Migrants, Trade and Market Access*

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Abstract

Migrants shape market access: first, they change the geographical location of demand and second, they reduce trade frictions. This paper shows that both effects are quantitatively relevant. It estimates the sensitivity of exports to immigrant population and uses a model of inter- and intra-national trade and migration calibrated to US states to conduct quantitative exercises. Reducing US migrant population share back to 1980s levels increases export trade costs by 3.2% on average and decreases welfare of US natives by 0.13%. The small aggregate effect of this nationwide policy masks large heterogeneities across US states, with real wage changes ranging from -0.44% to 0.20%. States with higher exposure to international immigrants demand (both from within the state and from other states) than to international migrant labor supply competition suffer more from the removal of migrants. States with higher export exposure suffer more from the increased trade costs.

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1 Introduction

Both migration and international trade have come to the fore of political discussions over the last few years. In this context, understanding migration’s effects on trade is important. Immigrants affect both the local supply of labor, and the demand for output produced by a geographic unit. The majority of research on the impact of immigration on natives has focused on understanding the wage impact of the migrant labor supply (e.g. Card (1990), Abramitzky and Boustan (2017)). This paper instead explores the impact of migration on market access – the demand for output produced by a geographic unit. I use data on US states’ intra- and international trade and migration to calibrate a multi-region model to estimate and quantify the impact of immigration into the United States on market access faced by US states.

I emphasize two economic mechanisms. First, immigrants increase the intra-national market access. Immigrants demand goods and services from both the state they reside, and other US states. A fall in the US migrant population is a reduction in US states’ market access, as overall demand shifts towards higher export trade cost destinations. The effect is heterogeneous: states that rely more on immigrant demand for their output, both from within-state migrants and from immigrants living in other US states, experience greater reductions in market access. In an environment with inter-state trade linkages, this change in market access is distinct from the change in the in-state immigrant population. Figure 1a illustrates this point by plotting the share of a state’s output sold to migrants residing in the US against the share of migrant population in the state.\footnote{Formally, I compute the share of output sold to migrants in the US, for a state $i$ as: $\text{share}_i = \frac{\sum_{j \in \text{US}} X_{ij} \ast \text{sh}_j}{\sum_j X_{ij}}$, where sh is the share of migrants in j’s population.} If the share of migrants was uniform across states, or if each state was a closed economy, all states would line up on the 45-degree line. States located above the line have a bigger exposure to migrant demand than their own immigrant population would imply, predicting they would suffer relatively more from a decrease in overall US migrant population. In this paper, I show that this heterogeneity across states leads to unequal effects of a nationwide change in migrant stocks.

Second, immigrants expand international market access, by reducing the costs of foreign trade (see e.g. Gould (1994), Ottaviano et al. (2018) or Cardoso and Ramanarayanan (2019)). Figure 1b illustrates this for the US, by plotting exports from a state to a country.
against the stock of migrants from that country residing in the state, after controlling for multilateral resistance and distance. In this paper, I estimate the causal impact of migrants on exports in the US using an instrumental variable approach based on push-pull factors similar to Burchardi et al. (2019). I show that migrants have a positive causal impact on exports from US states to their country of origin. I then embed this channel in the model, thus providing the first quantification of the welfare impact of the trade cost reduction channel of migrants in the US. In this context, lowering migrant population in the US increases trade costs and reduces market access for US producers. In an extension, I show that the positive effect of migrants on trade comes mainly through high-skill rather than low-skill migrants.

**Quantitative results** I build a model combining Ricardian trade, labor mobility, and an endogenous response of trade costs to migration. I calibrate it to an economy composed of the 50 US states, the District of Columbia, and 56 countries, to provide the first quantitative assessment of the effect of migration on natives’ welfare through shaping both international and intra-national market access of US states. I simulate a counterfactual scenario where migrant population in the US is reduced by half, about the same as bringing migrant population share to 1980 levels. This would increase export weighted trade costs by 3.5% on average across US states, which is of similar magnitude as the 4.9% increase.

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2The figure is a bin-scatter plot of the residual of exports from state s to country c after controlling for s and c fixed effects as well as bilateral distance, against the residual of the migrant stock from c living in s, after controlling for s and c fixed effects as well a bilateral distance.
current ad valorem export tariffs faced by US exporters (WEF (2016)). The reduction in migrant population would lead to a decrease in aggregate welfare by 0.13%. The average real wage change in US states drops by 0.16%, decomposed into −0.11% due to reduced international market access, −0.31% due to reduced market access from other states, and +0.26% due to own-state migrant reduction. There is substantial heterogeneity across US states, with changes in real wages ranging from −0.44% in Vermont to 0.20% in New Jersey. Differences in intra-national migrant demand exposure, export exposure, and local migrant population share explain the regional dispersion of wage changes.

To supplement these results, I also investigate different effect of migration on trade costs by skill. I find that high-skill migrants have a positive effect on exports, while low-skill migrants’ effect is muted. Adding a skill dimension to the counterfactual model as well as imperfect substitutability between native and migrant worked induces differential effects on high and low skill native workers’ wages, but doesn’t affect the main mechanisms affecting market access highlighted above. The reduction of overall migrant share by half would result in a decrease in US native workers’ welfare of 0.33% for low-skill and 0.37% for high-skill workers on average. Again, regional heterogeneity would occur because of differential migrant demand exposure across states. The larger overall drop in welfare is explained by complementarities between natives and migrants’ labor, and a larger increase in export trade costs in the skill model because high-skill migrants have a higher impact on export costs than in the pooled regression.

Related literature This paper connects to the literature on quantitative assessment of migration, more particularly in an international trade setting. Di Giovanni et al. (2015) study the importance of trade and remittances in determining welfare effects of migration in a model with exogenous migrant population. Caliendo et al. (2017) use a model with endogenous migration and trade to quantify welfare effects of the European Union expansion. Burstein et al. (2020) point out that an industry’s ability to increase output through exports mediates how its native workers wage react to immigrant inflows. Here, I emphasize that migrants themselves lead to a change in market access. The quantitative framework in the present paper not only includes international trade and migration, but also accounts for intra-national regional linkages and the trade costs reduction effect of migrants, which few papers have done before. Combes et al. (2005) models France’s internal trade costs as a function of internal migrant stocks, and Cardoso (2019) develops a general equilibrium model based on Melitz (2003), incorporating the trade costs reduction channel of migrants. I also model within-US trade and heterogeneity in migration and trade exposure to analyze the effect of migration on a finer geographical level, con-
necting to the recent strand of literature emphasizing the regional impact of trade (e.g. Caliendo et al. (2019)).

I also contribute to the empirical work on the trade cost reduction effect of migrants. Gould (1994) first documented the fact that US states export more to countries from which they have a lot of migrants, and Dunlevy (2006) showed the correlation depends on language proximity and corruption in the destination country. Cardoso and Ramanarayanan (2019) use Canadian firm level data to show a similar effect. Ottaviano et al. (2018) show that this also holds for exports in services. Bailey et al. (2020) use social connection data based on Facebook to show that countries with more social connection trade more. Some papers have used exogenous variation such as random spatial allocation of refugees (Parsons and Vézina (2018), Steingress (2018)) to identify the effect, but causal estimation of this phenomenon remains understudied (Felbermayr et al. (2015)). In this paper, I confirm that the positive effect of migrants on US exports survives an instrumental variable estimation, and show that the effect is different across skill levels.

I also borrow from the literature on skill level substitutability (e.g. Katz and Murphy (1992)) and migrant-native worker substitutability (e.g. Ottaviano and Peri (2012)) to add these mechanisms in the model in an additional exercise. While these mechanisms induce heterogeneity across skill, the market access and endogenous trade costs mechanisms remain at play.

The rest of the paper is structured as follows. Section 2 describes the quantitative framework used for the counterfactual analysis, section 3 estimates the sensitivity of exports to migrant population, and section 4 presents the main counterfactual results. Section 5 investigates the skill heterogeneity and imperfect substitutability between migrants and natives. and section 6 concludes.

2 Quantitative framework

2.1 Model set up

Preferences and worker efficiency  Workers born in region $i$ and living in region $n$ get the following utility: $^3$

$$U_{in}^s = \frac{W_{in}}{K_{in}}$$

$^3$In the whole paper, I adopt the notation where the first subscript denotes the origin, and the second denotes the destination.
where $W_n$ is a CES aggregator of the continuum of goods and $\kappa_{in}$ is a migration cost in term of utils. The CES aggregator is given by:

$$W_n = \left[ \int_0^1 (c_n(j))^{\frac{\sigma-1}{\sigma}} \, dj \right]^{\frac{\sigma}{\sigma-1}},$$

where $\sigma$ is the elasticity of substitution of consumption goods. For a given location, the price index is given by:

$$P_n = \left[ \int_0^1 (p_n(j))^{1-\sigma} \, dj \right]^{\frac{1}{1-\sigma}}.$$

Workers supply their endowment of labor inelastically in the location they reside, but have a different efficiency depending on where they were born and where they reside. Specifically, worker $\omega$ of born in region $i$ and living in region $n$ supplies a quantity $b_{in}(\omega)$ of efficiency units of labor. The efficiency is distributed according to the following Fréchet distribution:

$$F_{in}(b) = e^{-B_{in}b^{-\epsilon}},$$

where $\epsilon$ is the shape parameter governing the dispersion of efficiencies and $B_{in}$ is a location parameter: workers from region $i$ are in general more efficient in regions $n$ with higher $B_{in}$. This approach differs slightly from the location specific amenity taste shock used in Redding (2016). It is related to the Roy-Fréchet occupation and industry choice (Lagakos and Waugh (2013), Hsieh et al. (2019)) and has also been used to model internal and international migration decisions (e.g. Bryan and Morten (2019), Morales (2019)). It takes into account the fact that workers who self select into migration tend to have a higher productivity in their country of destination.

**Production and trade costs**  Labor is the only factor of production. Each location draws an idiosyncratic productivity $z(j)$ for each good $j$. The productivity draw is independent from taste shock and independent of residing population shares and follows a Fréchet distribution:

$$F_n(z) = e^{-A_nz^{-\theta}},$$

where $\theta$ is the shape parameter and $A_n$ is a scale parameter governing average productivity and $\theta$ governs the dispersion of productivity. Assuming perfect competition and an

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4This assumption implies that migrants have no impact on productivity.
iceberg trade cost $d_{ni}$, the price at which location $n$ can supply location $i$ with good $j$ is given by:

$$p_{ni}(j) = \frac{d_{ni}w_i}{z_n(j)}.$$

Trade costs are assumed to depend on the share of migrant in the exporter’s population, and be given by:

$$d_{ni} = \tau_{ni} \times \begin{cases} \left( \frac{N_{in}}{\sum_j N_{jn}} \right)^{-\eta} & \text{if } N_{in} \neq 0, \text{ and } n \in \text{US}, i \notin \text{US} \text{ or } i \in \text{US}, n \notin \text{US}, \\ 1 & \text{otherwise} \end{cases},$$

where $\tau_{ni}$ is an exogenous iceberg trade cost, and $N_{in}$ is the population born in location $i$ and residing in $n$. $\eta$ is the elasticity governing the sensitivity of trade costs to destination-born population residing in the origin location. I assume that migration only matters for cross-border trade costs (when at least one of $i$ or $n$ is not in the US), and not for within-US flows (when both $i$ and $n$ are in the US).

