative importance of these forces, we consider a scenario we refer to as 'minimalist'. In this scenario, all elasticities governing the migration-driven externalities are set to zero, such that the welfare differences are purely explained by changes in market size, nominal wages and trade. As shown in Table 2, under this scenario the welfare gains are smaller in the OECD countries while the losses in the non-OECD countries are more pronounced.

In a model without externalities, we find market size to be the dominant force, explaining 64% and 49% of the total welfare effects in OECD and non-OECD countries respectively. This result is consistent with findings in Iranzo & Peri (2009), di Giovanni *et al.* (2015), Aubry *et al.* (2016) as well as with the welfare gains obtained with the introduction of new varieties through international trade (Broda & Weinstein, 2006). On the contrary, the wage effect for the average never-migrant is quantitatively less important. While wages are affected by the skill bias in migration, its impact is redistributive; some workers gain and others lose, but the average effect remains small. For the OECD countries it represents 22%, and for the non-OECD countries 7% of the total effect. The role of trade is comparably low, with 4% and 2.4%, respectively. This is the case because without externalities, the only role of trade is to propagate the market size effect across trading partners. Finally, the residual explains over 40% of the effect in non-OECD countries. This mainly reflects changes driven by non-homothetic preferences. When preferences are non-homothetic, income changes lead to asymmetric effects on utility. An increase in income shifts consumption further towards the differentiated goods, over-proportionally increasing people's utility from consumption. On the other hand, a decrease in income does not affect the consumption of the traditional good, leading to an under-proportional decrease in utility. This is reflected in the positive sign of the residual in Table 2. Intuitively, while skill biased migration lowers market size in poor countries, the resulting loss in utility is dampened by consumers shifting away from expensive manufactured goods and towards the cheaper traditional good.[16]

Panel B shows that the migration-driven externalities increase the welfare effect by 0.4 percentage points in the OECD countries and 0.3 percentage points in the non-OECD countries. When we decompose this additional welfare effect, we find that the primary driver is the TFP externality, which explains two thirds of the effect in the OECD. While trade creation through migrant networks is important in OECD countries, it contributes little to the additional welfare in non-OECD countries. An important externality in the non-OECD countries is the brain gain mechanism, which explains about a quarter of the additional effect. Perhaps surprisingly, the role of remittances is negligible in explaining the welfare effect of the skill bias. This is the case because i) the number of migrants remains the same in the baseline and counterfactual and ii) due to our calibration of the income elasticity of remittances, $\gamma = 0.5$, remittances per migrant only partially respond to changes in income.

Sensitivity to calibration. To further assess the role of migration-driven externalities, we consider a 'maximalist' scenario in which the elasticities are set to values at the upper end of the spectrum found in the literature. Table 3 summarizes the calibration for all three scenarios — the minimalist scenario without externalities, the baseline scenario and the maximalist scenario with strong externalities. As shown in Figure 3, stronger externalities amplify the baseline effects. The global welfare effect shown in Figure 3(c) is about three times larger than the baseline effect while in the OECD countries the effect doubles. In the non-OECD countries, the sign of the average effect gets reversed. Whereas we find a small negative welfare effect in our baseline, stronger externalities would result in substantial average welfare gains in non-OECD

[16] In light of the literature showing that technological progress has a heterogenous effect on individuals with different education levels (Acemoglu, 2002, Autor *et al.*, 2003), one could also model the relative productivity of high-skilled workers as a function of the skill ratio of high-skilled to low-skilled workers. The drawback of doing so is the lack of credible estimates of these effects outside the US context. We run simulations that include skill-biased technical change, calibrated on estimates from Moretti (2004) and Diamond (2016). These results show that global welfare gains remain positive. The results are available upon request.

Table 2: Welfare effects of channels

	OECD	Non-OECD
Total welfare effect	**1.05%**	**-0.12%**
A. Welfare effect minimalist scenario	**0.64%**	**-0.45%**
Explained by (in %)		
Market size effect	63.54	49.07
Wage channel	21.97	6.88
Trade channel	4.09	2.36
Residual	10.40	41.70
B. Welfare difference due to externalities	**0.41%**	**0.33%**
Explained by (in %)		
Remittances	0.30	1.32
TFP externality	65.64	35.78
Network effects in trade	27.63	6.32
Brain gain mechanism	3.47	25.99
Residual	2.97	30.58

Note: own calculations based on a model without migration-driven externalities (minimalist scenario) and a model with migration-driven externalities. The model with externalities represents our baseline result. The total effects are decomposed into the adjustment mechanisms listed in both panels.

countries.

Table 3: Main models and parameters

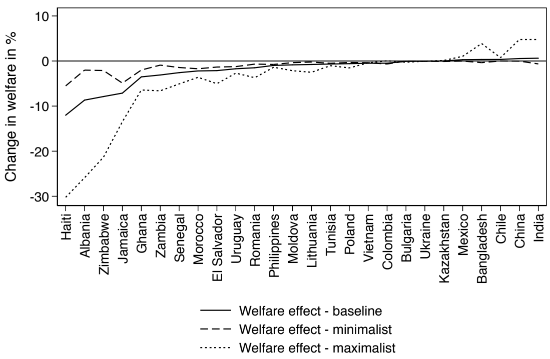
Externality	Parameter	Minimalist	Baseline	Maximalist
Remittances	γ	0	0.5	1
TFP externalities	σ_a	0	0.05	0.2
Network effects in trade	σ_t	0	-0.02	-0.05
Brain gain mechanism	σ_b	0	0.048	0.096

Note: This table summarizes the calibration of the externality parameters in different scenarios.

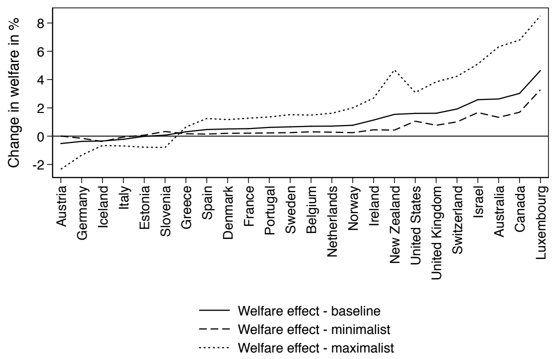
5.4 Who vs. how many: how important is the skill bias?

Thus far, we have found effects of the skill bias in migration on the welfare of never-migrants ranging between -0.5% and 4% in the receiving and between -17% and +0.6% in the sending countries. Once the effects are weighted by population and we look at the net effect in the world, we find a welfare gain of 0.63%. Upon first glance, this appears to be a small effect. However, to assess the magnitude of this effect, the results have to be put in perspective.

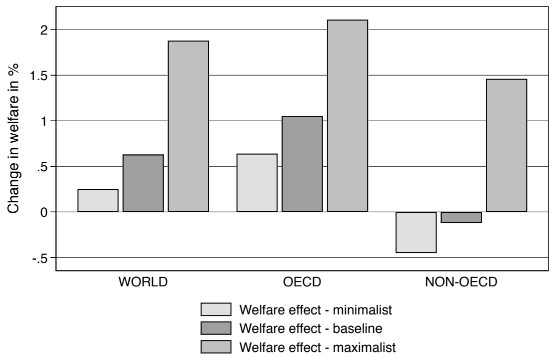
A first point of comparison is the share of migrants relative to the share of never-migrants. In 2010, never-migrants accounted for over 97% of the world population. The welfare effects from the skill bias in migration, while affecting most of the world population, are the result of



(a) Sending countries



(b) Receiving countries



(c) Aggregate results

Figure 3: Welfare effects under the different calibration of migration-driven externalities

Source: Own calculations.

Notes: This graph displays the impact of the skill bias in migration on welfare in selected countries. The countries on the horizontal axis are ordered by welfare impact per never-migrant. The solid line represents the effect on welfare per never-migrant under the baseline. The dashed lines represent the welfare effects under the minimalist scenario without migration-driven externalities and the maximalist scenario with strong externalities. The calibration is summarized in Table 3.

less than 3% of the world population being positively selected from their country of origin. If the share of migrants was higher or the skill bias was more pronounced or both, the global welfare contribution of the skill bias in migration would be much larger.

Another point of comparison is the welfare contribution of the skill bias in migration relative to the overall welfare contribution of migration. To obtain the overall welfare effect of migration, we simulate a counterfactual with zero migration, whereby all migrants are being repatriated to their country of origin. Figure 4 displays the simulation results for this counterfactual along with our baseline effects. The results are similar to those found in di Giovanni *et al.* (2015) and Aubry *et al.* (2016) who simulate a no-migration counterfactual in different model frameworks.

In the OECD countries, the skill bias accounts for around 16% of the total welfare effect of migration. In contrast, the total effect of migration in the non-OECD countries is positive while the effect of the skill bias is negative.[17] However, in relative terms, in these countries selection accounts for one third of the total effect of migration. Overall, these results suggest that the total welfare effect of migration is mainly driven by the scale of migration. However, the welfare impacts of the skill composition of migrants is substantial, especially in non-OECD countries.

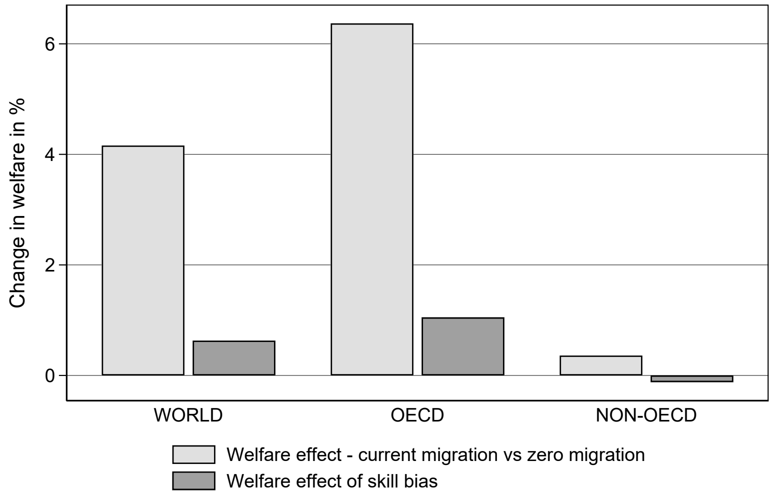


Figure 4: Selection vs. scale effects

Source:. Own calculations.
Notes: In this graph, we compare the welfare effect of the skill bias in migration to the welfare impact of migration *per se*, namely the welfare difference between the status quo and a world without migration. The vertical axis shows changes in welfare per never-migrant in percent.

5.5 The skill bias and heterogeneous wage effects

Besides having an impact on aggregate welfare, the skill bias in migration affects the nominal wage structure. A change in the skill composition of migrants alters the relative supply of high- vs. low-skilled workers, which in turn affects the nominal wage structure. Nominal wages are affected through direct competition on the labor market, as well as through complementarities between high-, medium- and low-skilled workers, and between immigrants and natives.

Figure 5 displays the impact of the skill bias in migration on the real wages for different education levels. As in the previous section, a positive value means that the respective groups have higher real wages in a world with skill-biased migration. Figure 5(a) shows the different effects in the sending countries for workers with different skill levels. In all sending countries, high-skilled workers gain and low-skilled workers lose, while in most countries the impact for medium-skilled workers hovers around zero. The gains in real wages are particularly pronounced for high-skilled workers in Albania (+20%), Haiti (+18%) and Zimbabwe (+18%), while in most

[17] The positive scale effect in non-OECD countries derives primarily from trade creation due to diaspora externalities. The scale effect is positive in almost half of the sending countries. Results available upon request.

other countries the effects are close to zero. The sign of the effects can be explained by a simple supply-and-demand mechanism. Most sending countries experience a severe outflow of high-skilled workers, such that high-skilled workers who stay behind become a scarcer resource in the labor market, thereby leading to wage increases. The opposite holds true for low-skilled workers. The magnitude of these effects depends on the skill distribution of the never-migrant population, as well as the direction and magnitude of the general equilibrium effects. Overall, the skill bias in migration increases the wage gap between high- and low-skilled workers in sending countries and in most countries, the gains for high-skilled workers are on average smaller than the losses for the low-skilled workers.

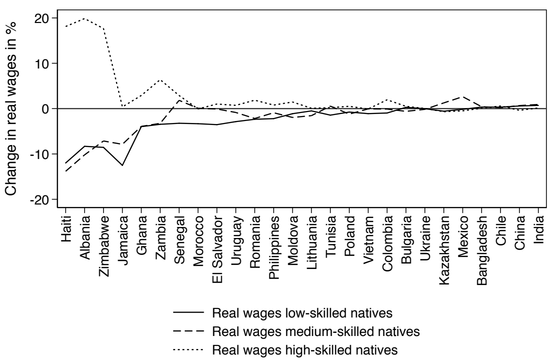
As Figure 5(b) shows, the skill bias has the opposite effect in the receiving countries: low-skilled workers gain, while high-skilled workers lose. The gains for low-skilled workers have three sources: first, with skill-biased migration, they face less competition on the labor market, leading to higher nominal wages; second, they benefit from the market size effect due to a larger number of available varieties and lower prices; and third, they benefit from increased efficiency due to higher TFP. For high-skilled workers, the effects are less clear. In most countries, high-skilled workers lose by a small margin while they gain in others. High-skilled workers benefit from the same positive market size effect as low-skilled workers, although they face more competition on the labor market. If these effects balance out, the net effect can be zero. Overall, the skill bias in migration reduces the wage gap between high- and low-skilled workers in the receiving countries.