### 2.2 Trade and migration shares

**Expenditure shares**  Following usual steps from Eaton and Kortum (2002), the expenditure shares are given by:

$$\pi_{ni}^{\text{trade}} = \frac{X_{ni}}{\sum_k X_{ki}} = \frac{A_n (d_{ni}w_n)^{-\theta}}{\sum_k A_k (d_{ki}w_k)^{-\theta}},$$

where $X_{ni}$ is the value of $i$’s purchases from $n$. The price index in location $n$ is given by:

$$P_n = \gamma \left[ \sum_s A_s (d_{si}w_s)^{-\theta} \right]^{-\frac{1}{\theta}} = \gamma \left( \frac{A_n (w_n)^{-\theta}}{\pi_{nn}^{\text{trade}}} \right)^{-\frac{1}{\theta}},$$

where $\gamma = \left[ \Gamma \left( \frac{\theta-(\sigma-1)}{\theta} \right) \right]^{-\frac{1}{\sigma}}$.

**Residential choice shares**  A worker’s indirect utility function can be written as:

$$V_n(\omega) = b_{in}(\omega) \frac{w_n}{P_n \kappa_{in}}.$$
where $w_n$ is the wage in region $n$ received by the worker, their only source of income. The worker chooses the location with the highest indirect utility, so usual steps using the Fréchet distribution properties give rise to the following residential choice shares:

$$
\pi_{\text{mig}}^{in} = \frac{N_{in}}{\sum_k N_{ik}} = \frac{B_{in}(\frac{w_n}{\kappa_{in}})^\varepsilon}{\sum_k B_{ik}(\frac{w_k}{\kappa_{ik}})^\varepsilon},
$$

where $N_{in}$ is the number of people born in $i$ and living in $n$. The corresponding amount of efficient labor units supplied by workers born in $i$ and living in $n$, denoted $L_{in}$, can be shown to be equal to

$$
L_{in} = (B_{in})^{\frac{1}{\varepsilon}} \left( \pi_{\text{mig}}^{in} \right)^{\frac{\varepsilon-1}{\varepsilon}} N_i \gamma,
$$

where $N_i$ is the total population born in region $i$, and $\gamma = \Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)$, with $\Gamma$ the Gamma function.\(^5\)

### 2.3 Equilibrium

The following set of equations characterize the equilibrium, given primitives $A_i$, $N_i$, $B_{in}$, $\kappa_{in}$ and $\tau_{in}$.

On the goods market, the trade shares satisfy

$$
\pi_{\text{trade}}^{ni} = \frac{A_n(d_{ni}w_n)^{-\theta}}{\sum_s A_s(d_{si}w_s)^{-\theta}}, \quad (1)
$$

and in the labor market, total labor factor revenue is equal to total output:\(^6\)

$$
X_n = w_n \sum_i L_{in} = \sum_i \pi_{\text{trade}}^{ni} \left( w_i \sum_j L_{ji} \right),
$$

where:

$$
L_{in} = (B_{in})^{\frac{1}{\varepsilon}} \left( \pi_{\text{mig}}^{in} \right)^{\frac{\varepsilon-1}{\varepsilon}} N_i \gamma.
$$

The migration shares satisfy

\(^5\)This expression is equal to the integral over efficiency draws $b_{in}(\omega)$, where the density measure is the density of $b_{in}(\omega)$ conditional on the individual choosing to live in location $n$, multiplied by the total population in $i$.

\(^6\)Here, I am assuming balanced trade. Appendix E.1 shows how to solve the model with trade deficits.
\[ \pi_{in}^{mig} = \frac{B_{in} \left( \frac{w_n}{\pi_{in}^{mig}} \right)^\varepsilon}{\sum_k B_{ik} \left( \frac{w_k}{\pi_{ik}^{mig}} \right)^\varepsilon}, \]

where

\[ P_n = \gamma \left( \frac{A_n(w_n)^{-\theta}}{\pi_{in}^{trade}} \right)^{-\frac{1}{\theta}}. \]

Finally, the trade costs are given by

\[ d_{ni} = \tau_{ni} \times \begin{cases} \left( \frac{N_{in}}{\sum_j N_{jn}} \right)^{-\eta} & \text{if } N_{in} \neq 0, \text{ and } n \in US, i \notin US \text{ or } i \in US, n \notin US, \\ 1 & \text{otherwise} \end{cases} \]

where

\[ N_{in} = \pi_{in}^{mig} N_i. \]

### 2.4 Equilibrium in changes

Following steps similar to Dekle et al. (2008), one can solve for the proportional change in variables (\( \hat{y} = y_{post} / y_{pre} \)). The equilibrium change in endogenous variables (\( \hat{\pi}_{ni}^{trade}, \hat{\pi}_{in}^{mig}, \hat{w}_n, \hat{P}_n \) and \( \hat{d}_{ni} \)) can be obtained from the following system of equations, given changes in exogenous variables (\( \hat{A}_n, \hat{B}_{in}, \hat{\kappa}_{in}, \hat{\tau}_{in} \)):

\[ \hat{\pi}_{ni}^{trade} = \frac{\hat{A}_n(d_{ni}\hat{w}_n)^{-\theta}}{\sum_s \hat{A}_s \left( d_{si}\hat{w}_s \right)^{-\theta} \pi_{si}^{trade}}, \]

\[ \hat{w}_n \sum_k \left( \hat{B}_{kn} \right)^{\frac{1}{2}} \left( \hat{\pi}_{kn}^{mig} \right)^{\frac{\varepsilon-1}{\varepsilon}} \frac{w_n L_{kn}}{X_n} = \sum_i \hat{\omega}_i \hat{\pi}_{ni}^{mig} \frac{X_{ni}}{X_n} \left( \sum_k \left( \hat{B}_{ki} \right)^{\frac{1}{2}} \left( \hat{\pi}_{ki}^{mig} \right)^{\frac{\varepsilon-1}{\varepsilon}} \frac{w_i L_{ki}}{X_i} \right), \]

\[ \hat{\pi}_{in}^{mig} = \frac{\hat{B}_{in} \left( \frac{\hat{w}_n}{\pi_{in}^{mig}} \right)^\varepsilon}{\sum_s \hat{B}_{is} \left( \frac{\hat{w}_s}{\pi_{is}^{mig}} \right)^\varepsilon \pi_{is}^{mig}}, \]

\[ \hat{P}_n = \left( \frac{\hat{A}_n(w_n)^{-\theta}}{\pi_{in}^{trade}} \right)^{-\frac{1}{\theta}}, \]
\[ d_{ni} = \hat{\tau}_{ni} \left\{ (i \mid n \notin \text{US}) \hat{\pi}_{in} \left( \sum_j \frac{\hat{\pi}_{jn} \hat{N}_{jn}}{\sum_j \hat{N}_{jn}} \right) + 1 \right\}^{\eta}. \]

Solving the model in proportional changes enables me to solve for counterfactual quantities by using only data on baseline trade, migration, and wage bill shares \( \pi^{\text{trade}}_i, \pi^{\text{mig}}_i, X_i, \) and \( \Theta_{in} = \frac{w_n L_{in}}{X_n} = \frac{w_n L_{in}}{w_n \sum_k L_{kn}} \), as well as parameter values for \( \varepsilon, \theta \) and \( \eta \).

### 2.4.1 Change in the welfare of natives

In a similar expression as in Redding (2016), the expected utility of a person born in location \( i \) is given by:

\[ \hat{U}_i = \delta \left[ \sum_n \hat{B}_{in} \left( \frac{\hat{w}_n \hat{P}_n \hat{\kappa}_{in}}{\hat{P}_n \hat{\kappa}_{in}} \right)^{\frac{1}{\varepsilon}} \right], \]

where \( \delta \) is a constant involving the Gamma function. Using the expression for \( \hat{\pi}_{in}^{\text{mig}} \) and solving for the change in welfare, one can show that the change in welfare for a person born in location \( i \) is given by:

\[ \hat{U}_i = \left[ \sum_n \hat{B}_{in} \left( \frac{\hat{w}_n \hat{P}_n \hat{\kappa}_{in}}{\hat{P}_n \hat{\kappa}_{in}} \right)^{\frac{\varepsilon}{\pi_{in}^{\text{mig}}}} \right]^{\frac{1}{\varepsilon}}. \]

In reporting results, I will compute an aggregate measure of US welfare that is simply the native-population weighted average of \( \hat{U}_i \), for \( i \in \text{US} \).

### 2.5 A simpler version to illustrate the mechanisms

To illustrate the mechanisms in play, consider a simpler version of the model where migration is exogenous and workers have the same efficiency everywhere. Suppose there are \( N \) states and a rest of the world region. Initially, every state is symmetric except for the fraction of migrant in the state’s total population. To fix ideas, assume that there is a total number of native US workers equal to \( L \), each attributed to a state in a fixed and exogenous proportion \( \beta_i \). The overall fraction of migrant in the US is \( \alpha \), and the total migrant population \( M \) in the US is attributed to a state in a fixed and exogenous proportion \( \gamma_i \).

It is straightforward to show that a state population is equal to \( \frac{a \gamma_i + (1-a) \beta_i}{1-a} L \). The rest of the world native population is given by \( R \), of which \( \frac{a}{1-a} L \) live in the US. For simplicity,
assume there is no migrants from the US into the rest of the world (RW). This is similar to the full model above, with an exogenous $\pi_{RWi}^{mig}$ equal to $\frac{\gamma_i}{R}$ for every state $i$.

We are interested in the reaction of wages in different states as the national fraction of migrant $\alpha$ varies.\footnote{One can think of this comparative static exercise as an approximation of what would happen in the full model if the migration costs to US states were to increase uniformly for all foreign countries.}

The labor market clearing implies that:

$$w_n \frac{\alpha \gamma_n + (1 - \alpha) \beta_n}{1 - \alpha} L = \sum_{i \in US} \left\{ \pi_{ni} w_i \frac{\alpha \gamma_i + (1 - \alpha) \beta_i}{1 - \alpha} L \right\} + \pi_{nROW} w_{ROW} \left( R - \frac{\alpha}{1 - \alpha} L \right)$$

Totally differentiating while keeping $\beta_i$ and $\gamma_i$ constant, one can show that the elasticity of state $n$’s wage with respect to $\alpha$, denoted $\xi_n$, satisfies:

$$\left( \xi_n - \sum_i \frac{X_{ni} \xi_i}{X_n} \right) + \theta \left( \xi_n - \sum_i \frac{X_{nk} \pi_{ik} \xi_i}{X_n} \right) = \frac{1}{1 - \alpha} \left( \sum_i \frac{X_{ni} shmig_i}{X_n} - shmig_n \right)$$

$$+ \frac{X_{nRW}}{X_n} \frac{1}{1 - \alpha} \left\{ \theta \eta \left[ \pi_{RWRW} - \left( shmig_n - \sum_k \pi_{kRW} shmig_k \right) \right] - \frac{MIGPOP}{RWPOP} \right\}$$

where RW denotes rest of the world. This expression implies that the deviation of state $n$’s elasticity ($\xi_n$) from a weighted average of other regions’ elasticities is depends on the difference between the exposure to demand of migrants and own migrant share, and a term that depends on export exposure. To ease intuition for this expression, start with the case where each state is identical and the rest of the world being big enough so that $\xi_{RW} \approx 0$. In that case, the elasticity is the same for all US states, and the migrant demand exposure is equal to the share of migrants, because the share of migrants is identical in every state and equal to $\alpha$. Furthermore, trade shares are identical for every state. In that case, the elasticity is given by:

$$\xi \left[ \frac{X_{nRW}}{X_n} + \theta \sum_i \frac{X_{ni}}{X_n} \pi_{RWi} \right] = \frac{X_{nRW}}{X_n} \left( \theta \eta \pi_{RWRW} - \frac{1}{1 - \alpha} \frac{MIGPOP}{RWPOP} \right)$$

The first term inside the parenthesis in the right-hand side captures the effect of the decrease in export trade costs. It is increasing in the trade elasticity $\theta$, and the migration trade cost elasticity $\eta$, which is intuitive: a change in migrant population affects trade
costs which in turns affects exports. The rest of the world own expenditure share $\pi_{RW|RW}$ captures the effect of the decreased export costs to the ROW’s price index. If the rest of the world own expenditure share $\pi_{RW|RW}$ is high, the RW’s price index is unaffected by the change in costs of goods from the US, which translates into a higher change in US exports. The term is scaled by the state’s export exposure $X_{nRW}/X_n$, as the state has more to gain from the reduced trade cost when export exposure is high.

The second term in the parenthesis illustrates the loss in revenue from exports, as demand moves towards the US. There is no compensation from the increased demand at home, since it is directly offset by the increased labor competition. The effect is higher when the migrant population in the US ($\textit{MIGPOP}$) is relatively big compared to the rest of the world’s population, because the proportional increase in migrant share in the US implies a bigger overall increased migration. Again, the term is scaled by the export exposure, as the loss in revenue from export is higher.

When the states are not identical, the relative elasticities depend the total migrant demand exposure and the share of migrant in the state’s labor force, the two quantities depicted in the introduction figure 1a.

Of course, these analytical results only hold for the simplified case where migration shares are exogenous, and don’t say anything about the evolution of the price index, which is likely to fall as the labor supply moves toward closer location in the US. However, even in nominal terms, wages might increase following an increase in migrant share if $\eta$ is big enough to compensate for the increased labor supply.

3 Parameter estimation and calibration

To solve the model, all that is left to do is specify values for the trade elasticity $\theta$, the migration cost elasticity $\epsilon$ and the trade cost migration elasticity $\eta$. The first two elasticities have been estimated in the literature, while the third one is still relatively understudied.

3.1 Trade cost elasticity of migration

To estimate $\eta$, I use the gravity equation coming from the model and estimate it using exports from the 50 US state and DC to the rest of the countries.\textsuperscript{8} Combining equations (1) and (2) and taking logs gives the following estimation equation, for exports from state $s$ to country $i$:

\textsuperscript{8}As will be apparent later, an instrument is needed for proper estimation, and the identification strategy requires data only available for the US.
\[
\log X_{si} = \gamma_s + \delta_i - \theta \log \tau_{si} + \theta \eta \log (N_{is}) + \epsilon_{si}.
\]

I parametrize trade costs as a function of distance, and common border dummy:

\[
\log X_{si} = \gamma_s + \delta_i + \theta \eta \log (N_{is}) - \beta_1 \log \text{dist}_{si} + \beta_2 \text{COMMON}_{si} + \epsilon_{si} \quad (3)
\]

**Instrument** Migrants might choose to settle in a state that exports to their home country because they know their country-specific skills might be needed for exports to their home country, or simply because unobservable trade frictions between their home country and the host state are correlated with unobservable migration costs.

Because of these endogeneity concerns, I instrument for migrant population using a similar instrument as Burchardi et al. (2019). I first define a leave-out pull factor for state \( i \) at time \( t \), computed as the share of migrants who entered the US at time \( t \) and who reside in state \( i \), excluding migrants from countries located in the same continent as \( j \):

\[
pull_{ji} = \frac{\sum_{j' \notin \text{continent}_j} M_{j'i,t}}{\sum_{j' \notin \text{continent}_j} \sum_i M_{j'i,t}},
\]

where \( M_{ij,t} \) is the number of migrant from country \( j' \) residing in state \( i \), who migrated at time \( t \). This leave-out pull factor represents the current attractiveness of state \( i \) to migrants from other continents. I then construct a leave-out push factor capturing population outflow from country \( j \), by computing the total migration from country \( j \) to the US at time \( t \), minus the migrant stock from country \( j \) to state \( i \) (\( M_{ji,t} = \sum_{j' \neq i} M_{j'i,t} \)). Multiplying the pull and push factors provides with an instrument for the number of migrants from country \( i \) who entered the US at time \( t \) and reside in state \( j \) that does not rely on any bilateral migration information. Finally, summing possible years of migration provides with an instrument of the stock of migrant population from country \( j \) in state \( i \):

\[
\hat{\text{migstock}}_{ji} = \sum_t pull_{ji} M_{ji,t}
\]

The main identifying assumption is that the shares (\( pull_{ji} \)) are uncorrelated with unobservables affecting trade between state \( i \) and country \( j \). In other words, migrants from different continents should not be choosing their state of destination based on that state’s exports to country \( j \). This is likely to be satisfied, as migrants might consider their own country’s or its neighbors’ ties to a specific destination, but not that of countries in other continents. The estimation will use \( \hat{\text{migstock}}_{ji} \) as an instrument for migrant stocks \( L_{ij} \). Note that this estimation strategy allows me to include imported and exporter fixed ef-
Table 1: Estimation of the effect of migrants on exports

<table>
<thead>
<tr>
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<th>OLS regression</th>
<th>IV regression</th>
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<tbody>
<tr>
<td></td>
<td>log (exports)</td>
<td>log (exports)</td>
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<td>log (migrants)</td>
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<td>0.208***</td>
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<td>Country clust. SE</td>
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<td>✓</td>
</tr>
<tr>
<td>First stage KPF-stat</td>
<td></td>
<td>791</td>
</tr>
<tr>
<td>N</td>
<td>2511</td>
<td>2511</td>
</tr>
</tbody>
</table>

Notes: Results from estimating equation 3, using the instrument described in the text. Standard errors in parenthesis, *: \(p < 0.1\), **: \(p < 0.05\), ***: \(p < 0.01\)

The positive effects of migrants on exports is robust to PPMLE estimation, preserving observations with 0 migrants, and using a larger set of countries.

---

9I use 56 countries because they are those for which I have data required to solve the quantitative model in the next section. Appendix A shows results using a larger sample of countries.
3.2 Calibration

I calibrate the model to the 50 US states, the District of Columbia, and 56 countries, and a composite “Rest of the World” (ROW), for a total of 108 regions. Table 2 summarizes the parameters and their calibrated value, as well as exogenous objects and their data counterpart, together with the data source.

Data sources I use migration data from the World Bank’s Bilateral Migration Matrix for 2013, and combine it with the American Community Survey (ACS) to construct measures of migrant stock in every regions. International trade data comes from the OECD Inter-Country Input-Output table for 2013, and within-US trade data comes from the Commodity Flow Survey (CFS). Wage bill shares are calibrated using survey data from the ACS for US states, and from other national surveys for other countries, obtained through IPUMS-International (MPC (2019)). Section C in the appendix provides additional details on the sources and the exact mapping between the data and the model objects.

Parameter values For the trade elasticity and the migration elasticity, I take values from the literature. I set the trade elasticity $\theta$ to 4, following Simonovska and Waugh (2014), and the migration elasticity $\varepsilon$ to 2.3 as in Caliendo et al. (2017). For the elasticity of trade costs to migration, I use my estimate of 0.2 from above, whose structural interpretation is $\eta \times \theta$, and thus set $\eta = 0.2 / \theta = 0.05$. In Appendix D, I explore different values of elasticities, with no significant differences in the results interpretation.

4 Counterfactual simulations

To quantify the effect of migration, I conduct the following counterfactual: I increase migration costs to the US uniformly for all foreign countries ($\kappa_{iUS}$) such that the migrant share of US population is reduced by 50%. This is similar to reducing the migrant population shares to that of 1980. It is also consistent with proposed legislation that aim to

---

10 The large majority of US trade flows and migrant stock are covered by the 56 countries: the ROW only accounts for 10% of US exports and 30% of migrant population.
11 See Appendix C.2 for a discussion of the data coverage in the CFS, and a robustness check for its limitations.
12 In 1980, the share of migrant population in the US was 6.2%. Reducing the migrant population in 2013 (base year for my analysis) by half would bring the migrant share to around 6.8%. 

---

14
Table 2: Link between the model and the data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon$</td>
<td>migration elasticity</td>
<td>2.3</td>
<td>Caliendo et al. (2017)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>trade elasticity</td>
<td>4</td>
<td>Simonovska and Waugh (2014)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>migration-elasticity of trade costs</td>
<td>$\eta = 0.2/\theta$</td>
<td>own estimate</td>
</tr>
</tbody>
</table>

Exogenous object

<table>
<thead>
<tr>
<th>$A_{n}, B_{in}, \kappa_{in}$</th>
<th>migration costs</th>
<th>keep constant uniformly increased for $i \not\in US, n \in US$, to target a reduction of 50% in total migrant stock living in the US</th>
</tr>
</thead>
</table>

Data

<table>
<thead>
<tr>
<th>$\pi_{in}^{mig}, N_{in}$</th>
<th>population data</th>
<th>ACS, World Bank</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_{in}^{trade}, X_{n}$</td>
<td>trade data (including services)</td>
<td>Census data on state level exports and imports, OECD ICIO, Commodity Flow Survey</td>
</tr>
</tbody>
</table>

| $\Theta_{in}$ | share of wage bill to migrants from $i$ in $n$’s output | American Community Survey, IPUMS-International |

Notes: see section C in the appendix for details on the sources and exact mapping between the data and the model objects.
reduce legal annual immigration flows by half.\textsuperscript{13} The resulting changes in variables can be interpreted as if the economy moved to a different steady state.

To further understand the role of migration in shaping market access of each state, I also run three additional counterfactuals for each state: the first increases migration costs in the particular state only, the second decreases migration costs in all other states except the state of interest, and the third leaves migration costs unchanged but increases the export trade costs to the level they reach in the main counterfactual.\textsuperscript{14} These counterfactuals decompose the full effect of the nation-wide reduction of migration into:

i. a shock to the labor supply and migrant-induced within-state market access in state \(s\), leaving demand from international migrants in other states unaffected and export trade costs unchanged;

ii. a shock to internal market access due to a decrease in demand from international migrants living in other states, leaving the labor supply and export trade costs in state \(s\) unaffected;

iii. a shock to international market access due to the increase in export trade costs.

4.1 Results

4.1.1 Aggregate results

Table 3 shows the average change in export trade costs across US states and the average change in exports as share of state output, as well as the average change in welfare in the US. Standard deviation across states are also shown in parentheses.

On average, export trade costs faced by US states increase by 3.7%, which is of similar magnitude as the 4.9% current ad valorem export tariffs faced by US exporters (WEF (2016)). The average change in welfare is close to 0 when trade costs are left constant, but becomes negative at -0.13% when export costs increase as migrant population decreases. This underpins the importance of the trade cost reduction channel of migrants. In fact,

\textsuperscript{13}While the proposed legislation reduces immigration flows by 50%, there is no concept of flows in the model and I assume that the reduction in flows would translate in a long-run reduction of migrant stock by half. See the following link for details of the proposed bill: https://www.congress.gov/bill/115th-congress/senate-bill/354

\textsuperscript{14}Precisely, I use the value of \(\hat{\kappa}_{iUS}, \forall i \notin US\) necessary to achieve the 50% reduction in migrant share in the main counterfactual, and the resulting change in export trade cost \(\hat{d}_{ij}, \forall i \in US, j \notin US\). I construct the first additional counterfactual by setting \(\hat{\kappa}_{is} = \hat{\kappa}_{iUS}, \forall i \notin US\) for state \(s\), and \(\hat{\kappa}_{is'} = 1, \forall s' \neq s\), and no effect of migrants on trade costs (\(\eta = 0\)). The second additional counterfactual uses \(\hat{\kappa}_{is} = 1, \forall i \notin US\) for state \(s\), and \(\hat{\kappa}_{is'} = \hat{\kappa}_{iUS}, \forall s' \neq s\), and no effect of migrants on trade costs (\(\eta = 0\)). The third is constructed using \(\hat{\kappa}_{ij} = 1\) and \(\hat{\tau}_{ij} = \hat{d}_{ij}\). 