Upon first glance, the gains for low-skilled workers in the receiving countries may seem puzzling in light of the evidence that migration reduces the wages of low-skilled natives (Borjas, 2003, Dustmann *et al.*, 2013). The main difference between these studies and ours is the choice of counterfactual. Most studies explore the impact of having *more* immigrants, whereas our interest lies in the impact of having *different* immigrants. Given that under skill-biased migration the receiving countries have fewer low-skilled immigrants than under the counterfactual, low-skilled never-migrants are better off under skill-biased migration. In fact, in Appendix D, we show that our model produces results similar to those in Borjas (2003) once we simulate a similar counterfactual and eliminate all externalities.

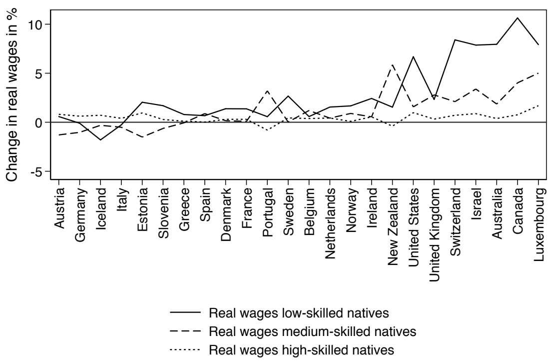
In Figure 5(c), we also report the real wage changes for the OECD and the world as a whole. Low-skilled workers in the OECD gain about 3%, low-skilled workers in the world gain around 2%, while the effects for high-skilled workers are closer to zero. Taken together, the results from Section 5.3 and this section suggest that skill-biased migration leads to a more efficient allocation of labor and greater productivity in the world, although it also changes relative wages, making some groups better and others worse off.

5.6 Sensitivity checks

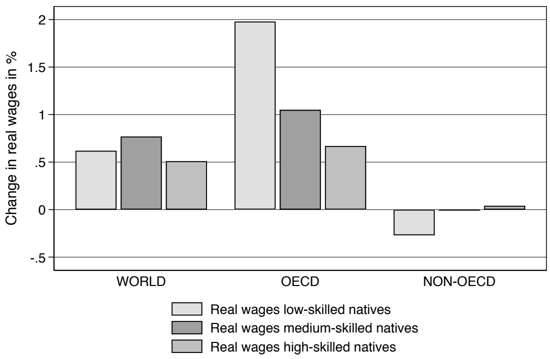
To assess the robustness of our results, we perform three sets of sensitivity checks. First, in Appendix E, we assess the sensitivity of the results to changes in the strength of the migration-driven externalities. We use the same calibration as in Table 3, although in this exercise we vary one parameter at a time. This allows us to assess the importance of each externality in



(a) Wage effects in selected non-OECD countries



(b) Wage effects in selected OECD countries



(c) Wage effects in OECD and non-OECD countries, and in the world

Figure 5: Distributional effects

Source:. Own calculations.

Notes: This graph shows the impact of the skill bias in migration on the real wages of low-, medium- and high-skilled workers. The countries on the horizontal axis are ordered by welfare impact per never-migrant. The vertical axis shows real wage changes, in percent, for high-, medium- and low-skilled workers.

the overall welfare effect. The results confirm the pattern shown in Table 2, namely that the TFP externality is the quantitatively most important one, whereas remittances, the brain gain mechanism and network externalities play a minor role. As an additional check, we allow for downskilling — the fact that many migrants work in occupations for which they are formally over-qualified. The results show that downskilling dampens the effect of the skill bias in the receiving countries, although the dampening effect is small.

Second, in Appendix F.1, we assess the sensitivity of our simulation results to changes in the preference and technology parameters. The results prove robust to a wide range of parameter values.

Third, in in Appendix F.2 we assess whether our results are driven by the choice of the nesting structure of the production function. We use a more fine-grained nesting structure as in Goldin & Katz (2007) but obtain similar results as in our baseline simulations.

6 Conclusion

The question of "*who migrates*" remains at the forefront of the policy debate on migration. Receiving countries are concerned whether they attract migrants with the right skills, whereas many sending countries worry about losing high-skilled workers. Despite the evident skill bias in global migration, we know little about its impact on global welfare. The existing literature mainly quantifies the welfare impact of changes in the scale of migration — having more or fewer migrants — rather than the skill composition of the migrants. This paper fills this gap by quantifying the relevance of the skill bias in migration for the welfare of never-migrants in receiving countries and sending countries. For this purpose, we develop a multi-country general equilibrium model based on which we compare the welfare in today's world to a counterfactual with the same number of migrants but without skill bias in migration.

Our analysis delivers three central findings. First, most receiving countries gain from the skill bias in immigration. In all except four countries, the welfare of never-migrants is between 0 and 4.6% higher because the immigrants in their country are positively and not neutrally selected from their countries of origin. Second, we find welfare gains at the global level, which result from the gains from the skill bias in the receiving countries exceeding the losses in many sending countries. Therefore a world with a skill bias in migration is one where talent is more efficiently allocated, that is, a larger number of high-skilled workers live and work in countries where they are most productive. Third, these global welfare gains arise even when we exclude migration-driven externalities such as remittances, brain gain or network effects in trade, that offset the negative effect in the sending countries.

This paper opens up several avenues for future research. Our paper simulates a counterfactual that eliminates the skill bias in global migration. While answering our main research question, namely quantifying the global effect of the skill bias in migration, this counterfactual is incongruent with actual migration policies. Future research could evaluate policy proposals related to the skill bias in migration, such as skill-selective migration policies. In addition, our baseline analysis shows that while more selective migration leads to global welfare gains, it also exacerbates income inequality between rich and poor countries. Given that some countries win and others lose while the global gains are positive, it should be possible to design a migration policy that increases the global welfare by encouraging more skill-biased migration, in combination with a scheme in which the winners compensate the losers. Finally, the impact of migration on global inequality becomes less clear once we consider the welfare of migrants themselves, which have been left out in this paper. We are comfortable calling the welfare effect global because it covers more than 97% of the world population, namely all never-migrants. But the simulations show that migrants seem to gain considerably. Quantifying the impact of selectivity on the migrants themselves therefore deserves further attention.

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Online Appendices

(For Online Publication)

A Theoretical model - components

This section provides a detailed description of the theoretical model that has been summarized in Section 3.

A.1 Consumer's decision

A consumer in country i with income $\widehat{w}_i$ maximizes utility

$$\begin{aligned}&\max_{\{T_i, x_{ij}(k), y_i(k)\}} \beta^T (T_i)^{\mu} + \left(1-\beta^T\right) \left[(1-\beta)(Y_i)^{\frac{\theta-1}{\theta}} + \beta(X_i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \\ &\text{subject to: } P_i^T T_i + P_i^Y Y_i + P_i^X X_i = \widehat{w}_i,\end{aligned} \tag{A.1}$$

where β is the relative preference for the tradable differentiated goods, β^T is a preference parameter for the traditional good, and θ is the elasticity of substitution between tradable and non-tradable goods X and Y. The consumption of traditional goods is subject to decreasing marginal utility, such that $\mu < 1$. Y_i and X_i are CES composites of different varieties k produced in the manufacturing sector,

$$X_i = \left[\sum_{j=1}^{J} \int_0^{N_j^X} (x_{ij}(k))^{\frac{\varepsilon-1}{\varepsilon}} dk\right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad Y_i = \left[\int_0^{N_i^Y} (y_i(k))^{\frac{\varepsilon-1}{\varepsilon}} dk\right]^{\frac{\varepsilon}{\varepsilon-1}}. \tag{A.2}$$

N_i^X and N_i^Y are the numbers of varieties of goods X_i and Y_i available in country i. Varieties of the composite tradable good X_i are either domestically produced, $x_{ii}(k)$, or imported from other countries $x_{ij}(k), j \neq i$, while all varieties of Y_i, $y_i(k)$, are domestically produced. The parameter ε is the elasticity of substitution between any two varieties within a sub-sector, with $\varepsilon > \theta > 1$. Therefore, consumer preferences exhibit love of variety, which means that consumers gain utility when the number of available varieties increases. This translates in a 'market size effect' similar to the one obtained by Iranzo & Peri (2009) and di Giovanni *et al.* (2015) in a two-sector model and Aubry *et al.* (2016) in a one-sector model.

After maximizing utility subject to the budget constraint in Equation (A.1), the individual demands for all types of consumption goods are as follows:

$$\begin{aligned}T_i^s &= \left(\frac{\beta^T \mu}{1-\beta^T} \frac{P_i}{P_i^T}\right)^{\frac{1}{1-\mu}}, \\ Y_i^s &= (\widehat{w}_i^s - T_i^s)(1-\beta)^{\theta} (P_i)^{\theta-1} (P_i^Y)^{-\theta}, \\ X_i^s &= (\widehat{w}_i^s - T_i^s)\beta^{\theta} (P_i)^{\theta-1} (P_i^X)^{-\theta}, \\ x_{ij}^s &= (\widehat{w}_i^s - T_i^s)\beta^{\theta} (P_i)^{\theta-1} (P_i^X)^{\varepsilon-\theta} (p_{ij})^{-\varepsilon}, \\ y_i^s &= (\widehat{w}_i^s - T_i^s)(1-\beta)^{\theta} (P_i)^{\theta-1} (P_i^Y)^{\varepsilon-\theta} (p_i)^{-\varepsilon}.\end{aligned} \tag{A.3}$$

The demand for the traditional good is the same for all individuals in country i, and is independent of their real wage. This follows from the assumption of non-homothetic preferences. Consumption of these goods can be seen as expenditure that is necessary for survival. Once consumers have more income, they spend a greater share of their income on differentiated goods. Thus, the relative demand for the goods X and Y increases with income.

Inserting the demands (A.3) into the utility function (A.1), we obtain an agent's indirect utility,

$$U_i^s = \beta^T \left(\frac{\beta^T \mu}{1-\beta^T} \frac{P_i}{P_i^T} \right)^{\frac{\mu}{1-\mu}} + (1-\beta^T) \frac{\hat{w}_i^s - T_i^s}{P_i}. \tag{A.4}$$

where P_i is the ideal price index in country i,

$$P_i = \left[(1-\beta)^\theta \left(P_i^Y\right)^{1-\theta} + \beta^\theta \left(P_i^X\right)^{1-\theta} \right]^{\frac{1}{1-\theta}},$$
$$\text{with: } P_i^X = \left[\sum_{j=1}^{J} \int_0^{N_j^X} (p_{ij}(k))^{1-\varepsilon} dk \right]^{\frac{1}{1-\varepsilon}}, \text{ and } P_i^Y = \left[\int_0^{N_i^Y} (p_i(k))^{1-\varepsilon} dk \right]^{\frac{1}{1-\varepsilon}}. \tag{A.5}$$

A.2 Labor demand and wages

The production functions of the traditional and the manufacturing sector are

$$\begin{aligned} Q_i^T &= A_i^T L_i^T, \\ Q_i^M = A_i^M L_i^M &= A_i^M \left[\alpha_i^L (L_i)^{\frac{\sigma_s-1}{\sigma_s}} + (1-\alpha_i^L-\alpha_i^H)(M_i)^{\frac{\sigma_s-1}{\sigma_s}} + \alpha_i^H (H_i)^{\frac{\sigma_s-1}{\sigma_s}} \right]^{\frac{\sigma_s}{\sigma_s-1}}. \end{aligned}$$

where L_i^T is the supply of low-skilled labor employed in the traditional sector, and A_i^T is the productivity residual, which equals the wage rate of the low-skilled workers over the price level in T:[18]

$$A_i^T = W_i^L / P_i^T. \tag{A.6}$$

The productivity in manufacturing sector is subject to a Lucas externality:

$$A_i^M = \bar{A}_i^M \left(\frac{H_i}{L_i + M_i + H_i} \right)^{\sigma_a}. \tag{A.7}$$

L_i, M_i and H_i represent the supplies of low-, medium- and high-skilled workers in the manufacturing sector. This production function assumes that all three skill levels are equally substitutable. In Appendix F.2, we allow for differential substitutability between skill groups by adding an additional nest to the production function. The parameters α_i^L and α_i^H indicate, respectively, the efficiency of low- and high-skilled workers in production. Each skill group consists of natives (labeled by superscripts N) and foreigners (with superscripts F). All domestic and foreign workers are assumed to be imperfect substitutes with a constant elasticity of substitution equal to σ_n. We define the efficient labor supplies for each sector and education group as

$$\begin{aligned} L_i^T &= \left[(1-\alpha_i^F)(L_i^{T,N})^{\frac{\sigma_n-1}{\sigma_n}} + \alpha_i^F (L_i^{T,F})^{\frac{\sigma_n-1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n-1}}, \\ L_i &= \left[(1-\alpha_i^F)(L_i^N)^{\frac{\sigma_n-1}{\sigma_n}} + \alpha_i^F (L_i^F)^{\frac{\sigma_n-1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n-1}}, \\ M_i &= \left[(1-\alpha_i^F)(M_i^N)^{\frac{\sigma_n-1}{\sigma_n}} + \alpha_i^F (M_i^F)^{\frac{\sigma_n-1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n-1}}, \\ H_i &= \left[(1-\alpha_i^F)(H_i^N)^{\frac{\sigma_n-1}{\sigma_n}} + \alpha_i^F (H_i^F)^{\frac{\sigma_n-1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n-1}}. \end{aligned} \tag{A.8}$$

[18] This wage is equal across sectors and across workers' origin. Therefore, any low-skilled worker from sector T has no incentives to move to sectors X and Y. In addition, the linear production function implies that the marginal productivity of low-skilled workers is constant in the traditional sector. In a set of results available upon request we confirm that using a non-linear production function of the form $Y_T = A_T L_T^\alpha$ with α=0.5 or 0.8 has no impact on the results.