16
Table 3: Average changes

<table>
<thead>
<tr>
<th></th>
<th>Constant trade costs</th>
<th>Endogenous trade costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Change in state export costs</td>
<td>0</td>
<td>3.7</td>
</tr>
<tr>
<td>(exports weighted)</td>
<td>(0)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>% Change in exports as share of output</td>
<td>1.56</td>
<td>-4.47</td>
</tr>
<tr>
<td></td>
<td>(0.56)</td>
<td>(1.07)</td>
</tr>
<tr>
<td>% Change in natives’ welfare</td>
<td>-0.01</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>

Notes: The table shows the percentage changes, after reducing the share of migrants in the US population by half. Numbers are average across US states, with standard deviation in parenthesis.

Exports as a share of output increase in the first case, as demand moves out of the US, but decreases in the second case, as the increase in export trade costs is high enough to offset the geographical shift in demand.

The standard deviation of trade costs changes is low compared to the average effect. This is because the uniform increase in migration costs leads, to a first order, to a proportional reduction of migrant population of every country in every state, hence affecting trade costs similarly.\(^{15}\) The dispersion of welfare changes across US states is however in the same order of magnitude as the average effect.

### 4.1.2 Regional heterogeneity

This section investigates what drives the heterogenous reaction to the drop in migrant population across states, focusing on explaining the variation in real wage change across US states.\(^{16}\)

Figure 2 plots the percentage change in a state’s real wage for the main counterfactual as well as the three additional counterfactuals. The first bar (in blue) displays the change

---

\(^{15}\)Some states are affected differentially depending on the composition of their migrant population. For example, almost 10% of Mexican-born population resides in the US. As about half of these move back to Mexico, thereby increasing labor supply, real wages in Mexico drop, which compensates the drop in attractiveness of the US due to the increased migration cost. Hence states with a high share of Mexican migrants will experience a slightly lower drop in migrant population, leading to a lower increase in trade costs. These effects, however, are all second-order, which is why the increase in trade costs are fairly homogenous.

\(^{16}\)Note that because of migration, the change in state-level real wage is somewhat different from the change in welfare of the state’s natives. I focus on change in real wages in this section as it is easier to interpret its reaction to migrant demand and export exposure through the lenses of the model.
in real wage for the main counterfactual, the second bar (in grey) displays the own-state effect (defined as the change in real wage when only own-state migrant population is reduced), the third bar (in white) displays the intra-national market access effect (defined as the change in real wage when other-state migrant population is reduced), and the international market access effect (defined as the change when only export trade costs are changed). While the sum of the additional counterfactuals is not completely identical to the main counterfactual, it is extremely close to it, so that they can be thought of as a decomposition of the main counterfactual. The average real wage change of $-0.16\%$ can thus be decomposed into an own-state effect of $+0.26\%$, an intra-national market access effect of $-0.31$, and an international market access effect of $-0.11\%$. The state-level results reveal several interesting patterns.

First, it is clear that the nationwide reduction of migrant population has heterogeneous effects across states, from Vermont’s real wage dropping by around .44% to New Jersey’s wage increasing by around .20%.

Second, even small overall wage changes can mask large underlying changes caused by labor supply reduction or market access. For example, Nevada’s real wage barely reacts to the nationwide migrant share reduction. However, if its migrant population were to decrease leaving the rest of the US’s migrant population constant, real wage would increase because the drop in labor supply would be larger than the drop in market access due to the reduction of its migrant population, as illustrated in the positive grey bar.

---

17 The correlation between the sum of the decompositions and the main counterfactual is 0.999, and the average absolute difference is around 0.002 percentage points.
However, because of its exposure to migrant demand from other states due to trade linkages with large migrant states such as California, its wage falls when migrants in other states disappear, as indicated by the negative white bar. Furthermore, the drop in international market access due to the increase in export costs depresses the wage even further, as evidenced by the negative purple bar.

Third, the share of population in a state is not enough to predict whether the own-state effect will dominate the intra-national market access effect. While on average, a state with a higher migrant share than the average would tend to have a bigger own-state effect than intra-national market access effect, this doesn’t hold necessarily, because heterogeneous trade patterns mean that the state can have a large exposure to other states with high migrant population. For example, both Rhode Island (RI) and Washington (WA) have the same share of migrant at about 0.13, RI has a higher exposure to internal migrant demand because of its large exposure to high-migrant states (e.g. New York). As a result, its reduction in intra-national market access is higher than WA.

Finally, the size of the intra-national market access effect is larger and more disperse than the international market access effect, implying that the heterogeneity across states is mostly driven by internal rather than international market access. The international component still remains sizable at negative .11% on average.

To clearly illustrate the mechanisms at play, Figure 3 plots the value of each decomposition bar against the relevant heuristic measure. As mentioned in section 2.5, one of the main determinant of the reaction of wages to the change in migration is the difference between the state’s share of migrants and its migrant demand exposure. The same mechanism applies for the first decomposition: as migrants from the state are removed, the labor supply is reduced by more than market access. States with a larger difference between the share of migrants in the labor supply and the share of own-migrant demand exposure have a larger gain from own-migrant reduction as shown in the left panel (a). The intra-national market access effect of removing migrants from other states depends on exposure to migrants from other states (middle panel b), and the international market access depends on export exposure (right panel c).

5 Skill heterogeneity and migrant-native work substitutability

The importance of the skill dimension and the imperfect substitutability between migrant and native workers in determining the effects of migration has long been recognized (see
e.g. Ottaviano and Peri (2012)). In this section, I show that the skill dimension also matters for the effect of migration on trade costs, but leaves the importance of regional exposure to migrant demand unchanged.

5.1 Empirical evidence on skill heterogeneity

To investigate the differential impact of skilled and unskilled migration on trade costs, I run the same regression as in section 3.1, separating high-skill migrants (defined as migrants with some college level education) and low-skill migrants. The instrumental variable approach is the same, except for the instrument being computed at the skill level.

Formally, I run the following regression:

$$\log X_{ni} = \gamma_s + \delta_i + \theta_H \log \left( N_{is}^H \right) + \theta_L \log \left( N_{is}^L \right) - \beta_1 \log dist_{si} + \beta_2 COMMON_{si} + \varepsilon_{si}$$

where $N_{is}^H$ and $N_{is}^L$ are the number of high- and low-skill migrants from country $i$ residing in state $s$. Table 4 reports the results of the regression, together with the pooled results from above for convenience. The results reveal that high skill migration is responsible for the positive impact of migration on exports, while low-skill migration has no significant effect.

5.2 Model

I modify the model in section 2 to include different skilled and unskilled labor, as well as imperfect substitutability between migrant and native workers. While details of the model are relegated to Appendix B and are mostly the same as the model in section 2, I present the main differences below.
Table 4: Estimation of the effect of migrants on exports by skill

<table>
<thead>
<tr>
<th></th>
<th>OLS regression</th>
<th>IV regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>log (exports)</td>
<td>log (exports)</td>
</tr>
<tr>
<td>log (migrants)</td>
<td>0.152**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td></td>
</tr>
<tr>
<td>log (HSmig)</td>
<td>0.091*</td>
<td>0.308***</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>log (LSmig)</td>
<td>0.057</td>
<td>-0.056</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>Adjacency</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Distance</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Imp. and exp. FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Country clust. SE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>First stage KPF-stat</td>
<td></td>
<td>791</td>
</tr>
<tr>
<td>N</td>
<td>2511</td>
<td>2511</td>
</tr>
</tbody>
</table>

Notes: Results from estimating equation 3, using the instrument described in the text. Standard errors in parenthesis, *: p < 0.1, **: p < 0.05, ***: p < 0.01
Production  There are now four types of labor used for production: migrant and native, high- and low-skill labor. Low-skill and high-skill labor ($L_L$ and $L_H$) are measured in efficiency units of labor, with migrant and domestic labor being imperfectly substitutable. More precisely, the production function for good $j$ is given by:

$$y(j) = z(j) \left[ \phi^L \left( L_L \right)^{\frac{\rho-1}{\rho}} + \phi^H \left( L_H \right)^{\frac{\rho-1}{\rho}} \right]^\frac{1}{\rho-1},$$

where $z(j)$ is a location-specific idiosyncratic productivity for each good $j$. The amount of $s$-skill labor, $L_s$, is itself a CES aggregate of native and migrant workers:

$$L_s = \left[ \phi^{sd} \left( L_{sd} \right)^{\frac{1}{\lambda}} + \phi^{sm} \left( L_{sm} \right)^{\frac{1}{\lambda}} \right]^\frac{1}{\frac{1}{\lambda}-1},$$

where $L_{sd}$ is the amount of domestic (native) units of labor of skill $s$ and $L_{sm}$ is the amount of migrant units of labor of skill $s$.

Preferences and worker efficiency  Workers of skill $s$ born in region $i$ and living in region $n$ get the following utility:

$$U_{in}^s = \frac{W_n}{\kappa_{in}^s}$$

where $W_n$ is a CES aggregator of the continuum of goods and $\kappa_{in}^s$ is a migration cost in term of utils. The CES aggregator is given by:

$$W_n = \left[ \int_0^1 \left( c_{in}(j) \right)^{\frac{1}{\sigma}} \, dj \right]^{\frac{1}{\sigma-1}},$$

where $\sigma$ is the elasticity of substitution of consumption goods.

Workers supply their endowment of labor inelastically in the location they reside, but have a different efficiency depending on where they were born and where they reside. Specifically, worker $\omega$ of skill $s$ born in region $i$ and living in region $n$ supplies $b_{in}^s(\omega)$ of efficiency units of labor.

Skill level can be either high ($s = H$) or low ($s = L$). The efficiency is distributed according to the following Fréchet distribution:

$$F_{in}^s(b) = e^{-B_{in}^s b^{-\varepsilon}},$$

where $\varepsilon$ is the shape parameter governing the dispersion of efficiencies and $B_{in}^s$ is a location parameter: workers of skill $s$ from region $i$ are in general more efficient in regions
\( n \) with higher \( B_{in}^s \).

**Trade costs** Consistent with the evidence in section 5.1, trade costs depend on the high and low-skill migration as follows:

\[
d_{ni} = \tau_{ni} \times \begin{cases} 
\left( \frac{N_{in}^L}{\sum_j s N_{jn}^L} \right)^{-\eta^L} \left( \frac{N_{in}^H}{\sum_j s N_{jn}^H} \right)^{-\eta^H} & \text{if } N_{in}^s \neq 0, \text{ and } n \in US, i \notin US \text{ or } i \in US, n \notin US, \\
1 & \text{otherwise}
\end{cases}
\]

That is, trade costs are negatively affected by the share of migrants of skill \( s \) in the exporter’s population, but the effect of different skill level is heterogeneous, governed by the two elasticities \( \eta^H \) and \( \eta^L \).

The rest of the model follow the quantitative framework in section 2, and additional description of the equilibrium with skill as well as calibration of the parameters is relegated to Appendix B. For the trade elasticity and migration elasticity, the parameter values are similar to the ones in the main model. Regarding trade cost elasticities, I set \( \eta^H = 0.3/\theta \) and \( \eta^L = 0 \) consistent with the estimates in 5.1. Finally, the elasticity of substitution between skills \( \rho \) is set to 1.6 following Katz and Murphy (1992), and the elasticity of substitution between native and migrant work is set to 20 following Ottaviano and Peri (2012). Alternative calibration is explored in Appendix D.

### 5.3 Counterfactual results

Table 5 shows the average change in export trade costs across US states and the average change in exports as share of state output, as well as the average change in wages in the US for different skill levels, defined as the native-population weighted average of wage changes in each state. Standard deviation across states are also shown in parentheses.

The average change in welfare is negative regardless of skill levels, at -0.17\% and -0.22\% for low and high skill respectively, when trade costs are left constant. Exports as a share of output increase, a demand moves out of the US when the migrants leave the US. When trade costs are endogenous, export trade costs faced by US states increase by 5.49\% on average, a larger increase than in the results that don’t account for skill differential, because the elasticity of trade costs on high-skill migrants is higher, and because of complementarities between native and migrant labor. Appendix D shows that the changes in welfare are dampened when the elasticity of substitution between migrants and natives’ labor is increased.
Table 5: Skill scenario: average changes across US states

<table>
<thead>
<tr>
<th></th>
<th>Constant trade costs</th>
<th>Endogenous trade costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>% change in state export costs</td>
<td>0</td>
<td>5.49</td>
</tr>
<tr>
<td>(exports weighted)</td>
<td>(0)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>% change in exports</td>
<td>1.46</td>
<td>-7.14</td>
</tr>
<tr>
<td>as share of output</td>
<td>(0.60)</td>
<td>(1.34)</td>
</tr>
<tr>
<td>% change in US low-skill welfare</td>
<td>-0.17</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>% change in US college welfare</td>
<td>-0.22</td>
<td>-0.37</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.07)</td>
</tr>
</tbody>
</table>

Notes: The table shows the percentage changes going from current migrant population in the US to a population of half. Numbers are weighted average across US states, with standard deviation in parenthesis.

Regional heterogeneity  As for the main counterfactual, I decompose the effect into an “own-state” reduction of migration an intra-national market access effect, and an international market access effect. Figure 4 reports displays the total change in real wage (first bar in blue), the own-state effect (second bar in gray), the intra-national market access effect (third bar in white), and international market access effect (fourth bar in purple). Subfigure 4a shows the reaction of native low-skill wages, while subfigure 4b depicts the reaction of native high-skill wages.

The shock to own-state migrant population, while having a positive impact on average, is negative in some states, as complementarities induce a lower wage for native workers after the reduction of migrant labor supply. Both intra- and international market access effects are negative, as the negative demand shock affects wages negatively.

Overall, the skill and native-migrant imperfect substitutability dimensions affect how the labor supply shock feeds in the economy: it affects the dimension, and even sometimes the sign of the own-state effect. The market access effect of reducing migrant population, however, remains unaffected by these production elasticities.
Figure 4: Skill scenario: decomposing regional effects
6 Conclusion

This paper shows the importance of migrants’ impact on trade market access. Migrants shape market access through two channels. They change the geographical location of demand, thereby benefiting regions closer to their migration destination, and they reduce trade frictions, thereby easing access of their host country to their home country’s market.

The evidence shows that migrants have a causal impact on exports from their host state to their home country, particularly so for high-skill migrants. Using a model of international and intra-national trade and migration calibrated to the US states, I show that a nationwide reduction in migrant population produces heterogeneous responses in wage through different effects on intra- and international market access. States with a high exposure to migrants inside the US are hurt more by the removal of migrants, and those with a high export exposure are hurt more by the increase in trade costs.

References


Lorenzo Caliendo, Maximiliano Dvorkin, and Fernando Parro. Trade and labor market


A Additional regression results

Table A1 displays the full results of the regression presented in the main body of the paper. All first stage results are strong, and the sign of bilateral controls are as expected.

Table A1: Full Results and First Stage Regressions

<table>
<thead>
<tr>
<th>log (exports)</th>
<th>First stage</th>
<th>ln(mig)</th>
<th>ln(HSmig)</th>
<th>ln(LSmig)</th>
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</thead>
<tbody>
<tr>
<td>ln(migrants)</td>
<td>OLS</td>
<td>IV</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.152***</td>
<td>0.208***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.059)</td>
<td>(.065)</td>
<td></td>
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<tr>
<td>ln(HSmig)</td>
<td>0.091+</td>
<td>0.308***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.052)</td>
<td>(.105)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(LSmig)</td>
<td>0.057</td>
<td>-0.056</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.038)</td>
<td>(.077)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(distance)</td>
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<td>-1.387**</td>
<td>-1.325**</td>
<td>-1.342**</td>
</tr>
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<td>(.621)</td>
<td>(.622)</td>
<td>(.595)</td>
<td>(.593)</td>
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<td>0.346***</td>
<td>0.304***</td>
<td>0.289***</td>
</tr>
<tr>
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<td>(0.164)</td>
<td>(0.161)</td>
<td>(0.164)</td>
<td>(0.168)</td>
</tr>
<tr>
<td>ln(instr.)</td>
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<td></td>
<td>(0.026)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>ln(instr.HS)</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>0.520***</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(instr.LS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.404***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

KP F-Stat | 791.3 | 140.7
Imp. and exp. FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓
Country clust. SE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓
N | 2511 | 2511 | 2511 | 2511 | 2511 | 2511 | 2511

Notes: Standard errors in parenthesis, +: p < 0.1, **: p < 0.05, ***: p < 0.01

Table A2 shows additional results. Columns 1 and 2 show results of a PPMLE (see Silva and Tenreyro (2006)) estimation, columns 3-4 show the results using log (1 + mig) in order to avoid dropping observations where states have positive exports, but no migrant
population, and columns 5-6 show results using all countries to which a US state has positive exports.\textsuperscript{18} All regressions use the same instrumental variable strategy as the main ones. In all robustness checks, the positive effect of migrants remains, and the difference in skills as well.

Table A2: Robustness results

<table>
<thead>
<tr>
<th></th>
<th>(1) PPMLE</th>
<th>(2) extended sample</th>
<th>(3) ( \ln(migrants) = 1 + \text{mig} )</th>
<th>(4) ( \ln(HSmig) )</th>
<th>(5) ( \ln(\text{LSmig}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(migrants) )</td>
<td>0.275***</td>
<td>0.204***</td>
<td>0.141***</td>
<td>0.489***</td>
<td>0.305***</td>
</tr>
<tr>
<td>( \ln(HSmig) )</td>
<td>0.141***</td>
<td>0.305***</td>
<td>0.489***</td>
<td>0.489***</td>
<td>0.305***</td>
</tr>
<tr>
<td>( \ln(\text{LSmig}) )</td>
<td>-0.121</td>
<td>-0.041</td>
<td>-0.098**</td>
<td>-0.121</td>
<td>-0.041</td>
</tr>
</tbody>
</table>

KP F-Stat

<table>
<thead>
<tr>
<th></th>
<th>(5) Extended sample</th>
<th>(6) Extended sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(migrants) )</td>
<td>586.2</td>
<td>352.9</td>
</tr>
<tr>
<td>( \ln(HSmig) )</td>
<td>99.2</td>
<td>2387.5</td>
</tr>
<tr>
<td>( \ln(\text{LSmig}) )</td>
<td>2704</td>
<td>5150</td>
</tr>
</tbody>
</table>

Imp. and exp. FE

<table>
<thead>
<tr>
<th></th>
<th>(1) PPMLE</th>
<th>(2) extended sample</th>
<th>(3) ( \ln(migrants) = 1 + \text{mig} )</th>
<th>(4) ( \ln(HSmig) )</th>
<th>(5) ( \ln(\text{LSmig}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Errors</td>
<td>robust</td>
<td>robust</td>
<td>imp. clust.</td>
<td>imp. clust.</td>
<td>imp. clust.</td>
</tr>
<tr>
<td>N</td>
<td>2719</td>
<td>2517</td>
<td>2704</td>
<td>2552</td>
<td>5918</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parenthesis, *: \( p < 0.1 \), **: \( p < 0.05 \), ***: \( p < 0.01 \)

B Skill and imperfect substitutability model

B.1 Model details

The following set of equations characterize the equilibrium in the skill model. Most of the derivations are the same as the ones presented for the main model.

On the goods market, the trade shares satisfy

\[
\pi_{\text{trade}}^{ni} = \frac{A_n(d_{ni}C_n)^{-\theta}}{\sum_s A_s(d_{si}C_s)^{-\theta}}, \tag{5}
\]

where the labor bundle cost \( C_n \) is given by:

\textsuperscript{18}In the bigger sample, there are a total of 135 countries, but not all states export to them. Due to convergence issues, the PPMLE standard errors are not clustered at the importing country level.
\[ C = \left[ \phi^L \left( C^L \right)^{1-\rho} + \phi^H \left( C^H \right)^{1-\rho} \right]^{\frac{1}{1-\rho}} \]

and each skill labor bundle cost is itself given by:

\[ C^s = \left[ \phi^{sd} \left( w^{sd} \right)^{1-\lambda} + \phi^{sm} \left( w^{sm} \right)^{1-\lambda} \right]^{\frac{1}{1-\lambda}} \]

where the labor bundle costs are derived from the firm’s profit maximization problem. Total revenue is equal to total output:

\[ X_n = \sum_i \pi^\text{trade}_{ni} X_i. \]

On the labor market, for each skill \( s \):

\[ C^s_n \left[ \phi^{sd} \left( L^{sd} \right)^{\frac{\lambda-1}{\lambda}} + \phi^{sm} \left( L^{sm} \right)^{\frac{\lambda-1}{\lambda}} \right]^{\frac{\lambda}{\lambda-1}} = w_n^{sd} L_{nn}^s + w_n^{sm} \sum_{i\neq n} L_{in}^s \]

where labor supply from migration choices implies that:

\[ L_{nn}^s = \left( B_{nn}^s \right)^{\frac{1}{1-\tau}} \left( \pi_{nn}^{s,\text{mig}} \right)^{\frac{\tau-1}{\tau}} N_n^s \gamma, \]

\[ \sum_{i\neq n} L_{in}^s = \sum_{i\neq n} \left( B_{in}^s \right)^{\frac{1}{1-\tau}} \left( \pi_{in}^{s,\text{mig}} \right)^{\frac{\tau-1}{\tau}} N_i^s \gamma, \]

where \( \gamma = \Gamma \left( \frac{e-1}{\tau} \right) \) and \( \Gamma(.) \) is the gamma function. And total revenue is equal to total labor revenue:\(^{19}\)

\[ X_n = \sum_{s \in \{L,H\}} \left[ w_n^{sd} L_{nn}^s + w_n^{sm} \sum_{i\neq n} L_{in}^s \right]. \]

The migration shares satisfy

\(^{19}\)For expository convenience, I am omitting the fact that when \( n \in \text{US} \), workers from every US states get wage \( w_{n}^{sd} \). In that case, one would have:

\[ X_n = \sum_{s \in \{L,H\}} \left[ w_n^{sd} \sum_{i \in \text{US}} L_{in}^s + w_n^{sm} \sum_{i \notin \text{US}} L_{in}^s \right]. \]
\[ \pi_{in}^{s,mig} \] 

\[ = \frac{B_{in}^s \left( \frac{(w_{sd}^i)^{i=n}(w_{sm}^i)^{i\neq n}}{p_{in}^i} \right)}{\sum_k B_{ik}^s \left( \frac{(w_{sd}^k)^{i=k}(w_{sm}^k)^{i\neq k}}{p_{ik}^k} \right)} \varepsilon, \]

where

\[ P_n = \gamma \left( \frac{A_n (C_n)^{-\theta}}{\pi_{inn}^{trade}} \right)^{-\frac{1}{\theta}}. \]