We assume a fixed, country-specific share of outputs of natives and foreigners ($(1-\alpha_F)$ and α_F respectively), and for $s \in \{L, M, H\}$ we assume: $s_i^F = \sum_{j\neq i} s_{ij}$.

Firms solve their cost-minimization problem, taking wages as given. Demand for each type of labor is then set as

$$
\begin{aligned}
L_i^N &= \frac{Q_i^M}{A_i^M}\left[\frac{(1-\alpha_i^F)W_i^L}{w_i^{LN}}\right]^{\sigma_n}\left[\frac{\alpha_i^L W_i}{W_i^L}\right]^{\sigma_s}, & L_i^{T,N} &= \frac{Q_i^T}{A_i^T}\left[\frac{(1-\alpha_i^F)W_i^L}{w_i^{LN}}\right]^{\sigma_n}, \\
L_i^F &= \frac{Q_i^M}{A_i^M}\left[\frac{\alpha_i^F W_i^L}{w_i^{LF}}\right]^{\sigma_n}\left[\frac{\alpha_i^L W_i}{W_i^L}\right]^{\sigma_s}, & L_i^{T,F} &= \frac{Q_i^T}{A_i^T}\left[\frac{\alpha_i^F W_i^L}{w_i^{LF}}\right]^{\sigma_n}, \\
M_i^N &= \frac{Q_i^M}{A_i^M}\left[\frac{(1-\alpha_i^F)W_i^M}{w_i^{MN}}\right]^{\sigma_n}\left[\frac{(1-\alpha_i^H-\alpha_i^L)W_i}{W_i^M}\right]^{\sigma_s}, & H_i^N &= \frac{Q_i^M}{A_i^M}\left[\frac{(1-\alpha_i^F)W_i^H}{w_i^{HN}}\right]^{\sigma_n}\left[\frac{\alpha_i^H W_i}{W_i^H}\right]^{\sigma_s}, \\
M_i^F &= \frac{Q_i^M}{A_i^M}\left[\frac{\alpha_i^F W_i^M}{w_i^{MF}}\right]^{\sigma_n}\left[\frac{(1-\alpha_i^H-\alpha_i^L)W_i}{W_i^M}\right]^{\sigma_s}, & H_i^F &= \frac{Q_i^M}{A_i^M}\left[\frac{\alpha_i^F W_i^H}{w_i^{HF}}\right]^{\sigma_n}\left[\frac{\alpha_i^H W_i}{W_i^H}\right]^{\sigma_s},
\end{aligned}
\tag{A.9}
$$

where the wage indices for the low-, medium- and high-skilled workers are equal to:

$$
\begin{aligned}
W_i^L &= \left[(1-\alpha_i^F)^{\sigma_n}(w_i^{LN})^{1-\sigma_n} + (\alpha_i^F)^{\sigma_n}(w_i^{LF})^{1-\sigma_n}\right]^{\frac{1}{1-\sigma_n}}, \\
W_i^M &= \left[(1-\alpha_i^F)^{\sigma_n}(w_i^{MN})^{1-\sigma_n} + (\alpha_i^F)^{\sigma_n}(w_i^{MF})^{1-\sigma_n}\right]^{\frac{1}{1-\sigma_n}}, \\
W_i^H &= \left[(1-\alpha_i^F)^{\sigma_n}(w_i^{HN})^{1-\sigma_n} + (\alpha_i^F)^{\sigma_n}(w_i^{HF})^{1-\sigma_n}\right]^{\frac{1}{1-\sigma_n}},
\end{aligned}
\tag{A.10}
$$

and the overall wage index in the manufacturing sector is given by:

$$
W_i = \left[(\alpha_i^L)^{\sigma_s}(W_i^L)^{1-\sigma_s} + (1-\alpha_i^L-\alpha_i^H)^{\sigma_s}(W_i^M)^{1-\sigma_s} + (\alpha_i^H)^{\sigma_s}(W_i^H)^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}}. \tag{A.11}
$$

Remittances. Out of their wages, migrants send remittances to their home countries. Assume that the amount remitted by an individual of type $s \in \{L, M, H\}$ residing in country i and originating from country j equals:

$$
R_{ji}^s = \eta_{ij}(w_i^{sF})^{\gamma}. \tag{A.12}
$$

The income after remittances becomes:

$$
\hat{w}_i^{sF} = w_i^{sF} - \eta_{ij}\left(w_i^{sF}\right)^{\gamma}, \tag{A.13}
$$

where w_i^{sF} is the wage income before remittances and the second term indicates residual remittances. These range from a fixed amount of income η_{ij}, when $\gamma = 0$, to a share η_{ij} of wages remitted when $\gamma = 1$. Note that γ is the elasticity of remittances to income. If γ=0, each immigrant remits the same amount whereas γ=1 implies that remittances are proportional to wages. Intermediate values of γ imply a positive elasticity of remittances with respect to wages and thus allow to account for intermediate scenarios between constant amount and constant wage share for the remittances sent from country j to country i. For a given γ, the propensity to remit η_{ij} is assessed using data on the volume of bilateral remittances flowing from country i to country j, denoted R_{ji}. Thus,

$$
R_{ji} = \sum_{s=L,M,H} s_{ij}\eta_{ij}\left(w_i^{sF}\right)^{\gamma}, \tag{A.14}
$$

where s_{ij} is the number of emigrants with skill s from country j living in i. The propensity to remit (η_{ij}) can then be recovered using Equation (A.14) with data on R_{ji}, the emigration matrix (s_{ij}) and the calibrated values for the wages (w_i^{sF}). Next, the total volume of remittances received by natives living in the origin country j is assessed by summing the remittance flows across all destination countries:

$$R_j = \sum_{i \neq j} R_{ji}. \tag{A.15}$$

In the origin countries, the total amount of remittances received is then split equally among the never-migrating nationals, independent of their skill level. The per-worker amount, $\bar{R}_j$, is then defined as:

$$\bar{R}_j = \frac{R_j}{\sum_{s=L,M,H} s_j^N}. \tag{A.16}$$

Thus, the total income after remittances of a never-migrant in country j of type s is given by:

$$\hat{w}_j^{sN} = w_j^{sN} + \bar{R}_j, \tag{A.17}$$

where w_j^{sN} is the skill-specific wage rate.[19]

Brain gain mechanism. Our model also includes a 'brain gain' mechanism (Mountford, 1997, Stark *et al.*, 1997, Beine *et al.*, 2001, Chand & Clemens, 2008, Beine *et al.*, 2008, Batista *et al.*, 2011, Shrestha, 2015, Dinkelman & Mariotti, 2016), which is a dynamic feedback effect of emigrants' skill selection on the population of their origin country. This human capital externality compensates for the detrimental 'brain drain' effects and increases the share of high-skilled workers in the sending country, as a result of improving prospects for all individuals left behind. Formally, we allow the share of high-skilled population in the origin country i to be dependent on the share of high-skilled emigrants from the country (following Beine *et al.*, 2008):

$$\widehat{sh_i^P} = sh_i^P \left(\frac{\widehat{sh_i^E}}{sh_i^E} \right)^{\sigma_b}, \tag{A.18}$$

where $sh_i^P = \left(H_i^N + H_i^E\right) / \left(H_i^N + M_i^N + L_i^N + H_i^E + M_i^E + L_i^E\right)$ is the share of high-skilled in the native population of country i, whereas $sh_i^E = \left(H_i^E\right) / \left(H_i^E + M_i^E + L_i^E\right)$, defines the respective share for emigrants from i. The elasticity σ_b describes the strength of the brain gain mechanism. If $\sigma_b = 0$, there is no additional investment in education, whereas if σ_b is positive, the share of high-skilled natives becomes an increasing function in the share of high-skilled emigrants. Variables $\widehat{sh_i^P}$ and $\widehat{sh_i^E}$ indicate respective shares under the counterfactual.

The model assumes a 'brain gain' externality in the sending country. Define $sh_i^P = \left(H_i^N + H_i^E\right) / \left(H_i^N + M_i^N + L_i^N + H_i^E + M_i^E + L_i^E\right)$ and $sh_i^E = H_i^E / \left(H_i^E + M_i^E + L_i^E\right)$, respectively, as the share of high-skilled natives in country i and emigrants from i under the baseline scenario, and $\widehat{sh_i^P}$ and $\widehat{sh_i^E}$ as the equivalent shares under the counterfactual. We compute the new counterfactual share of high-skilled stayers as

$$\widehat{sh_i^P} = \widehat{sh_i^E} = \left(sh_i^P\right)^{\frac{1}{1-\sigma_b}} \left(sh_i^E\right)^{\frac{-\sigma_b}{1-\sigma_b}}, \tag{A.19}$$

which is a consequence of defining the brain gain externality as: $\widehat{sh_i^P} = sh_i^P \left(\widehat{sh_i^E}/sh_i^E\right)^{\sigma_b}$. The

[19] We have also adapted Equation (A.14) to account for skill-specific remitting behavior among emigrants. The results are available upon request.

elasticity σ_b describes the strength of the brain gain mechanism. If $\sigma_b = 0$, there is no additional investment in education, whereas if σ_b is positive, the share of high-skilled stayers becomes an increasing function in the share of high-skilled emigrants.

A.3 Firm's decision

Firms within a country are homogeneous. The manufacturing sector is monopolistically competitive, such that firms have some price-setting power. Each firm produces one variety of a differentiated good. Firms can freely enter the manufacturing sector, but incur a sunk entry cost of f_i^Y and f_i^X units of efficient labor in the respective sector. Sub-sectors Y and X both use identical production technologies.

Each firm k in sector X (the same applies to firms in sector Y) maximizes its profit

$$\max_{p_i(k)} \left(p_i(k) - c_i(k)\right) x_i(k) - f_i^X W_i, \tag{A.20}$$

where $x_i(k)$ is the total demand faced by firm k. This leads to a price which is a constant mark-up over the marginal cost of production,

$$p_i(k) = p_i = \frac{\varepsilon}{\varepsilon - 1} c_i, \tag{A.21}$$

where the $c_i = \frac{W_i}{A_i^M}$ is the marginal cost of production, and W_i is the overall wage index of the manufacturing sector given by Equation (A.11).

A.4 Market clearing conditions

Since all firms earn zero profits, the total wage bill must equal the value added produced in all sectors:

$$\begin{aligned} GDP_i^T &= W_i^L L_i^T = w_i^{LN} L_i^{T,N} + w_i^{LF} L_i^{T,F}, \\ GDP_i^X + GDP_i^Y &= W_i L_i^M = \\ &= w_i^L \left(L_i^N + L_i^F\right) + w_i^{MN} M_i^N + w_i^{MF} M_i^F + w_i^{HN} H_i^N + w_i^{HF} H_i^F. \end{aligned} \tag{A.22}$$

In equilibrium, when demand equals the value of production, the total value-added in the traditional sector equals the expenditures: $GDP_i^T = P_i^T A_i^T L_i^T$. Furthermore, in the tradable and non-tradable manufacturing sectors the value-added equals the aggregated value of production of all N_i^X and N_i^Y firms:

$$\begin{aligned} GDP_i^X &= N_i^X \sum_{j=1}^{J} p_{ji} x_{ji} = N_i^X p_i x_i, \\ GDP_i^Y &= N_i^Y p_i y_i. \end{aligned} \tag{A.23}$$

where x_{ji} is the demand in country j for a product of any firm operating in sector X in country i. For simplicity, we aggregate this quantity into one number, namely the total demand for the products of one firm in country i: $x_i = \sum_{j=1}^{J} \tau_{ji} x_{ji}$. Due to the iceberg trade costs, in order to sell x_{ji} units in country j, the firm from country i has to ship $\tau_{ji} x_{ji}$ units of this good (with $\tau_{ji} \geq 1$).

The aggregation of the values of agents' individual demands gives the level of nominal GDP in country i (equivalent to the sum of all expenditure):

$$GDP_i = GDP_i^T + GDP_i^X + GDP_i^Y = P_i^T T_i + P_i^Y Y_i + P_i^X X_i. \tag{A.24}$$

Consequently, the share of value-added produced in the traditional sector is equal to:

$$sh_i^T \equiv \frac{GDP_i^T}{GDP_i} = \frac{POP_i}{GDP_i}\left(\frac{\beta^T \mu}{1-\beta^T}\frac{P_i}{P_i^T}\right)^{\frac{1}{1-\mu}}, \tag{A.25}$$

where POP_i stands for the number of people living in country i (since every person consumes the same amount of good T).[20] The remainder of GDP is spent on the differentiated good. We provide expressions for the shares of goods X and Y in Appendix A.5. Based on sh_i^Y and sh_i^X, we derive the optimal number of varieties in equilibrium using the zero-profit and free-entry conditions.