Finally, the trade costs are given by

\[ d_{ni} = \tau_{ni} \prod_s \left( 1 \left( i \mid n \notin US \right) \frac{1 + N_{jn}^s}{\sum_{s,j} N_{jn}^s} + 1 \left( i, n \in US \right) \right)^{-\eta^s}, \]

where

\[ N_{jn}^s = \pi_{jn}^{s,mig} N_j^s. \]

### B.1.1 Equilibrium in changes

Following steps similar to Dekle et al. (2008), one can solve for the proportional change in variables. The equilibrium changes in endogenous variable \( \pi_{in}^{s,mig}, \pi_{in}^{trade}, \hat{\omega}_{nd}, \hat{\omega}_{nm}, \hat{p}_n, \hat{d}_ni, \hat{C}_n, \hat{C}_n, \hat{X}_n \) following changes in exogenous parameters \( \hat{B}_{in}^s, \hat{\kappa}_{in}^s, \hat{A}_n, \hat{\tau}_{in} \) can be obtained from the following system of equations (where \( \hat{y} = y_1 / y_0 \) is the ratio between the value of variable \( y \) before and after the counterfactual shock to exogenous variables):

\[ \hat{\pi}_{in}^{s,mig} = \frac{B_{in}^s \left( \frac{(\hat{\omega}_{nd}^i)^{i=n}(\hat{\omega}_{nm}^i)^{i\neq n}}{\hat{p}_{in}^i} \right)}{\sum_k B_{ik}^s \left( \frac{(\hat{\omega}_{sd}^k)^{i=k}(\hat{\omega}_{sm}^k)^{i\neq k}}{\hat{p}_{ik}^k} \right)} \varepsilon, \]

\[ \hat{\pi}_{in}^{trade} = \frac{\hat{A}_n (\hat{d}_ni \hat{C}_n)^{-\theta}}{\sum_k \hat{A}_k (\hat{d}_ki \hat{C}_k)^{-\theta} \pi_{inn}^{trade}} \]

\[ \hat{p}_n = \left( \frac{\hat{A}_n (\hat{C}_n)^{-\theta}}{\hat{\pi}_{inn}^{trade}} \right)^{\frac{1}{\theta}} \]
\[ C_n = \left( \hat{C}_n \right)^{1-\rho} \sum_i \Theta_{in}^L + \left( \hat{C}_n \right)^{1-\rho} \sum_i \Theta_{in}^H \right]^{1-\rho}, \]

where \( \Theta_{in}^s \) is the initial share of the wage bill going to \( s \)-skill workers from \( i \), in country \( n \) \( (\Theta_{in}^s = \frac{w_{in}^s L_{in}}{X_n} \text{ if } i \neq n, \Theta_{nn}^s = \frac{w_{nn}^s L_{nn}}{X_n}) \), and

\[ \hat{C}_n = \left( \hat{\omega}_n^{sd} \right)^{1-\lambda} \sum_i \frac{\Theta_{in}^s}{\sum_j \Theta_{jn}^s} + \left( \hat{\omega}_n^{sm} \right)^{1-\lambda} \sum_i \frac{\Theta_{in}^s}{\sum_j \Theta_{jn}^s} \right] \]

\[ \hat{d}_{ni} = \hat{\tau}_{ni} \prod_{s \in \{L, H\}} \left[ 1 \left( i \mid n \notin US \right) \left( \frac{1 + \hat{\tau}_{in}^{s, mig} N_{in}^s}{1 + N_{in}^s} \right) \left( \frac{\sum_j \hat{\tau}_{jn}^{s, mig} N_{jn}^s}{\sum_i \Theta_{jn}^s N_{jn}^s} \right) + 1 \left( i, n \in US \right) \right]^{-\eta^s} \]

\[ \hat{X}_n X_n = \sum_i \hat{\tau}_{in}^{\text{trade}} \pi_{in}^{\text{trade}} (\hat{X}_i X_i) \]

\[ \hat{X}_n = \hat{C}_n^{H L_n} \sum_i \Theta_{in}^H + \hat{C}_n^{L n} \sum_i \Theta_{in}^L \]

\[ \hat{C}_n^{H L_n} = \hat{C}_n^{L n} \left( \frac{\hat{C}_n^H}{\hat{C}_n^L} \right)^{1-\rho} \]

\[ \frac{\hat{\omega}_n^{sd}}{\hat{\omega}_n^{sm}} = \left( \sum_{i \neq n} \hat{\tau}_{in}^s \sum_{k \neq n} \Theta_{kn}^s \right)^{-\frac{1}{\lambda}} \left( \hat{L}_{nn}^s \right)^{-\frac{1}{\lambda}} \]

\[ \hat{C}_n^{s n} \hat{L}_n = \hat{\omega}_n^{sd} \hat{L}_{nn}^s \sum_k \Theta_{kn}^s + \hat{\omega}_n^{sm} \sum_{i \neq n} \hat{L}_{in}^s \sum_k \Theta_{kn}^s \]

\[ \hat{\omega}_n^{sd} = \left( \sum_{i \neq n} \hat{\tau}_{in}^s \sum_{k \neq n} \Theta_{kn}^s \right)^{-\frac{1}{\lambda}} \left( \sum_{i \notin US} \hat{\tau}_{in}^s \Theta_{kn}^s \right)^{-\frac{1}{\lambda}} \]

\[ \hat{\omega}_n^{sm} = \left( \sum_{i \notin US} \hat{\tau}_{in}^s \Theta_{kn}^s \right)^{-\frac{1}{\lambda}} \left( \sum_{i \in US} \hat{\tau}_{in}^s \Theta_{kn}^s \right)^{-\frac{1}{\lambda}} \]

\[ \text{20 When } n \in US, \]

\[ \hat{C}_n^s = \left[ \left( \hat{\omega}_n^{sd} \right)^{1-\lambda} \sum_{i \notin US} \frac{\Theta_{in}^s}{\sum_j \Theta_{jn}^s} + \left( \hat{\omega}_n^{sm} \right)^{1-\lambda} \sum_i \frac{\Theta_{in}^s}{\sum_j \Theta_{jn}^s} \right]^{1-\lambda} \]

\[ \text{21 When } n \in US \]
Solving the model in changes enables me to solve for counterfactual quantities given exogenous changes in technology $A, B$, and migration and trade costs $\kappa$ and $\tau$, by using only data on trade, migration, and age bill shares ($\pi_{ik}^{\text{trade}}, \pi_{ik}^{\text{smig}}, X_{i}, N_{ik}^{sd}, N_{ik}^{sm}, \Theta_{in}^{s}$), as well as parameter values for $\varepsilon, \theta, \rho, \lambda$ and $\eta^{s}$. Subsection B.2 details how to map these objects into the data.

### B.2 Calibration of the skill model

Table A3 lists the value of the parameters and their source. The following subsections provide additional details on the link between the data and the model.

## C Data and calibration

### C.1 Population data

**Total migrant stock** To get the total number of migrants born in $i$ and living in $j$, I combine the American Community Survey 2013 data that provides information on place of birth of residents in each US states with estimates from the World Bank on residing population in each country ($POP_{i}$), and estimates of Bilateral Migration Matrix for 2013 ($MIG_{ij}$ for $i \neq j$, which translates directly into $N_{ij}$ in the model).\footnote{When $n \in US$}

The 2013 ACS is the survey used in the construction of the 2013 World Bank Bilateral Migration Matrix, ensuring consistency.

For $i \notin US$, I construct the total number of native from in country $i$ ($N_{i}$ in the model) as:

$$N_{i} = POP_{i} + \sum_{j \neq i, j \notin US} (MIG_{ij} - MIG_{ji}) + (MIG_{i,US} - MIG_{US,i})$$

For $i$ or $j$ in the US, I first use the ACS to construct $N_{i,US}$, which I define as the total population born in state $i$ and residing in the US ($N_{i,US} = \sum_{j \in US} N_{ij}$, where $N_{ij}$ comes\footnote{http://www.worldbank.org/en/topic/migrationremittancesdiasporaissues/brief/migration-remittances-data}
Table A3: Link between the model and the data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\epsilon$</td>
<td>migration elasticity</td>
<td>2.3</td>
<td>Caliendo et al. (2017)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Elasticity of substitution between skill</td>
<td>1.6</td>
<td>Katz and Murphy (1992)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Elasticity of substitution between native and migrant work</td>
<td>20</td>
<td>Ottaviano and Peri (2012)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>trade elasticity</td>
<td>4</td>
<td>Simonovska and Waugh (2014)</td>
</tr>
<tr>
<td>$\eta^s$</td>
<td>migration-elasticity of trade costs</td>
<td>$\eta^H = 0.3/\theta$</td>
<td>own estimate</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\eta^L = 0$</td>
<td></td>
</tr>
<tr>
<td>Exogenous object</td>
<td></td>
<td>1</td>
<td>keep constant</td>
</tr>
<tr>
<td>$A_n$, $B^n_s$, $\tilde{x}_in$</td>
<td>migration costs</td>
<td></td>
<td>Uniformly increased to target a reduction of 50% in total migrant stock living in the US</td>
</tr>
<tr>
<td>$\hat{\kappa}^s_{in}$</td>
<td>migration costs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi^{s,mig}_in$, $N^{s}_in$</td>
<td>population data</td>
<td></td>
<td>ACS, World Bank, OECD</td>
</tr>
<tr>
<td>$\pi^{trade}_in$, $X_n$</td>
<td>trade data (including services)</td>
<td></td>
<td>Census data on state level exports and imports, WIOD, CFS</td>
</tr>
<tr>
<td>$\Theta^s_{in}$</td>
<td>initial wage bill shares</td>
<td></td>
<td>ACS, IPMUS-International</td>
</tr>
</tbody>
</table>

Notes: see below for details on the sources and exact mapping between the data and the model objects.
directly from the ACS data). I then use the aggregate World Bank data on US natives living abroad and attribute them to each state proportionally to $N_{i,US}$. That is, for a US state $i$ and an other country $j$, I compute $L_{ij}$ as:

$$N_{ij} = MIG_{US,j} \frac{N_{i,US}}{\sum_{n \in US} N_{n,US}}.$$ 

When both $i$ and $j$ are US states, $N_{ij}$ comes directly from the ACS data. I can then construct $N_i = \sum_j N_{ij}$.

**Skill and unskilled migration shares** For the model with different skill levels, I collect additional data on education attainment. I defined skill as having completed some tertiary education (ISCED $\geq 5$). To compute the shares of skill and unskilled workers per country pair, I use various data sources.

When $j \in US$, I use the ACS data obtained through IPUMS to compute the share of skill and unskilled migrants from country $i$: $sh\text{skill}_{ij}^s = \frac{ACS_{ij}^s}{ACS_{ij}}$.

When $j \in \{CAN, MEX\}$, I use survey data from IPUMS-International (corresponding to the 2011 Census for Canada and 2010 Census for Mexico$^{24}$) and compute the skill share: $sh\text{skill}_{ij}^s = \frac{IPUMS_{ij}^s}{IPUMS_{ij}}$. When $i \in US$, there is no information on the state of origin. In that case, I use the ACS data to apportion the skilled and unskilled by state $i$:

$$sh\text{skill}_{ij}^s = \frac{\sum_{n \in US} ACS_{n,US}^s IPUMS_{n,US}^s}{\sum_{n \in US} ACS_{n,US}^s IPUMS_{n,US}}.$$ 

When $j \notin \{US, CAN, MEX\}$ and $i = j$, I impute $sh\text{skill}_{jj}^s$ as the overall skill share in the country, using data from the OECD’s World Indicators of Skills for Employment database.$^{25}$ As long as the total migrant share is low, this provides a good approximation of the native’s skill composition. When $i \neq j$, I impute $sh_{ij}^s$ using the average skill shares of natives from $i$ in countries where I have data: $sh\text{skill}_{ij}^s = \overline{sh\text{skill}_{i,REST}^s}$.

Finally I compute $N_{ij}^s$ as: $N_{ij}^s = sh\text{skill}_{ij}^s \ast N_{ij}$.

It is important to note that migrant stocks for population residing in US states come directly from the ACS and are precisely measured. Similarly, data for Canada and Mexico (countries that will be most relevant in my counterfactual) comes from survey data. Imputation only occurs for foreign countries, where the counterfactual only has a second order effect. Hence the results won’t be sensitive to the imputation method.

---

$^{24}$The 2013 World Bank Bilateral Migration Matrix is based on the United Nations database POP/DB/MIG/Stock/Rev.2013, which uses country-level Census rounds. The 2011 Canada and 2010 Mexico censuses were the last one available for the construction of these datasets, thus ensuring consistency between the migration data and the skill shares.

C.2 Expenditure data:

I combine data from the OECD Inter-Country Input Output Table (ICIO) for 2013, the Commodity Flow Survey, and Census data on state level exports and imports to compute expenditure data.

If \(i, j \notin \text{US}\), I simply use the total ICIO exports from \(i\) to \(j\):

\[
X_{ij} = X_{ij}^{\text{ICIO}}
\]

If \(i \in \text{US}, j \notin \text{US}\):

\[
X_{ij} = X_{ij}^{\text{ICIO}} \frac{X_{ij}^{\text{census,EX}}}{\sum_{n \in \text{US}} X_{nj}^{\text{census,EX}}}
\]

where \(X_{ij}^{\text{census,EX}}\) is the Census Origin of Movement export value. That is, I allocate the US export value from the ICIO to each state using the share of exports originating from the state.

If \(i \notin \text{US}, j \in \text{US}\):

\[
X_{ij} = X_{ij}^{\text{ICIO}} \frac{X_{ij}^{\text{census,IM}}}{\sum_{n \in \text{US}} X_{nj}^{\text{census,IM}}}
\]

where \(X_{ij}^{\text{census,IM}}\) is the Census state of destination import value. That is, I allocate the US import value from the ICIO to each state using the share of imports going to the state.

If \(i, j \in \text{US}\):

\[
X_{ij} = X_{ij}^{\text{ICIO}} \frac{X_{ij}^{\text{CFS}}}{\sum_{n,m \in \text{US}} X_{nm}^{\text{CFS}}}
\]

where \(X_{ij}^{\text{CFS}}\) is the total value of shipments from state \(i\) to state \(j\) in the Commodity Flow Survey public use micro data. This potentially overestimate the total trade between states, as industries covered in the CFS don’t include services, which are more tradable.\(^{26}\) In Appendix D, I check the robustness of my results to this assumption by assuming that the same fraction of service output that is exported by the US to the rest of the world is also traded within the US. More precisely, define the share of tradable in services as

\[
\sigma = \frac{X_{\text{US,ROW}}^{\text{SERVICE}}}{(X_{\text{US,US}}^{\text{SERVICES}} + X_{\text{US,ROW}}^{\text{SERVICES}})}
\]

Then when computing \(X_{ij}\) for \(i \neq j\), \(i, j \in \text{US}\),

\(^{26}\)In the ICIO data, the share of US exports in US service output is around 5%, while it is around 15% for non-services. I define services as anything that is not agriculture, mining or manufacturing.
use that same share to compute trade flows:

\[ X_{ij} = \left( X_{ICIO,NOSERVICE}^{US,US} + \sigma X_{ICIO,SERVICES}^{US,US} \frac{emp_{SERVICES}^i}{emp_{US}^i} \right) \frac{X_{ij}^{CFS}}{ \sum_{n,m \in US} X_{nm}^{CFS}} \]

where I use sectoral employment data to attribute the service production to each state. For own-state flow, I use: \(^{27}\)

\[ X_{ii} = (1 - \sigma) X_{ICIO,SERVICES}^{US,US} \frac{emp_{SERVICES}^i}{emp_{US}^i} + \left( X_{ICIO,NOSERVICE}^{US,US} + \sigma X_{ICIO,SERVICES}^{US,US} \frac{emp_{SERVICES}^i}{emp_{US}^i} \right) \frac{X_{ii}^{CFS}}{ \sum_{n,m \in US} X_{nm}^{CFS}}. \]

### C.3 Wage bill data by origin and skill

For the US states, Canada and Mexico, I compute the shares of wage bill required to solve the model (\(\Theta_{in}\) in the main model, \(\Theta_{in}^s\) in the skill model) directly from the survey data also used to construct the migration shares.\(^{28}\) This ensures that the migration and wage bill data are consistent with each other. For other countries where survey data is not readily available, I simply use migrant population shares to input the wage bill shares. This assumes that the average wage of all workers in the country is the same, which ignores selection into migration. However, when using the same method to impute wage bill shares for US states, Canada and Mexico, the correlation is high at 0.99. Furthermore, the counterfactual will mostly affect the US, Canada and Mexico to a lesser extent, and the rest of the world much less. Hence the parameters for the rest of the world imputed from US, Canada and Mexican data don’t have a significant quantitative importance.

### C.4 List of regions in the model

Table A4 lists the regions in the model. It is comprised of the US 50 states plus the District of Columbia, as well as 56 countries and a composite Rest of the World (ROW). A large

\(^{27}\)This is probably an underestimation of within US service trade flows, as services are probably more tradable domestically than internationally.

\(^{28}\)I use the average wage of migrants to skill \(s\) from \(i\) in \(n\), multiplied by the total number of migrants \(N_{in}^s\), to get the total wage bill paid to migrants from \(i\) in \(n\), and compute the shares from there.
majority of migrant population and trade flows are covered by the individual countries. The ROW accounts for on average 10% of a state’s exports and 31% of a state’s migrant population. The main missing migrant countries are Central American countries such as El Salvador, Cuba, the Dominican Republic or Guatemala, which are all small trading partners.

D Robustness checks

In this section, I assess the robustness of the results to different values of the trade and migration elasticity, as well as an alternative way of computing within-US trade flows.

Main model Table A5 displays the average changes in trade costs, export as share of output, and welfare for alternative calibration for the main counterfactual. Overall, the results are fairly stable when changing the migration elasticity. The change in export trade costs is sensitive to the trade elasticity, because I calibrate \( \eta = 0.2/\theta \), but the effect on exports as share of output is stable. The change in welfare is larger for a small trade elasticity, as wages need to fall by more to achieve the same change in exports. Figure A1 shows the average changes in real wages across US states, decomposed into the average own-state effect, internal market access effect, and international market access, for the same set of robustness checks. In all cases, the own-state effect is positive, because the reduced labor supply is not offset by a larger reduction in market access when only migrant population in the state is reduced. The intra- and international market access effects are negative throughout.

Skill and imperfect substitutability model Table A6 displays the average changes in trade costs, export as share of output, and welfare for alternative calibration for the main counterfactual with the skill and substitutability model. Figure A2 shows the average changes in real wages across US states, decomposed into the average own-state effect, internal market access effect, and international market access. The native/migrant elasticity of substitution plays an important role in determining whether the own-state effect (driven mainly by the labor supply effect) is positive or negative. With a low elasticity of substitution, the effect of the reduction in migration is large and negative, while a high substitutability moves the results closer to the main model.\(^{30}\) The skill substitutability

\(^{29}\)See section C.2.

\(^{30}\)The baseline model without skills and imperfect native-migrant substitutability does not produce exactly the same results as the refined model even when both \( \lambda \) and \( \rho \) are set to infinity, because of the dif-
<table>
<thead>
<tr>
<th>US States</th>
<th>Countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
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<td>North Carolina</td>
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<tr>
<td>Montana</td>
<td>Ireland</td>
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<td></td>
<td>South Africa</td>
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</table>
### Table A5: Sensitivity analysis for the main model

<table>
<thead>
<tr>
<th>Migration elasticity</th>
<th>Trade elasticity</th>
<th>Less tradable services&lt;sup&gt;29&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon = 1.5$</td>
<td>$\varepsilon = 3$</td>
<td>$\theta = 2$</td>
</tr>
<tr>
<td>Change in state export costs (exports weighted)</td>
<td>3.67%</td>
<td>3.69%</td>
</tr>
<tr>
<td></td>
<td>(.16)</td>
<td>(.16)</td>
</tr>
<tr>
<td>Change in exports as share of output</td>
<td>-4.97%</td>
<td>-4.27%</td>
</tr>
<tr>
<td></td>
<td>(0.92)</td>
<td>(1.10)</td>
</tr>
<tr>
<td>Change in natives’ welfare</td>
<td>-0.13%</td>
<td>-0.13%</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.10)</td>
</tr>
</tbody>
</table>

Notes: The table shows the percentage changes, after reducing the share of migrants in the US population by half. Numbers are average across US states, with standard deviation in parenthesis.

### Figure A1: Real wage change decomposition: robustness

![Real wage change decomposition: robustness](image-url)
Table A6: Sensitivity analysis for the skill and imperfect substitutability model

<table>
<thead>
<tr>
<th></th>
<th>Native/migrant substitutability</th>
<th>Skill substitutability</th>
<th>Less tradable services$^{31}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\lambda = 5$</td>
<td>$\lambda = 100$</td>
<td>$\rho = 50$</td>
</tr>
<tr>
<td>Change in state export costs</td>
<td>5.44% (0.22)</td>
<td>5.50% (0.23)</td>
<td>5.49% (0.23)</td>
</tr>
<tr>
<td>(exports weighted)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in exports as share of</td>
<td>-6.82% (1.35)</td>
<td>-7.22% (1.34)</td>
<td>-7.09% (1.34)</td>
</tr>
<tr>
<td>output</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in US low-skill welfare</td>
<td>-0.84% (0.24)</td>
<td>-0.21% (0.21)</td>
<td>-0.36% (0.06)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in US college welfare</td>
<td>-0.93% (0.19)</td>
<td>-0.23% (0.07)</td>
<td>-0.36% (0.05)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table shows the percentage changes, after reducing the share of migrants in the US population by half. Numbers are average across US states, with standard deviation in parenthesis.

matters less. Overall, both the intra- and international market access effects stay large and negative, regardless of the production function elasticities.

E  Algorithms

E.1  Algorithm for the main model

This section describes how to solve the model in changes. This solution allows for trade deficits $D_n$ to exist, hence the relevant income for location is not wage $w_n$ but $v_n = w_n + D_n/L_n$. Results in the paper come from first creating a deficit-free equilibrium different migration shares of skilled and unskilled workers. Since the model interprets high migration shares as reflecting a high $B_{in}$, the fall in effective labor supply is different in the two models even with infinite substitutability.

$^{31}$See section C.2.