A.5 Market size

Each firm produces a single variety of a differentiated good. In equilibrium, firms make zero profits and all goods markets clear. These conditions — together with the optimal pricing rule (A.21) — pin down the optimal number of varieties, N_i^X and N_i^Y. To derive an expression for the optimal number of firms in sub-sectors X and Y, we first derive the shares of value-added in the manufacturing sector, which are given by

$$sh_i^X \equiv \frac{P_i^X X_i}{GDP_i^X + GDP_i^Y} = \beta^\theta \left(\frac{P_i^X}{P_i}\right)^{1-\theta}, \text{ and } sh_i^Y = (1-\beta)^\theta \left(\frac{P_i^Y}{P_i}\right)^{1-\theta}, \tag{A.26}$$

where GDP_i^X and GDP_i^Y are the sums of the wage bills of all workers in the respective sector.[21] Combining Equation (A.26) and the optimal pricing rule (A.21) yields the resource constraints of the economy:

$$sh_i^X A_i^M L_i^M = \frac{\varepsilon}{\varepsilon - 1} N_i^X x_i, \quad sh_i^Y A_i^M L_i^M = \frac{\varepsilon}{\varepsilon - 1} N_i^Y y_i. \tag{A.27}$$

The resource constraints state that the effective labor supply in a given sector (left-hand side) has to equal labor demand by firms in this sector (right-hand side). The zero-profit condition implies that $p_i x_i = \varepsilon W_i f_i^X$ and $p_i y_i = \varepsilon W_i f_i^Y$, which yields the number of units produced by each firm,

$$x_i = A_i^M f_i^X (\varepsilon - 1), \quad y_i = A_i^M f_i^Y (\varepsilon - 1). \tag{A.28}$$

Combining (A.27) and (A.28), we obtain the optimal market size

$$N_i^X = \frac{sh_i^X L_i^M}{\varepsilon f_i^X}, \quad N_i^Y = \frac{sh_i^Y L_i^M}{\varepsilon f_i^Y}, \tag{A.29}$$

which states that the number of firms in sectors X and Y, operating in country i, are proportional to the efficient labor supplies employed in these sectors and inversely proportional to the fixed

[20] Total population has the following structure: $POP_i = L_i^{T,N} + L_i^{T,F} + L_i^N + L_i^F + M_i^N + M_i^F + H_i^N + H_i^F$. The low-skilled natives and foreigners are divided into those who work in the traditional sector and those who are employed in the differentiated good sector. The medium- and high-skilled workers are only employed sectors X and Y.

[21] Note that, by construction, $sh_i^X + sh_i^Y = 1$, following from Equations (A.5) and (A.26).

costs of entry.[22]

A.6 International trade

Varieties of the manufactured good X are traded between countries such that an expansion in market size in one country is passed on to its trading partners. The volume of trade depends on trade costs as well as differences in consumer demand and price levels. Exports from country i to country j, denoted by X_{ji}, are subject to iceberg trade costs $\tau_{ji} > 1$. Trade costs are asymmetric, such that $\tau_{ji} \neq \tau_{ij}$ and influenced by the actual skill composition of respective migration flows. Assume that $\tau_{ji} = \bar{\tau}_{ji} \left(H_{ji}/(L_{ji} + M_{ji} + H_{ji})\right)^{\sigma_t}$, $\sigma_t < 0$, so that trade costs are reduced when the selectivity of migrants improves. X_{ji} is given by

$$X_{ji} = \int_{k \in N_i^X} x_{ji} p_{ji} dk = N_i^X GDP_j^X \left[\frac{P_j^X}{\tau_{ji} p_i} \right]^{\varepsilon - 1}, \tag{A.30}$$

where p_{ji} and x_{ji} are the price and quantity of a variety produced in country i, consumed in country j. Given that $\varepsilon > 1$, trade negatively depends on import prices and trade costs, $\tau_{ji} p_i$, and positively on the domestic price level. The total value-added in sector X in country i is computed as the sum of all trade flows to country i, including domestic consumption X_{ii}, and is given by

$$GDP_i^X = N_i^X \sum_{j=1}^{J} GDP_j^X \left(\frac{P_j^X}{\tau_{ji} p_i} \right)^{\varepsilon - 1}. \tag{A.31}$$

Solving Equation (A.31) for N_i^X and substituting into (A.30), we can express the share of exports as a total share of production in sector X as

$$\frac{X_{ji}}{GDP_i^X} = \frac{GDP_j^X \left(P_j^X / \tau_{ji} \right)^{\varepsilon - 1}}{\sum_{h=1}^{J} GDP_h^X \left(P_h^X / \tau_{hi} \right)^{\varepsilon - 1}}. \tag{A.32}$$

Equation (A.32) can be interpreted as a gravity equation. The share of exports from country i to country j in GDP of country i increases with GDP in the foreign country. This ratio grows when the foreign price level increases and shrinks when bilateral trade costs increase. In equilibrium, the balance of payments condition implies that trade is not balanced within each country, but the equivalence is reached after incorporating remittances:

$$\sum_{j=1}^{J} X_{ij} + \sum_{j=1}^{J} R_{ji} = \sum_{j=1}^{J} X_{ji} + \sum_{j=1}^{J} R_{ij}. \tag{A.33}$$

In Appendix A.7, we provide a detailed definition of the equilibrium.

[22] Thus, the sector-specific barriers to enter production (captured by the fixed cost of entry) are the main driving forces of the market size effect. Calibrating different entry costs for tradable and non-tradable sectors separately allows us to introduce both the selection mechanism in firms' trade choices (represented by uneven market size effects in tradable/non-tradable sectors) as well as changing terms of trade (the movement of relative prices of traded and non-traded bundles of varieties) within a Krugman (1980)-type model. A change in the skill distribution affects the number of varieties produced and consumed in the destination countries, and, therefore, has an indirect impact on the welfare of native citizens.

A.7 Definition of equilibrium

Definition 2 *For a set* $\{\beta, \beta^T, \theta, \mu, \varepsilon, \sigma_s, \sigma_n, \sigma_a, \sigma_t, \sigma_b, \gamma, \}$ *of structural parameters, a set* $\{A_i^T, \bar{A}_i^M, \alpha_i^F, \alpha_i^H, \ \alpha_i^L, L_i^{T,N}, L_i^{T,F}, L_i^N, L_i^F, M_i^N, M_i^F, H_i^N, H_i^F, f_i^X, f_i^Y\}_{\forall i}$ *of exogenous country-specific institutional, demographic and technological characteristics, a set* $\{\bar{\tau}_{ji}\}_{\forall i,j}$ *of bilateral trade cost residuals and a set of bilateral remittances residuals* $\{\eta_{ij}\}_{\forall i,j}$

- *consumption of the three types of goods* $\left\{x_{ij}^s, y_i^s, T_i^s\right\}$ *maximizes an agent's utility (A.1) subject to the budget constraint,*
- *assuming full employment and cost-minimizing behavior of firms, the labor market clearing conditions (A.9) equalize the wage rates to marginal productivities, and determine the nominal wages for all types of workers:* $\{w_i^{LN}, w_i^{LF}, w_i^{MN}, w_i^{MF}, w_i^{HN}, w_i^{HF}\}$
- *the price of one variety,* $p_i(k)$*, maximizes firm's profits given the demand that it faces (A.21),*
- *the price of a unit of traditional good,* P_i^T*, equals the marginal productivity of a low-skilled worker in (A.6),*
- *the number of varieties in sector* X *and* Y*,* N_i^X *and* N_i^Y*, is such that the zero-profit conditions hold in (A.29),*
- *the value-added in sector* X *equals the aggregated value of production in sector* X *in (A.31),*
- *the net trade balance equals the negative value of the balance in remittances as follows from (A.33).*

B Calibration and simulation

B.1 Classification of skill groups

Table B.1 provides some details about the aggregation of skill groups in both datasets.

Table B.1: Classification of skill groups

	DIOC	Barro and Lee (2010)
Low-skilled	No schooling	No schooling
	Some primary education	Some primary education
	Completed primary education	Completed primary education
	Lower secondary education	Non-completed secondary education
Medium-skilled	(Upper) secondary education	Completed secondary education
	Post-secondary non-tertiary education	
High-skilled	First stage of tertiary education	Tertiary education
	Second stage of tertiary education	(Non-completed and completed)

Note: This table details the classification of skill groups in Barro & Lee (2010) and DIOC.

B.2 Imputation of trade flows

To compute the bilateral trade costs, we require a (146×146) matrix of gross trade flows between all countries in the sample (145 countries plus the Rest of the World). The UN Comtrade database provides information to fill 66.5% of all entries of this matrix, whereas the remaining trade flows are missing. Because we require every trade flow to be non-negative for computational purposes, we impute the missing trade flows based on a gravity equation. We first fit the following linear fixed-effect regression on all observed trade flows:

$$\ln(trade)_{od} = \boldsymbol{X'_{od}}\boldsymbol{\Gamma} + \delta_o + \delta_d + \varepsilon_{od}, \tag{B.34}$$

where index o denotes the origin and d the destination of a trade flow. $\boldsymbol{X_{od}}$ is a vector of dyad-specific determinants of trade flows, and includes: a common border dummy, a dummy for a common official language, the log distance between the capital cities, a dummy for a common colonial past. These data are taken from the CEPII Gravity dataset (Mayer *et al.*, 2010, Head & Mayer, 2015). ε_{od} is an i.i.d error term. δ_o and δ_d are origin and destination fixed effects. Based on the fitted values, we then predict the trade flows for all remaining dyads.

B.3 Imputation of missing wage ratios

The two country-specific wage ratios (high-skilled to medium-skilled and medium-skilled to low-skilled) are obtained as follows. For the 34 OECD countries, the wage ratios are provided by the "OECD Education at a Glance" report 2010 (OECD, 2010). The WageIndicator Foundation provides information on 38 additional high-skill to medium-skill and 27 medium-skill to low-skill wage ratios. For the remaining countries, we construct wage ratios as a function of the average return of one additional year of schooling[23] (λ) and the difference in years of schooling (d) between two education levels (k,m)

$$w_i^k / w_i^m = (1 + \lambda_{km})^d, \tag{B.35}$$

using data from Barro & Lee (2010).

B.4 Equilibrium prices and quantities

In this section, we explain how we calibrate the free parameters of the model and compute equilibrium prices and quantities. The calibration of bilateral trade flows depends on goods prices in each country, which are a function of TFP levels and bilateral trade costs. For a given matrix of bilateral trade costs, the combination of the zero-profit condition and the expression of units produced per firm in Equation (A.28) yield the level of country-specific TFP in the manufacturing sector. Based on the TFP level, we can assess the marginal cost of production and recover all prices and price aggregates from Equations (A.5) and (A.21). Combining these with trade costs allows us to assess the value of bilateral trade flows. For this purpose, we use the gravity equation (A.32) to iterate over TFP and trade costs until the trade flows in the model match the trade flows in the data as closely as possible.

The iterative procedure is carried out in two steps. We first define an outer loop in which the trade cost matrix $[\tau_{ji}]_{j,i \in J}$ is determined iteratively, based on the gravity equation (A.32). In each iteration, a new matrix of τ's is computed from the gravity equation. A new general equilibrium is then obtained by iterating on A_i^M (i.e. the inner loop) until the distance between the trade matrix from the data and the trade matrix in the model is minimized. The inner loop

[23] These are assessed based on the countries for which wage ratios and average years of education are available.

takes trade costs as given, and iterates on the TFP in the manufacturing sector, A_i^M, such that the zero-profit conditions are fulfilled for firms in all the countries at the same time (and hence the general equilibrium is guaranteed). The iteration uses the whole vector of country-specific TFP in the manufacturing sector, A_i^M, because profits in country i are dependent on the prices of goods in all other countries (P_i in Equation (A.5) is a weighted sum of prices of all imported goods, and hence depends on the trade costs defined in the previous step of the outer loop). Once we obtained the vector of TFP, we use the trade costs along with the equilibrium conditions (A.27) and (A.28) to compute the vectors of unit prices p_i, and the price indexes, Pi^X and Pi^Y, for both sectors.

To compute the fixed cost of entry for the non-tradable manufacturing sector, we first compute the equilibrium number of varieties produced in sector Y, N_i^Y, given the price level Pi^Y. We then back out the fixed cost f_i^Y from Equation (A.29) to match the number of varieties. The last parameter to be calibrated is the preference towards goods produced in the traditional sector, β^T. Its value of 0.139 is such that we match consumption of the traditional good to its production.

B.5 Simulation algorithm

To simulate the counterfactual scenario, we impose an exogenous shock (on the skill structure of migrants) to the general equilibrium of the system of J economies. We then need to compute new wages, price indices and values of production in all sectors. The first equilibrium to compute is in the market for the traditional good. Equalizing its demand and supply in all countries, we can compute first guesses of the number of people who work in agriculture, and the wage levels of low-skilled workers. Then, taking the first guess on the GDP levels in manufacturing sector, we compute the wage indices (using the system of J zero-profit equations in sectors X and Y). However, we have no information about the shares of GDP^X and GDP^Y in manufacturing (which are driven by peoples' preferences towards different varieties of products and prices). Thus, we make an initial guess of the variable sh^X — on which we iterate — to meet the definitions of price indices and numbers of varieties (Equations (A.5), and (A.29)). Additionally, according to the current value of sh^X, we calculate the price indices, numbers of varieties and GDPs in X and Y. With a new guess for sh^X we return to the outer loop and re-compute the equilibrium wage for the low-skilled workers and GDP^T, using the T market clearing condition.

Having pinned down the nominal wage of low-skilled workers and the values of GDPs in all sectors, we can calculate the exact wage index in the manufacturing sector and the wages of all types of workers (using the system of labor demand equations, (A.9)). Now, unlike in the calibration procedure, the wage premium between high-/medium-skilled and medium-/low-skilled workers is endogenous and determined by the skill composition of the workforce. Having computed the equilibrium wages, we can calculate the new bilateral flows of remittances as well as the updated magnitudes of all the skill-dependent externalities (TFP, trade costs).

Once again, the final step is to compute the endogenously determined trade matrix for the given levels of GDP^X, price indexes and trade costs (taken as given). Using the system of gravity equations (A.32), we are able to determine all the bilateral trade flows across J countries.

C Construction of the population of never-migrants

Figure C.1 provides further intuition for the construction of the population of never-migrants in the sending countries. The population of never-migrants are those residing in the country in both cases, as indicated by the dashed line. For simplicity, in this figure the numbers of high- and low-skilled never-migrants are equal, although this need not be the case in the actual exercise. The figure shows the skill composition of stayers in a migrant sending country in a scenario when over-proportionally many high-skilled workers have left the country (Panel A), and when the skill selection of migrants is neutral (Panel B), such that the number of high-skilled workers at home is higher and the number of low-skilled workers is lower. Welfare per capita would be mechanically higher under the baseline than under the counterfactual. As we show in the paper, isolating the treatment effect from this mechanical composition effect is very important, as the welfare effects are considerably higher per capita than per never-migrant.

D Immigration and wages: further simulations

As discussed in the paper, the skill bias in migration affects workers of different skill levels by altering the relative supply of high- vs. low-skilled workers. The results, shown in Figure 5 reveal that, in the sending countries, high-skilled workers gain from the skill bias in migration, while in the receiving countries low-skilled workers gain. These results differ from those in studies on the labor market effects of migration. The crucial difference is that labor market studies typically measure the impact of more migration, whereas our analysis measures the impact of *different* migration.

To verify the credibility of our model and calibration, we show that our model reproduces the effects found in studies on the labor market effects of immigration, for example Borjas (2003) or Dustmann *et al.* (2013). We exclude all the additional migration-related adjustments that were in our baseline and focus instead on the minimalist scenario. Next we simulate two additional counterfactuals. First, we compare the findings from the minimalist scenario with the distributional impact of turning from a world without migration to the current world with migration. Second, we simulate a change from zero migration to today's levels and skill composition of migration, while at the same time assuming that migrants and natives with the same skills are perfect substitutes and setting the market size effect to zero.

The results are shown in Figure D.2. In the second scenario, which is conceptually close to the framework of analysis in Borjas (2003), we find effects similar to those in well-cited partial equilibrium studies on the labor market effects of immigration, with low-skilled workers facing a wage loss of about 3%.

E The effects of externalities

In Section 5.6, we summarized the sensitivity of our results to changing the parametrization of all the migration-driven mechanisms of our model. In this appendix, we add one externality at a time and vary its parametrization, from the minimalist to the maximalist scenarios, as introduced in Table 3.

Remittances. To measure remittances, we use bilateral data on the volume of remittances from the World Bank (2015). Our model allows remittances to range from a fixed amount of income η_{ij}, when $\gamma = 0$, to a share η_{ij} of wages remitted when $\gamma = 1$. Intermediate values of γ imply a positive elasticity of remittances with respect to wages and thus allow to account for intermediate scenarios between constant amount and constant wage share for the remittances sent from country j to country i.

Figure E.3 displays the welfare effects under different assumptions about the propensity to remit. We start from a scenario in which $\gamma = 0$ so each immigrant remits the same amount. We label this as minimalist scenario as in this case skill-biased migration will not change the amount

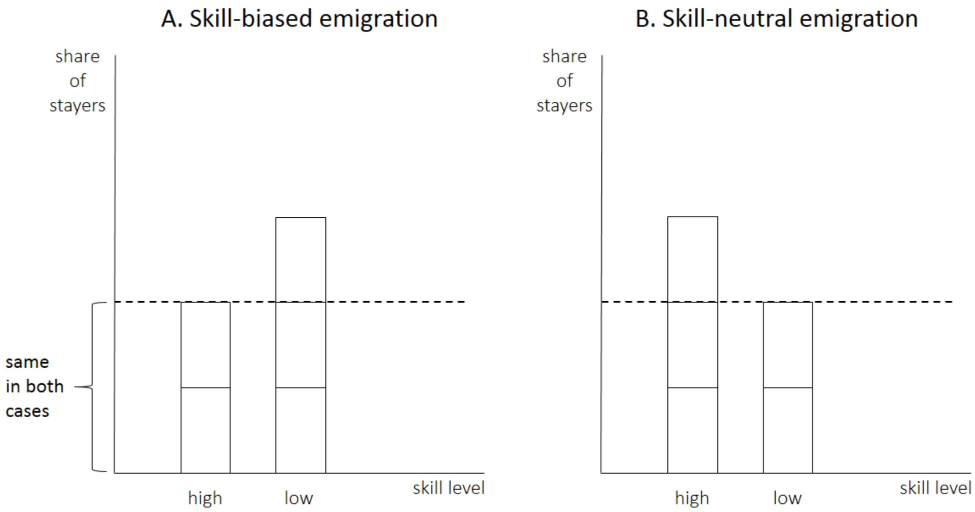


Figure C.1: Skill distribution of stayers under the baseline and counterfactual.
Note: See text for explanation. This figure shows the skill composition of stayers in a migrant sending country in a scenario when over-proportionally many high-skilled workers have left the country (Panel A), and when the skill selection of migrants is neutral (Panel B), such that the number of high-skilled workers at home is higher and the number of low-skilled workers is lower. The population of never-migrants is those residing in the country in both cases, as indicated by the dashed line. For simplicity, in this figure the numbers of high- and low-skilled never-migrants are equal, although this need not be the case in the actual exercise.

of remittances sent. We then include our baseline scenario with $\gamma = 0.5$ and finally a maximalist scenario in which the amount remitted is a constant fraction of the wage ($\gamma = 1$). In these latter two cases, the amount of remittances sent will less than proportionally and proportionally change with skill-biased migration, as the income received by the migrants will be higher in the current world than in the one with skill neutrality.

As we discussed in Table 2, remittances play a limited role compared to other migration mechanisms. Losses in sending countries decrease as the elasticity of remittances to income increases (i.e. the more remittances are proportional to income). However, the effects are small overall and the results are robust to different parametrization of this particular adjustment.

Human capital externalities in TFP. A further human capital externality in our model works through total factor productivity (TFP). Here we vary the parameter σ_a from zero (minimalist) to 0.2 (maximalist).

As shown in Figure E.4, the welfare effects of skill-biased migration are larger at high levels of σ_a. The overall effect on world welfare is of similar size as the effect without the externality, whereas the gap between OECD and non-OECD countries is larger.[24] These results suggest that our baseline simulation results presented in Figure 2 represent an intermediate scenario.

[24] A further — negative — externality through which migration affects TFP in the receiving countries is institutions. As highlighted by Collier (2013) and Borjas (2015), migrants from countries with poor institutions may import these institutions in the receiving country. However, recent work by Clemens & Pritchett (2016) suggests that large negative effects only unfold under fairly extreme conditions. Moreover, in the receiving countries, the diversity of high-skilled migrants could have an additional effect on TFP. Alesina *et al.* (2016) find an inverse U-shaped relationship between birthplace diversity and GDP per capita.

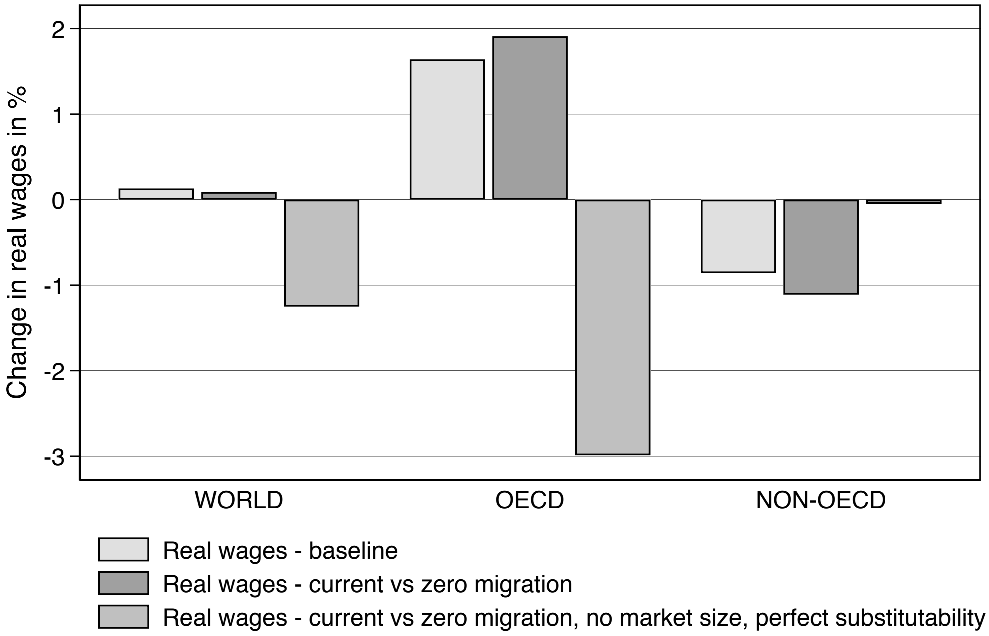


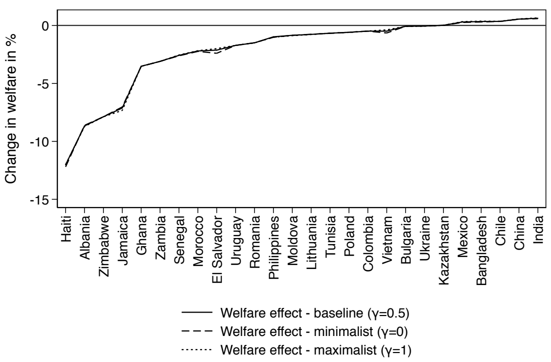
Figure D.2: Changes in real wages of low-skilled never-migrants, different scenarios

Source: Own calculations.
Notes: This graph displays the impact of migration on the real wages of low-skilled workers. Results are reported for three different scenarios: the minimalist scenario, a minimalist scenario of current vs zero migration, a minimalist scenario of current vs zero migration without market size effects and with perfect substitutability between migrants and never-migrants. The vertical axis shows changes in real wages, in percent.

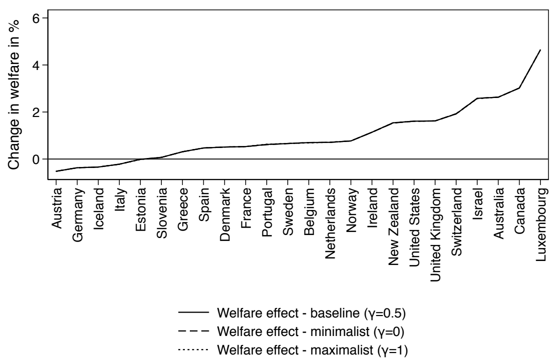
Network effects in trade. To assess the importance of skill-biased migration for trade, we simulate two additional scenarios: one in which σ_t is set to zero and one in which it equals -0.05. The results are shown in Figure E.5. The extent of network externalities has virtually no effect on the sending countries, but it affects the size of the welfare effects in the receiving countries. A higher elasticity means that high-skilled immigration leads to stronger reductions in trade costs. The higher this elasticity is in absolute value, the larger are the welfare effects in the OECD.

Down-skilling of immigrants. As a further sensitivity check, we account for the skill depreciation of migrants in the receiving country. It is common that immigrants — especially those from developing countries — work in jobs for which they are formally over-qualified (Mattoo *et al.*, 2008). This qualification mismatch might imply that we over-estimate the welfare effects of skill-biased migration in the receiving countries, because replacing a high-skilled with a low-skilled worker may not lead to a change in productivity if both were working in low-skilled jobs to begin with.