$^{32}$That is, I assume that the deficit is redistributed uniformly to each efficiency unit of labor. Using the following equation, one can solve for $\delta_n$: 

$$X_n^{cons} \sum_i L_{in} = X_n^{outp} + D_n$$

$$\delta_n \sum_i ^{v_n L_{in}} \bar{X}_n^{outp} = \bar{X}_n^{outp} + \frac{D_n}{\bar{X}_n^{outp}} \bar{D}_n$$
Figure A2: Skill scenario robustness: decomposition

(a) Low-skill, native wage changes

(b) High-skill, native wage change
by solving the system of equation below setting $\hat{D}_n = 0$ while keeping other exogenous variables constant, and then using the resulting trade, migration and wage bill shares to solve for a counterfactual change in migration costs.\textsuperscript{33}

i. Guess $\hat{\pi}^{mig}_{in}$

ii. Solve for $\hat{N}_{ni}$ and $\hat{d}_{ni}$ using

$$\hat{N}_{ni} = \hat{\pi}^{mig}_{in}$$

$$\hat{d}_{ni} = \hat{c}_{ni} \left( \frac{1 + 1 (i,n \notin \text{US}) \hat{N}_{in} N_{in}}{1 + 1 (i,n \notin \text{US}) N_{in}} \right)^{-\eta} \left( \frac{\sum_j \hat{N}_{jn} N_{jn}}{\sum_j N_{jn}} \right)^{-\eta}$$

iii. Solve for $\hat{w}_i$ : guess for $\hat{w}_i$

(a) Solve for $\hat{\pi}^{trade}_{ni}$ using

$$\hat{\pi}^{trade}_{ni} = \frac{\hat{A}_n (\hat{d}_{ni} \hat{w}_n)^{-\theta}}{\sum_s \hat{A}_s (\hat{d}_{si} \hat{w}_s)^{-\theta} \hat{\pi}^{trade}_{si}}$$

(b) Solve for $\hat{X}_n^{outp}$ using

$$\hat{X}_i^{outp} X_i^{outp} = \sum_j \hat{\pi}^{trade}_{ij} \hat{\pi}^{trade}_{ij} \left( \hat{X}_j^{outp} X_j^{outp} + \hat{D}_j D_j \right)$$

and normalize the new output such that total world output remains constant, that is:

$$\sum_i \hat{X}_i^{outp} X_i^{outp} = \sum_i X_i^{outp}$$

(c) Solve for $\hat{\pi}^{mig}_{n}$ using

$$\hat{X}_n^{outp} = \hat{\pi}^{mig}_{n} \left( \hat{\pi}^{mig}_{in} \right)^{-\frac{1}{\epsilon}} \hat{N}_i \Theta_{in}$$

(d) Go back to (a) using updated $\hat{\pi}^{mig}_{n}$

\textsuperscript{33}The new wage bill shares can be computed as:

$$\Theta'_{in} = \frac{\hat{w}_n L_{in}'}{X_n} = \frac{\hat{w}_n L_{in}'}{X_n} \Theta_{in} = \frac{\hat{w}_n (\hat{B}_{in})^\frac{1}{\epsilon} \left( \hat{\pi}^{mig}_{in} \right)^\frac{\epsilon-1}{\epsilon} \hat{N}_i \Theta_{in}}{X_n} \Theta_{in}$$
iv. Solve for \( \hat{v}_n \), \( \hat{P}_n \) and \( \hat{\pi}_{in}^{mig} \) using:

\[
\hat{v}_n \sum_i (\hat{B}_n)^{1/2} \left( \pi_{in}^{mig} \right)^{\varepsilon - 1} \hat{N}_i \Theta_{in} \frac{X_{cons}}{X_{outp}} = \hat{X}_{outp} + \frac{D_n}{X_n} \hat{D}_n
\]

\[
\hat{P}_n = \left( \frac{\hat{A}_n \left( \hat{w}_n \right)^{-\theta}}{\hat{\pi}_{trade}^{mig}} \right)^{-1/\theta}
\]

\[
\hat{\pi}_{in}^{mig} = \frac{\hat{B}_n \left( \hat{\pi}_{in} \right)}{\sum_k \hat{B}_k \left( \hat{\pi}_{ik} \right)^{\varepsilon \pi_{in}^{mig}}}
\]

v. Go back to 1 using updated \( \hat{\pi}_{in}^{mig} \)

E.2 Algorithm for the skill model

This section describes how to solve the model in changes. This solution allows for trade deficits \( D_n \) to exist, hence the relevant income for location is not wage \( w_{sm} \) or \( w_{sd} \) but \( v_{sm} \) or \( v_{sd} \), where I assume that deficits are redistributed proportionally to income.\(^{34}\) Results in the paper come from first creating a deficit-free equilibrium by solving the system of equation below setting \( \hat{D}_n = 0 \) while keeping other exogenous variables constant, and then using the resulting trade and migration shares to solve for a counterfactual change in migration costs.

i. Guess \( \hat{\pi}_{in}^{s,mig} \)

ii. Solve for \( \hat{N}_{in}^{s}, \hat{L}_{in}^{s} \) and \( \hat{d}_n \) using

\[
\hat{N}_{in}^{s} = \hat{\pi}_{in}^{s,mig}
\]

\[^{34}\text{That is:}
\]

\[
L_{nn}^{s} v_{n}^{sd} = L_{nn}^{s} w_{n}^{sd} + \Theta_{nn} D_n = \Theta_{nn} \left( X_{n}^{outp} + D_n \right)
\]

\[
L_{in}^{s} v_{n}^{sm} = L_{in}^{s} w_{n}^{sm} + \Theta_{in}^{s} D_n = \Theta_{in}^{s} \left( X_{n}^{outp} + D_n \right)
\]

In changes:

\[
\hat{L}_{nn}^{s} v_{n}^{sd} = \hat{\Theta}_{nn} \left( X_{n}^{outp} X_{outp} + \hat{D}_n D_n \right) = \hat{\Theta}_{nn} \left( X_{n}^{outp} + D_n \right)
\]

\[
\hat{L}_{in}^{s} v_{n}^{sm} = \hat{\Theta}_{in}^{s} \left( X_{n}^{outp} X_{outp} + \hat{D}_n D_n \right) = \hat{\Theta}_{in}^{s} \left( X_{n}^{outp} + D_n \right)
\]

so

\[
\hat{v}_{n}^{sd} = \frac{\hat{\Theta}_{nn}}{\hat{X}_{n}^{outp}} \left( X_{n}^{outp} + \hat{D}_n D_n \right), \hat{v}_{n}^{sm} = \frac{\hat{\Theta}_{in}^{s}}{\hat{X}_{n}^{outp}} \left( X_{n}^{outp} + \hat{D}_n D_n \right)
\]

45
\[ \hat{l}_{in} = (\hat{B}_{in})^{\frac{1}{t}} (\hat{n}_{in}^{s,mig})^{\frac{s-1}{t}} \hat{N}_i \]
\[ \hat{d}_{ni} = \hat{\tau}_{ni} \prod_{s \in \{L,H\}} [1 (i | n \notin US) \left( \frac{1 + \hat{N}_{i,n}^{s} N_{in}^{s}}{1 + \hat{N}_{in}^{s}} \right) \left( \frac{\sum_{j} \hat{N}_{j,n}^{s} N_{jn}^{s}}{\sum_{s,j} N_{jn}^{s}} \right) + 1 (i, n \in US)]^{-\eta^s} \]

iii. Solve for \( \hat{w}_{sd}^n, \hat{w}_{sm}^n \): guess \( (\hat{w}_{sd}^n, \hat{w}_{sm}^n) \)

(a) Solve for \( \hat{C}^s_n \) and \( \hat{C}_n \) using

\[ \hat{C}^s_n = \left[ (\hat{w}_{n}^{sd})^{1-\lambda} \sum_{i} \Theta_{in}^{s} + (\hat{w}_{n}^{sm})^{1-\lambda} \sum_{i \neq n} \Theta_{in}^{s} \right]^{\frac{1}{1-\lambda}}, \]
\[ \hat{C}_n = \left[ (\hat{C}^L_n)^{1-\rho} \sum_{i} \Theta_{in}^{L} + (\hat{C}^H_n)^{1-\rho} \sum_{i} \Theta_{in}^{H} \right]^{\frac{1}{1-\rho}}. \]

(b) Solve for \( \hat{\pi}_{ni}^{trade} \) using

\[ \hat{\pi}_{ni}^{trade} = \frac{\hat{A}_n (\hat{d}_{ni} \hat{C}_n)^{-\theta}}{\sum_k \hat{A}_k (\hat{d}_{ki} \hat{C}_k)^{-\theta} \hat{\pi}_{ki}^{trade}} \]

(c) Solve for \( \hat{X}_{n}^{outp} \) using

\[ \hat{X}_{n}^{outp} X_{n}^{outp} = \sum_{j} \hat{\pi}_{nj} \hat{\pi}_{nj}^{trade} \left( \hat{X}_{j}^{outp} X_{j}^{outp} + \hat{D}_j D_j \right) \]

and normalize the new output such that total world output remains constant, that is:

\[ \sum_i \hat{X}_{i}^{outp} X_{i}^{outp} = \sum_i X_{i}^{outp} \]

(d) Compute \( \hat{w}_{n}^{sd}, \hat{w}_{n}^{sm} \) using:

\[ \hat{C}^L_n \hat{L}_n = \hat{X}_n \left( \sum_i \Theta_{in}^{L} + \left( \frac{\hat{C}^H_n}{\hat{C}_n} \right)^{1-\rho} \sum_i \Theta_{in}^{H} \right) \]
\[ \hat{C}^H_n \hat{L}_n = \hat{C}^L_n \hat{L}_n \left( \frac{\hat{C}^H_n}{\hat{C}_n} \right)^{1-\rho} \]
\[
\hat{w}_{sd}^{sm} = \left( \sum_{i \neq n} \hat{f}_{in}^{s} \frac{\hat{\Theta}_{in}^{s}}{\sum_{k \neq n} \hat{\Theta}_{kn}^{s}} \right)^{-\frac{1}{\lambda}}.
\]

\[
\hat{C}_{n}^{s} = \hat{w}_{sd}^{s} \hat{f}_{in}^{s} \frac{\hat{\Theta}_{in}^{s}}{\sum_{k} \hat{\Theta}_{kn}^{s}} + \hat{w}_{sm}^{s} \sum_{i \neq n} \hat{f}_{in}^{s} \frac{\hat{\Theta}_{in}^{s}}{\sum_{k} \hat{\Theta}_{kn}^{s}}.
\]

(e) Go back to (a) using updated \(\hat{w}_{sd}^{s} \).

iv. Solve for \(\hat{v}_{sd}^{s}, \hat{v}_{sm}^{s}, \hat{P}_{n} \) and \(\hat{\pi}_{in}^{s, mig} \) using:

\[
\hat{v}_{sd}^{s} = \frac{\hat{w}_{sd}^{s}}{\hat{X}_{n}^{outp}} \left( \hat{X}_{n}^{outp} \hat{X}_{n}^{outp} + \hat{D}_{n} \hat{D}_{n} \right), \quad \hat{v}_{sm}^{s} = \frac{\hat{w}_{sm}^{s}}{\hat{X}_{n}^{outp}} \left( \hat{X}_{n}^{outp} + \hat{D}_{n} \right).
\]

\[
\hat{P}_{n} = \left( \hat{A}_{n} (\hat{w}_{n})^{-\theta} \right)^{-\frac{1}{\theta}}
\]

\[
\hat{\pi}_{in}^{s, mig} = \frac{\hat{B}_{n}^{s} \left( \hat{\gamma}_{n}^{s} (i=n) \hat{\gamma}_{m}^{s} (i \neq n) \right)^{\epsilon}}{\sum_{k} \hat{B}_{ik}^{s} \left( \hat{\gamma}_{k}^{s} (i=n) \hat{\gamma}_{ik}^{s} (i \neq n) \right)^{\epsilon} \hat{\pi}_{ik}^{s, mig}}
\]

v. Go back to 1 using the updated \(\hat{\pi}_{in}^{s, mig} \).