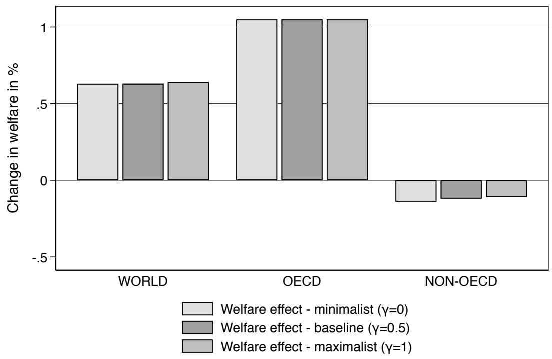
To account for the skill depreciation of immigrants, we compute origin-country-specific down-skilling rates, which measure — for example — the likelihood that a high-skilled Senegalese migrant works in France in a job in which most French workers are low-skilled. Across all sending countries, 29% of all high-skilled emigrants are working in the OECD in medium-skilled occupations, 10% in low-skilled occupations and 24% of all medium-skilled emigrants are working



(a) In the sending countries



(b) In the receiving countries



(c) In OECD and non-OECD countries, and in the world

Figure E.3: Sensitivity check: remittances

Source: Own calculations.

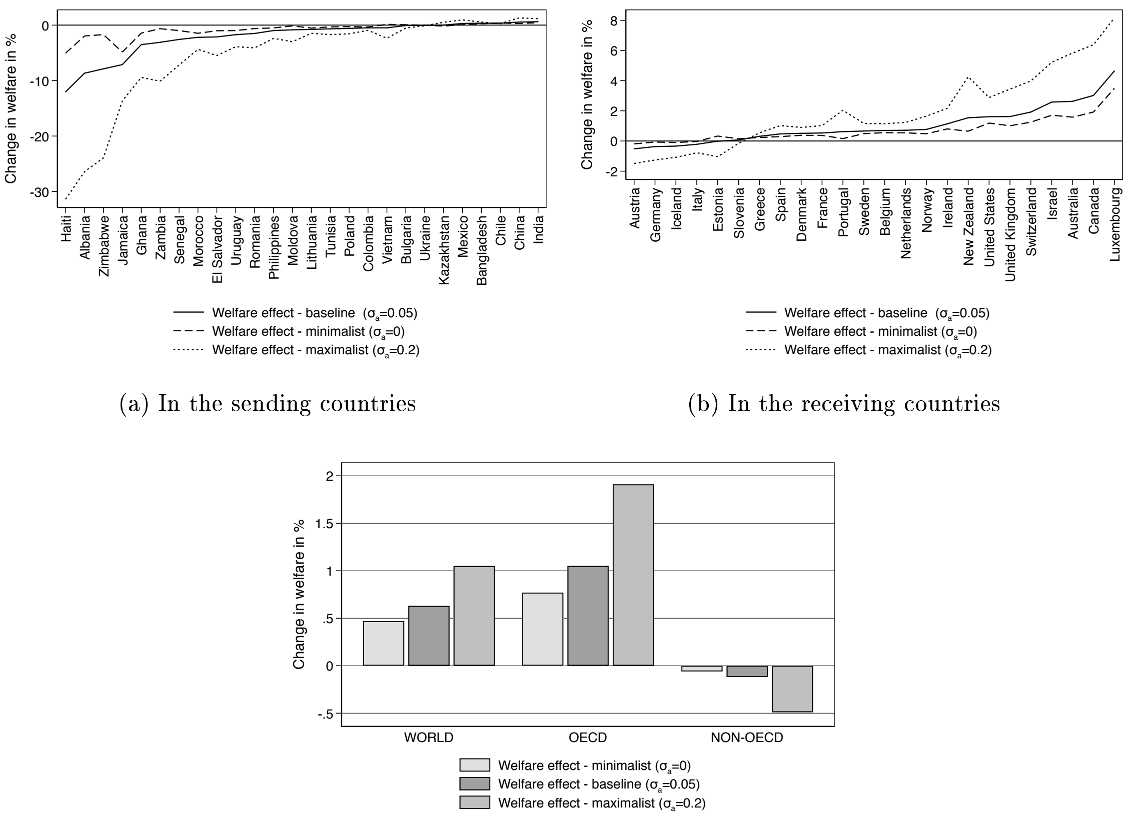
Notes: This graph displays the impact of the skill bias in migration for varying elasticities to remit. The solid line represents the effect on welfare per never-migrant under the baseline. The dashed lines represent the effects under the polar cases in which every migrant remits a fixed amount ($\gamma = 0$) or a fixed share of income ($\gamma = 1$).

in low-skilled jobs.

To compute the down-skilling rates for a given sending country, we use the OECD-DIOC data, which has information on the skill requirement for occupations at the ISCO one-digit level, as well as the skill distribution of immigrants within each occupation by sending country. For instance, we know how many high-skilled Senegalese are working in low-skilled occupations in France, Canada, the UK and all other OECD countries. Based on this information, we can compute the three down-skilling rates for every country pair, for example, $d^H_{M,ij}$. To compute the sending-country-specific down-skilling rates, we compute a weighted average over all receiving countries (index d),

$$d^H_{M,i} = \sum_j \left(\frac{H^{emig}_{ij}}{H^{emig}_i} \right) d^H_{M,ij},$$

with the weights $\frac{H^{emig}_{ij}}{H^{emig}_i}$ being the share of high-skilled emigrants in receiving country j among all high-skilled emigrants from sending country i. The remaining down-skilling rates are computed



(a) In the sending countries

(b) In the receiving countries

(c) In OECD and non-OECD countries, and in the world

Figure E.4: Sensitivity check: TFP externality

Source:. Own calculations.

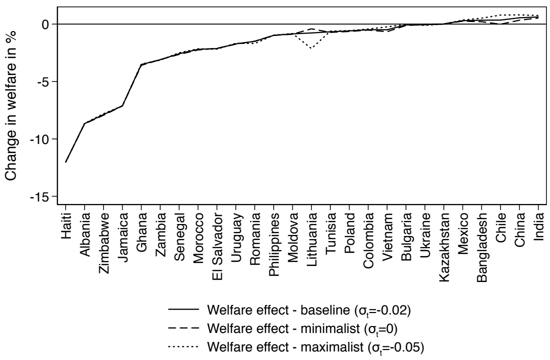
Notes: This graph displays the welfare effects of the skill bias in migration with a varying Lucas-type externality on TFP. The solid line represents the effect on welfare per never-migrant under the baseline. The dashed lines represent the effect on welfare per never-migrant without this externality ($\sigma_a = 0$) and with a strong externality ($\sigma_a = 0.2$).

analogously.

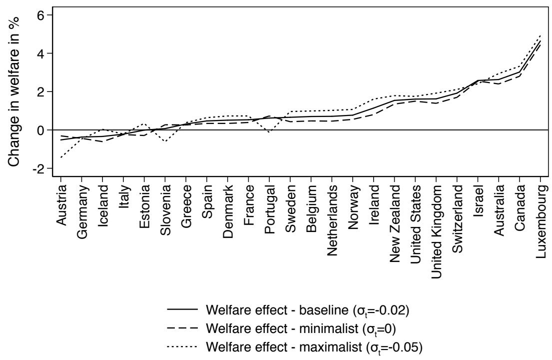
As shown in Figure E.6, down-skilling reduces the welfare effects of skill-biased migration in the receiving countries, while leaving the effect in the sending countries roughly unchanged. The global effect is smaller but remains positive at around 0.33%.

Brain gain - investment in education. Also in this case we present three scenarios, where we vary the brain gain elasticity σ_b from zero (minimalist) to 0.096 (maximalist).

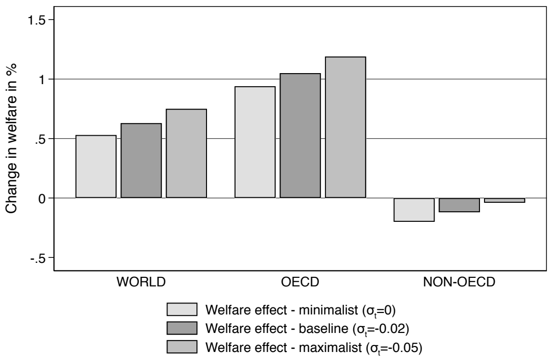
The simulation results are displayed in Figure E.7. The brain gain channel dampens substantially the welfare losses from skill-biased migration in the sending countries, even leading to an overall welfare gain. The receiving countries are only mildly affected due to general equilibrium effects. In the maximalist scenario, with a brain gain elasticity of $\sigma_b = 0.096$, the impact of the skill bias in migration on world welfare is twice as large as without a brain gain mechanism. However, one should be cautious when interpreting the difference in results with and without brain gain because they do not represent marginal effects. In some countries, the share of high-skilled emigrants under the baseline is a multiple of the share of high-skilled emigrants under



(a) In the sending countries



(b) In the receiving countries



(c) In OECD and non-OECD countries, and in the world

Figure E.5: Sensitivity check: networks in trade

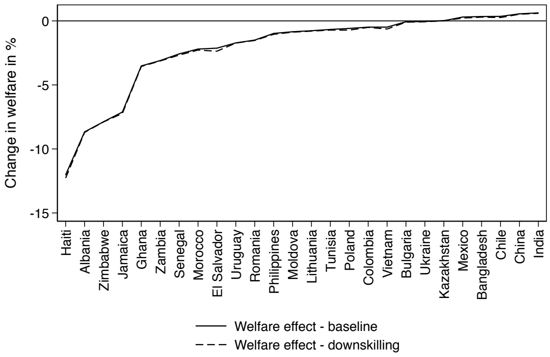
Source:. Own calculations.

Notes: This graph displays the welfare effects of the skill bias in migration with varying strength of network effects of migration on trade. The solid line represents the effect on welfare per never-migrant under the baseline ($\sigma_t = -0.02$). The dashed lines represents the effect on welfare per never-migrant when network effects are excluded ($\sigma_t = 0$) and when they are strong ($\sigma_t = -0.05$). The countries on the horizontal axis are ordered by welfare impact per never-migrant.

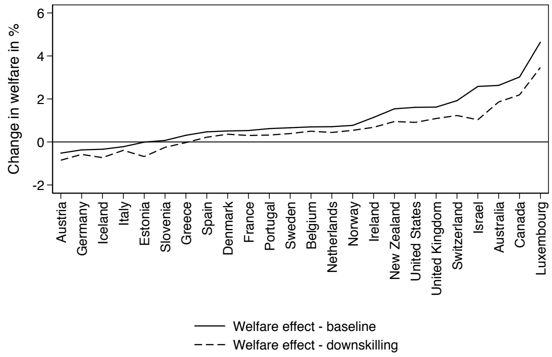
the counterfactual. Thus, an elasticity of $\sigma_b = 0.096$ is probably too high to account for these substantial differences in high-skilled emigration rates. However, even at a smaller brain gain elasticity of $\sigma_b = 0.048$, the welfare losses in the sending countries are considerably lower than in a world without brain gain.

F Sensitivity checks

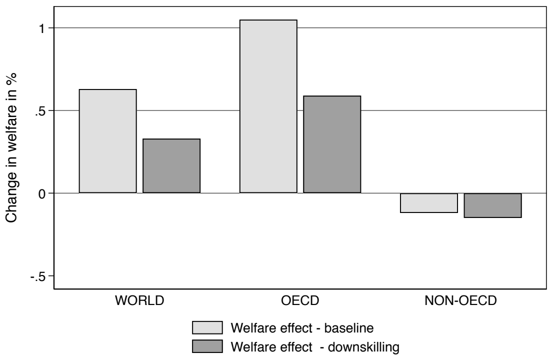
In this section we report sensitivity checks of: i) the benchmark model to changes in structural parameters, and ii) the benchmark model with a more finely nested three-level CES production function. Table F.2 summarizes the parameter values used in the sensitivity checks.



(a) In the sending countries



(b) In the receiving countries



(c) In OECD and non-OECD countries, and in the world

Figure E.6: Allowing for down-skilling in the receiving country

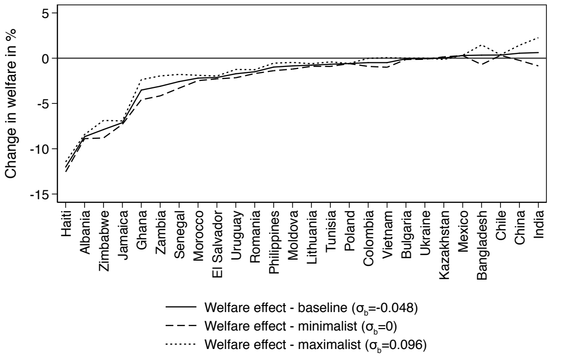
Source:. Own calculations.

Notes: This graph displays the average welfare effects of the skill bias in migration with down-skilling of migrants. The solid line represents the effect on welfare per never-migrant under the baseline. The dashed lines represent the effect on welfare per never-migrant with downskilling.

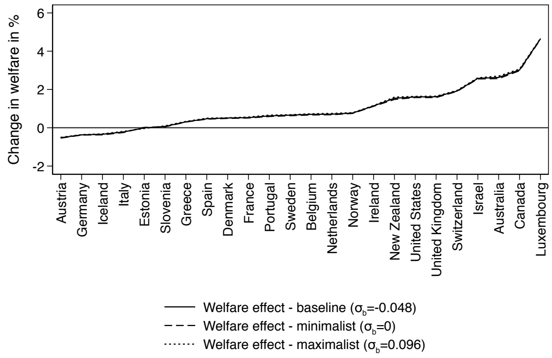
Table F.2: Sensitivity checks to structural parameters

Parameters	Minimalist	Baseline	Maximalist
ε	5	4	3
θ	0.5	3	3.9
σ_s	2	5	8
σ_n	100	20	10
μ	0.1	0.5	0.6
β	0.1	0.5	0.9
f_x	-	$f_x \times 1$	$f_x \times 10$

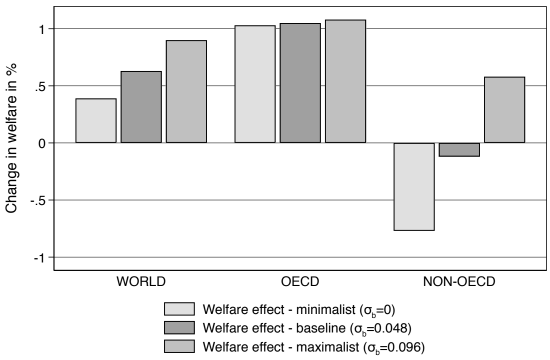
Note: This table summarizes the calibration of the structural parameters in the sensitivity checks reported in Section F.1.



(a) In the sending countries



(b) In the receiving countries



(c) In OECD and non-OECD countries, and in the world

Figure E.7: Sensitivity check: brain gain mechanism

Source:. Own calculations.

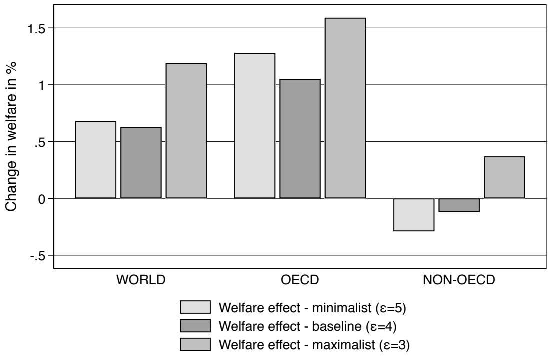
Notes: This graph displays the welfare effects of the skill bias in migration with varying endogenous investment in education in the sending countries (brain gain). The solid line represents the effect on welfare per never-migrant under the baseline. The dashed lines represent the effect on welfare per never-migrant without a brain gain mechanism ($\sigma_b = 0$) and a strong brain gain mechanism ($\sigma_b = 0.096$).

F.1 Sensitivity of the benchmark model to structural parameters

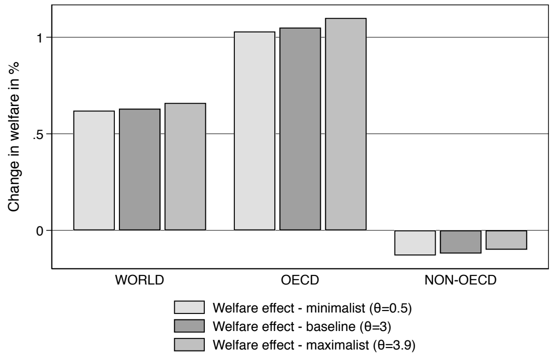
In Figure F.7 panels (a)-(g), we perform a series of sensitivity checks with respect to the structural parameters. Overall, the results are both quantitatively and qualitatively robust to changes in parameters, although some parameters have a greater influence than others. The details are as follows:

- In panel (a), we vary the elasticity of substitution between varieties of X and Y. A higher elasticity of substitution translates into a more pronounced market size effect, which leads to higher gains in the receiving and higher losses in the sending countries.
- In panel (b), we vary the elasticity of substitution between tradable and non-tradable goods. The results are very similar to the baseline results. A higher elasticity of substitution leads to a greater response in trade flows, and dampens the overall effect.

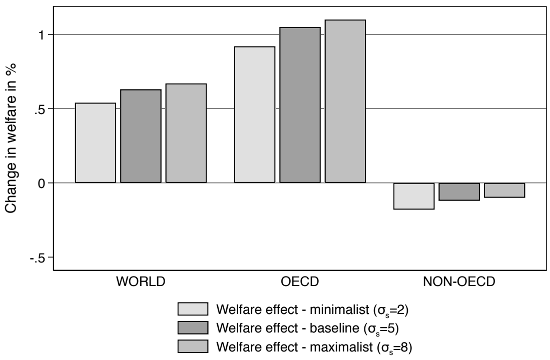
- In panel (c), we vary the elasticity of substitution between different education levels, σ_s. A low substitutability between high- and low-skilled workers has a particularly strong impact on the sending countries, because it becomes more difficult for low-skilled workers to replace high-skilled emigrants.
- In panel (d), we vary the elasticity of substitution between migrants and natives, σ_n. In the sending countries, this parameter only affects the overall welfare effect through trade, but the results hardly respond to changes in σ_n. In the receiving countries, the effects are larger when migrants and natives are closer substitutes.
- In panel (e), we vary the preference parameter for the output from the traditional sector, μ. If this parameter is very low, the effects are smaller because a given change in consumption of T has a smaller impact on utility.
- In panel (f), when we vary β, the relative preference for the tradable manufactured good, it turns out that the largest effect in the sending countries occurs if both goods receive equal weight, and the increase in market size is spread across both sectors, X and Y. In the receiving countries, the welfare effect is almost unaffected by changes in β.
- In panel (g), we increase the fixed costs of entry by multiplying the original fixed costs with a factor 10. The effects in the sending countries are stronger, because even fewer varieties are produced in the baseline compared to the counterfactual.



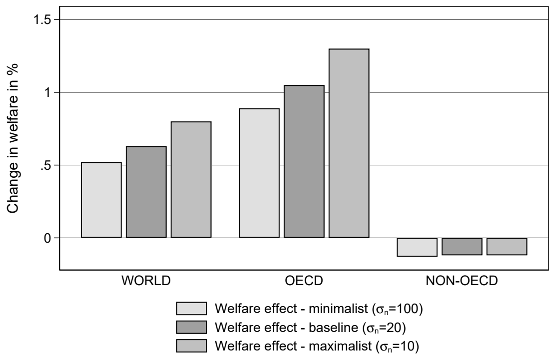
(a) Varying ε



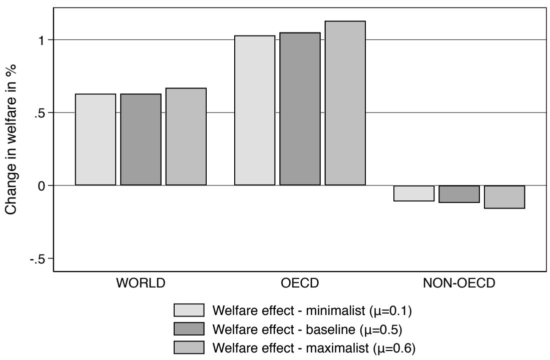
(b) Varying θ



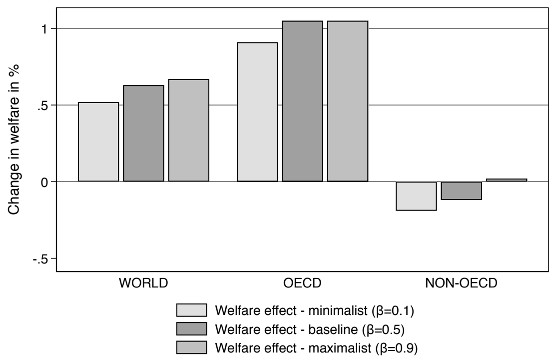
(c) Varying σ_s



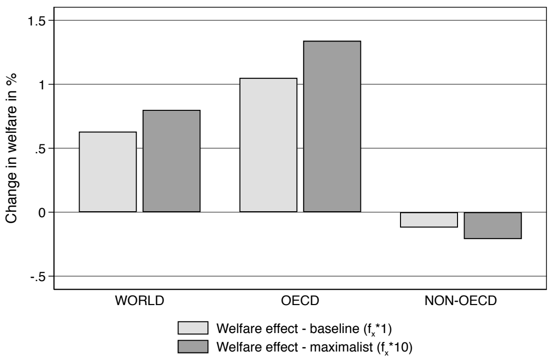
(d) Varying σ_n



(e) Varying μ



(f) Varying β



(g) Varying f_x

Figure F.7: Sensitivity Checks

Source:. Own calculations.

Notes: The figure displays the results from sensitivity checks in which we vary the values of preference and technology parameters. See text for details.

F.2 Sensitivity checks to different nesting of the CES

To further check the sensitivity of our model, we model production using the nested CES structure for the labor-composite suggested by Ottaviano & Peri (2012). L_i, M_i and H_i represent the supplies of low-, medium- and high-skilled workers in the manufacturing sector. The parameter α_i^a indicates the efficiency of the low-skill labor composite in production. The low-skill labor-composite consists of less-educated and medium-educated workers

$$Q_i^{M,l} = \left[\alpha_i^b \left(L_i\right)^{\frac{\sigma_2-1}{\sigma_2}} + (1-\alpha_i^b)\left(M_i\right)^{\frac{\sigma_2-1}{\sigma_2}}\right]^{\frac{\sigma_2}{\sigma_2-1}}, \tag{F.36}$$

where α_i^b is the efficiency of the less-educated workers. Each skill-group (L_i, M_i and H_i) consists of natives (labeled by superscripts N) and foreigners (with superscripts F). All domestic and foreign workers are assumed to be imperfect substitutes with a constant elasticity of substitution equal to σ_3. We define the efficient labor supplies for each sector and education group as

$$\begin{aligned}
L_i^T &= \left[(1-\alpha_i^c)(L_i^{T,N})^{\frac{\sigma_3-1}{\sigma_3}} + \alpha_i^c(L_i^{T,F})^{\frac{\sigma_3-1}{\sigma_3}}\right]^{\frac{\sigma_3}{\sigma_3-1}}, \\
L_i &= \left[(1-\alpha_i^c)(L_i^{N})^{\frac{\sigma_3-1}{\sigma_3}} + \alpha_i^c(L_i^{F})^{\frac{\sigma_3-1}{\sigma_3}}\right]^{\frac{\sigma_3}{\sigma_3-1}}, \\
M_i &= \left[(1-\alpha_i^c)(M_i^{N})^{\frac{\sigma_3-1}{\sigma_3}} + \alpha_i^c(M_i^{F})^{\frac{\sigma_3-1}{\sigma_3}}\right]^{\frac{\sigma_3}{\sigma_3-1}}, \\
H_i &= \left[(1-\alpha_i^c)(H_i^{N})^{\frac{\sigma_3-1}{\sigma_3}} + \alpha_i^c(H_i^{F})^{\frac{\sigma_3-1}{\sigma_3}}\right]^{\frac{\sigma_3}{\sigma_3-1}}.
\end{aligned} \tag{F.37}$$

We assume a fixed, country-specific share of outputs of natives and foreigners ($(1-\alpha_i^c)$ and α_i^c respectively).

Firms solve their cost-minimization problem, taking wages as given. Demand for each type of labor is then set as

$$\begin{aligned}
L_i^N &= \frac{Z_i^M}{A_i^M}\left[\frac{(1-\alpha_i^c)W_i^L}{w_i^{LN}}\right]^{\sigma_3}\left[\frac{\alpha_i^b W_i^c}{W_i^L}\right]^{\sigma_2}\left[\frac{\alpha_i^a W_i}{W_i^c}\right]^{\sigma_1}, & L_i^{T,N} &= \frac{Z_i^T}{A_i^T}\left[\frac{(1-\alpha_i^c)W_i^L}{w_i^{LN}}\right]^{\sigma_3}, \\
L_i^F &= \frac{Z_i^M}{A_i^M}\left[\frac{\alpha_i^c W_i^L}{w_i^{LF}}\right]^{\sigma_3}\left[\frac{\alpha_i^b W_i^c}{W_i^L}\right]^{\sigma_2}\left[\frac{\alpha_i^a W_i}{W_i^c}\right]^{\sigma_1}, & L_i^{T,F} &= \frac{Z_i^T}{A_i^T}\left[\frac{\alpha_i^c W_i^L}{w_i^{LF}}\right]^{\sigma_3}, \\
M_i^N &= \frac{Z_i^M}{A_i^M}\left[\frac{(1-\alpha_i^c)W_i^M}{w_i^{MN}}\right]^{\sigma_3}\left[\frac{(1-\alpha_i^b)W_i^c}{W_i^M}\right]^{\sigma_2}\left[\frac{\alpha_i^a W_i}{W_i^c}\right]^{\sigma_1}, & H_i^N &= \frac{Z_i^M}{A_i^M}\left[\frac{(1-\alpha_i^c)W_i^H}{w_i^{HN}}\right]^{\sigma_3}\left[\frac{(1-\alpha_i^a)W_i}{W_i^H}\right]^{\sigma_1}, \\
M_i^F &= \frac{Z_i^M}{A_i^M}\left[\frac{\alpha_i^c W_i^M}{w_i^{MF}}\right]^{\sigma_3}\left[\frac{(1-\alpha_i^b)W_i^c}{W_i^M}\right]^{\sigma_2}\left[\frac{\alpha_i^a W_i}{W_i^c}\right]^{\sigma_1}, & H_i^F &= \frac{Z_i^M}{A_i^M}\left[\frac{\alpha_i^c W_i^H}{w_i^{HF}}\right]^{\sigma_3}\left[\frac{(1-\alpha_i^a)W_i}{W_i^H}\right]^{\sigma_1},
\end{aligned} \tag{F.38}$$

where the wage indices for the medium- and high-skilled workers are equal to:

$$\begin{aligned}
W_i^L &= \left[(1-\alpha_i^c)^{\sigma_3}(w_i^{LN})^{1-\sigma_3} + (\alpha_i^c)^{\sigma_3}(w_i^{LF})^{1-\sigma_3}\right]^{\frac{1}{1-\sigma_3}}, \\
W_i^M &= \left[(1-\alpha_i^c)^{\sigma_3}(w_i^{MN})^{1-\sigma_3} + (\alpha_i^c)^{\sigma_3}(w_i^{MF})^{1-\sigma_3}\right]^{\frac{1}{1-\sigma_3}}, \\
W_i^H &= \left[(1-\alpha_i^c)^{\sigma_3}(w_i^{HN})^{1-\sigma_3} + (\alpha_i^c)^{\sigma_3}(w_i^{HF})^{1-\sigma_3}\right]^{\frac{1}{1-\sigma_3}},
\end{aligned} \tag{F.39}$$

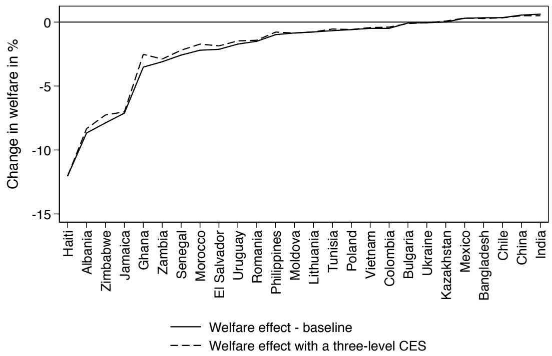
the wage index of the less- and medium-educated workers is given by:

$$W_i^c = \left[(\alpha_i^b)^{\sigma_2}(W_i^L)^{1-\sigma_2} + (1-\alpha_i^b)^{\sigma_2}(W_i^M)^{1-\sigma_2}\right]^{\frac{1}{1-\sigma_2}}, \tag{F.40}$$

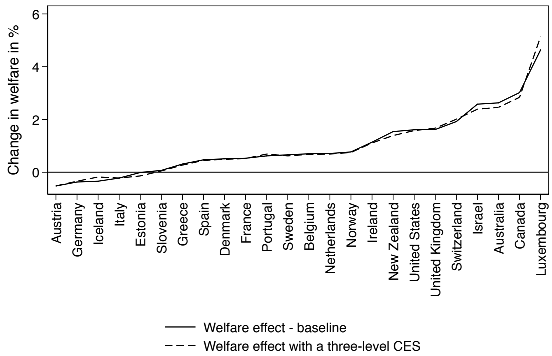
and the overall wage index in the manufacturing sector is given by:

$$W_i = \left[(\alpha_i^a)^{\sigma_1}(W_i^c)^{1-\sigma_1} + (1-\alpha_i^a)^{\sigma_1}(W_i^H)^{1-\sigma_1}\right]^{\frac{1}{1-\sigma_1}}. \tag{F.41}$$

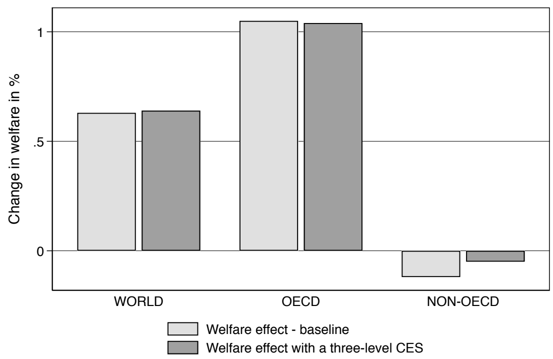
Following Ottaviano & Peri (2012) we set $\sigma_1 = 2, \sigma_2 = 30, \sigma_3 = 20$. Results using this different production function are shown in Figure F.8. The consequences are very minimal and, if anything, our baseline results are slightly more conservative: global welfare gains are 0.64% with a three-level CES vs 0.63% in our baseline.



(a) In the sending countries



(b) In the receiving countries



(c) In OECD and non-OECD countries, and in the world

Figure F.8: Changing nesting in the CES production function

Source:. Own calculations.

Notes: This graph displays the welfare effects of the skill bias in migration with a nested CES production function. We set $\sigma_1 = 2, \sigma_2 = 30, \sigma_3 = 20$. The solid line represents the effect on welfare per never-migrant under the baseline. The dashed lines represent the effect on welfare per never-migrant with a nested CES production function. The countries on the horizontal axis are ordered by welfare impact per never-migrant. The vertical axis shows changes in welfare per never-migrant in percent. Panel (a) focuses on selected sending countries, while panel (b) focuses on selected receiving countries. Panel (c) shows the average effect in all non-OECD and OECD countries as well as across the whole world.

G List of abbreviations and full baseline results

Table G.3: List of Country Abbreviations and Baseline Results

Abbreviation	Country	Welfare per capita	Welfare per never-migrant
	Overall Average Effects		
WORLD	WORLD average	1.82	0.63
OECD	OECD average	2.94	1.05
NON-OECD	NON-OECD average	-0.46	-0.12
	OECD countries		
AUS	Australia	6.19%	2.63%
AUT	Austria	-0.52%	-0.52%
BEL	Belgium	0.85%	0.70%
CAN	Canada	7.94%	3.02%
CHE	Switzerland	5.76%	1.92%
CHL	Chile	0.29%	0.35%
CZE	Czech Republic	-0.47%	-0.09%
DEU	Germany	-0.85%	-0.37%
DNK	Denmark	0.80%	0.51%
ESP	Spain	0.83%	0.47%
EST	Estonia	-0.46%	-0.01%
FIN	Finland	0.04%	0.09%
FRA	France	1.06%	0.53%
GBR	United Kingdom	3.45%	1.62%
GRC	Greece	0.64%	0.31%
HUN	Hungary	-0.27%	0.07%
IRL	Ireland	1.89%	1.14%
ISL	Iceland	-1.12%	-0.34%
ISR	Israel	6.91%	2.58%
ITA	Italy	-0.41%	-0.22%
JPN	Japan	0.28%	0.22%
KOR	Korea, Rep.	-0.40%	-0.09%
LUX	Luxembourg	7.55%	4.64%
MEX	Mexico	0.25%	0.30%
NLD	Netherlands	1.40%	0.71%
NOR	Norway	1.28%	0.77%
NZL	New Zealand	2.62%	1.54%
POL	Poland	-1.54%	-0.59%
PRT	Portugal	1.31%	0.62%
SVK	Slovak Republic	-2.00%	-0.91%
SVN	Slovenia	0.46%	0.07%
SWE	Sweden	1.22%	0.66%
TUR	Turkey	0.05%	0.11%
USA	United States	4.68%	1.61%
	NON-OECD countries		

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Table G.3 – continued from previous page

Abbreviation	Country	Welfare per capita	Welfare per never-migrant
AFG	Afghanistan	-1.21%	-0.64%
ALB	Albania	-9.90%	-8.67%
ARE	United Arab Emirates	1.02%	0.46%
ARG	Argentina	-1.52%	-0.61%
ARM	Armenia	-2.75%	-1.03%
BDI	Burundi	-4.55%	-3.76%
BEN	Benin	-0.47%	-0.31%
BGD	Bangladesh	0.38%	0.34%
BGR	Bulgaria	-0.11%	-0.07%
BHR	Bahrain	-1.54%	-0.58%
BLZ	Belize	-17.48%	-9.81%
BOL	Bolivia	-0.80%	-0.25%
BRA	Brazil	0.67%	0.32%
BRB	Barbados	-24.09%	-16.78%
BRN	Brunei Darussalam	-3.03%	-1.61%
BWA	Botswana	-0.30%	-0.06%
CAF	Central African Republic	-3.46%	-2.66%
CHN	China	0.61%	0.55%
CIV	Cote d'Ivoire	-1.33%	-0.55%
CMR	Cameroon	-5.46%	-3.36%
COD	Democratic Republic of the Congo	-3.66%	-2.79%
COG	Congo	-4.16%	-2.34%
COL	Colombia	-1.43%	-0.49%
CRI	Costa Rica	-0.78%	-0.24%
CUB	Cuba	-7.95%	-3.35%
CYP	Cyprus	-0.54%	-0.23%
DOM	Dominican Republic	-4.83%	-1.97%
DZA	Algeria	-3.47%	-1.25%
ECU	Ecuador	-3.26%	-1.18%
EGY	Egypt	-0.04%	0.07%
FJI	Fiji	-7.66%	-4.60%
GAB	Gabon	-2.80%	-1.02%
GHA	Ghana	-5.07%	-3.52%
GMB	Gambia, The	-6.13%	-3.67%
GTM	Guatemala	-21.39%	-20.36%
GUY	Guyana	-25.80%	-23.58%
HKG	Hong Kong SAR, China	-4.15%	-1.79%
HND	Honduras	-8.18%	-2.92%
HRV	Croatia	0.80%	0.21%
HTI	Haiti	-17.38%	-12.02%
IDN	Indonesia	0.91%	0.70%
IND	India	1.18%	0.62%
IRN	Iran	-1.16%	-0.46%

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Table G.3 – continued from previous page

Abbreviation	Country	Welfare per capita	Welfare per never-migrant
IRQ	Iraq	-1.97%	-0.78%
JAM	Jamaica	-16.82%	-7.12%
JOR	Jordan	-1.07%	-0.08%
KAZ	Kazakhstan	-0.28%	0.01%
KEN	Kenya	-3.84%	-1.78%
KGZ	Kyrgyz Republic	3.71%	3.06%
KHM	Cambodia	-3.52%	-2.79%
KWT	Kuwait	-3.43%	-1.49%
LAO	Lao PDR	-5.61%	-4.41%
LBR	Liberia	-10.73%	-6.52%
LBY	Libya	-0.45%	-0.08%
LKA	Sri Lanka	-2.67%	-1.09%
LSO	Lesotho	0.51%	0.37%
LTU	Lithuania	-1.41%	-0.77%
LVA	Latvia	-3.09%	-1.19%
MAC	Macao SAR, China	111.69%	95.01%
MAR	Morocco	-5.20%	-2.20%
MDA	Moldova	-2.76%	-0.85%
MDV	Maldives	-0.52%	-0.32%
MLI	Mali	-1.36%	-0.99%
MLT	Malta	-9.11%	-2.92%
MMR	Myanmar	1.11%	0.89%
MNG	Mongolia	4.02%	3.89%
MOZ	Mozambique	-4.89%	-4.21%
MRT	Mauritania	-1.65%	-0.93%
MUS	Mauritius	-13.36%	-7.21%
MWI	Malawi	-3.73%	-3.32%
MYS	Malaysia	-0.26%	0.00%
NAM	Namibia	-1.68%	-0.97%
NER	Niger	0.86%	0.83%
NIC	Nicaragua	-8.09%	-3.35%
NPL	Nepal	-1.37%	-0.75%
PAK	Pakistan	-1.21%	-0.58%
PAN	Panama	-3.84%	-1.27%
PER	Peru	-1.53%	-0.49%
PHL	Philippines	-1.98%	-0.98%
PNG	Papua New Guinea	-2.84%	-2.48%
PRY	Paraguay	-0.60%	-0.17%
QAT	Qatar	0.67%	0.36%
ROU	Romania	-2.87%	-1.50%
RUS	Russian Federation	-0.29%	-0.12%
RWA	Rwanda	-3.07%	-2.30%
SAU	Saudi Arabia	1.17%	0.66%

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Table G.3 – continued from previous page

Abbreviation	Country	Welfare per capita	Welfare per never-migrant
SDN	Sudan	-0.07%	-0.01%
SEN	Senegal	-4.66%	-2.58%
SGP	Singapore	-0.43%	-0.05%
SLE	Sierra Leone	-14.76%	-11.77%
SLV	El Salvador	-4.49%	-2.13%
SRB	Serbia	0.17%	0.07%
SWZ	Swaziland	-3.40%	-2.44%
SYR	Syrian Arab Republic	-1.75%	-1.08%
TGO	Togo	-0.30%	0.26%
THA	Thailand	0.21%	0.16%
TJK	Tajikistan	4.14%	3.56%
TON	Tonga	-5.94%	-4.36%
TTO	Trinidad and Tobago	-17.20%	-7.89%
TUN	Tunisia	-2.48%	-0.67%
TWN	Taiwan	-0.55%	-0.24%
TZA	Tanzania	-3.03%	-2.43%
UGA	Uganda	-1.95%	-1.21%
UKR	Ukraine	-0.08%	-0.05%
URY	Uruguay	-3.98%	-1.72%
VEN	Venezuela	-1.44%	-0.58%
VNM	Vietnam	-1.16%	-0.49%
YEM	Yemen	-0.08%	0.05%
ZAF	South Africa	-3.88%	-1.67%
ZMB	Zambia	-4.22%	-3.10%
ZWE	Zimbabwe	-9.82%	-7.88%
ROW	Rest of World	-1.55%	-0.72%