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Abstract

Migrants shape market access: first, they reduce international trade frictions and second, they change the geographical location of domestic demand. This paper shows that both effects are quantitatively relevant. It estimates the sensitivity of exports and imports to immigrant population and quantifies these effects in a model of inter- and intra-national trade and migration calibrated to US states and foreign countries. Reducing US migrant population shares back to 1980s levels increases import (export) trade costs by 7% (2.5%) on average and decreases US natives' real wages by more than 2%. States with higher exposure to immigrant consumer demand (both from within the state and from other states) than to migrant labor supply competition suffer more from the removal of migrants. States with higher export and import exposure suffer more from the increased trade costs.

JEL-Codes: F160, F220.

Keywords: migration, market access, trade.

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1 Introduction

Immigrants affect both the local supply of labor, and the demand for output produced by a geographic unit. The majority of the public debate and 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) or the migrants' impact on productivity (Alesina et al., 2016; Peri, 2012). 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 inter-national trade and migration and 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 expand international market access by reducing the costs of foreign trade (see e.g. Gould, 1994; Ottaviano et al., 2018). The left panel of Figure 1 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.[1] States with more immigrants from a particular country export more to that country, conditional on basic gravity determinants of trade. In this paper, I estimate the causal impact of migrants on exports and imports in the US using an instrumental variable approach based on push-pull factors. I show that migrants have a positive causal impact on both exports from US states to their country of origin, and on imports from their origin-country. The positive effect of migrants on trade comes mainly through high-skill rather than low-skill migrants. I ground my estimate in a theoretical framework that allows for country of origin-bias in tastes of immigrants, which also lets me estimate a causal impact of migrants on imports while controlling for a potentially heterogenous demand across immigrants and natives.

The second mechanism is that immigrants increase the intra-national market access. Immigrants demand goods and services from both the state where they reside, and other US

[1]The 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.

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 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. The right panel of Figure 1 illustrates this point by plotting the estimated share of a state's output sold to migrants residing in the US against the share of migrant population in the state.[2] 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 population.

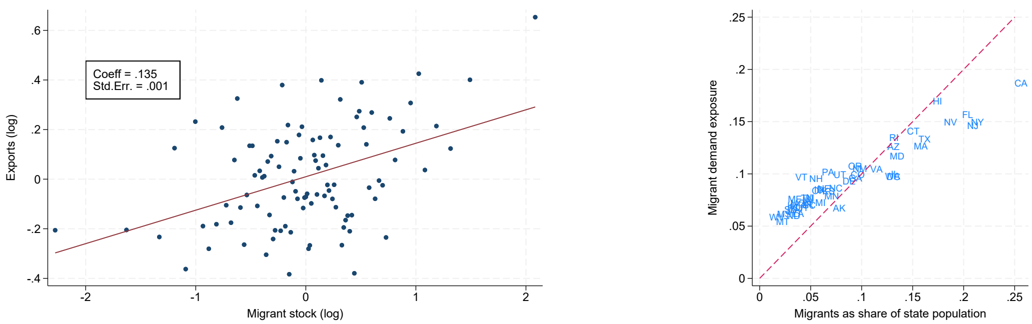
I extend a Melitz (2003) model with trade, mobile labor of different skills, origin-bias in tastes, and an endogenous reaction of trade costs to migration. I calibrate it to an economy composed of all US states and 56 countries, to provide the first quantitative assessment of the effect of migration on natives' welfare through shaping both intra- and inter-national market access of US states. In addition to standard structural elasticities common in quantitative models, my framework requires 3 novel parameters: 2 elasticities of international trade costs with respect to migrant population, and the origin-bias of migrants' consumption. I use econometric estimates to discipline these elasticities. I estimate an elasticity of exports to high-skill migrant population of around 0.15 and an elasticity of imports to high-skill migrants of around 0.3. I also estimate an origin-bias parameter that implies that international migrants in the US spend around 10% of their income on goods from their origin country.

[2] Formally, I compute the share of output sold to migrants in the US, for a state i as:

$$share_i = \frac{\sum_{j \in US} X_{ij} * sh\_mig_j}{\sum_j X_{ij}},$$

where sh_mig_j is the share of migrants in j's population, and X_{ij} are total sales of i to j.

Figure 1: The two mechanisms in the data



a) Exports and migration b) Migrant exposure and migrant share

Notes: The left panel displays the residuals of exports of a state to a country against the residuals of the migrant population in the state, from that country, after controlling or multilateral resistance and distance. The right panel of the figure plots the migrant demand exposure of a state, against the share of migrants in the state's population.

I simulate a counterfactual scenario where the share of migrants in the US by country and skill is brought back to 1980 levels. This would increase export-weighted trade costs by 2.5% on average across US states, around half of the 4.9% current ad-valorem export tariffs faced by US exporters (WEF, 2016). Import trade costs would increase by 7%, much more than current import tariffs imposed by the US (around 1.5%). The reduction in migrant population would decrease average real wages of US natives of low-skill and high-skill by 2.46 and 2.36 percent respectively. I decompose this overall effect into three main components. First, changes in market access account for about 0.8% (-0.33% due to reduced international market access from higher trade costs, -0.47% due to reduced market access from lower demand in other states). Second, the decrease in migrant population also brings about firm exit, a channel that accounts for a fall of 1.4% in real wages. The third channel comes from the reduction in the own-state migrant population. This channel is more muted because the reduction in labor competition within the state is mostly compensated by the loss of within-state aggregate demand from own-state migrants. It accounts for a fall in real wages of -0.2% for low-skill, and close to 0 for high-skill natives.

There is substantial heterogeneity across US states. Changes in real wages range from close to -5% in California to half a percent decrease in South Dakota. Differences in intra-national migrant demand exposure, international exposure, and local migrant population shares explain well the regional heterogeneity. By and large, states with large migrant population suffer the most from firm exit. However, states that do not host many immigrants themselves, but sell to states with large immigrant populations also suffer from reductions in US-wide immigrant stocks, as their labor supply is unaffected but their market access drops. States with higher international trade exposure lose more from the increase in trade costs.

This paper contributes to the literature on quantitative assessment of migration (e.g. Docquier et al., 2014; Aubry et al., 2016), 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, and emphasize the scale effect of migrants through firm entry. Caliendo et al. (2021) 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 reacts 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, heterogenous tastes between migrants and natives, and a trade costs reduction effect of migrants. 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, incorporating the trade costs reduction channel of migrants. Here, I also model origin-bias, within-US trade, and heterogeneity in migration and trade exposure to analyze the effect of migration at a finer geographical level, connecting to the 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 (2022) use firm level data to show a similar effect. Ottaviano et al. (2018) show that this also holds for exports in services. Bailey et al. (2021) use Facebook data to show that countries with more social connections 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 based on Burchardi et al. (2019), and show that the effect is different across skill levels. Furthermore, it remains an open question whether the impact of migrants on imports is evidence a drop in import costs or driven by origin-bias in tastes. Here, I use a novel theoretical framework to provide an estimation strategy of the effect of migrants on imports netting out origin-bias in preferences. I also show that the pro-trade impact of migrants is stronger for countries whose language is the furthest from English, and for industries with large contracting intensity (Nunn, 2007).

The rest of the paper is structured as follows. Section 2 describes the quantitative framework, Section 3 estimates origin-bias and the sensitivity of trade costs to migrant population, and Section 4 presents the counterfactual results. Section 5 concludes.

2 Quantitative framework

2.1 Model set up

There are N regions in the model, denoted by i, o and d. Agents get utility from consumption, can be high or low-skill, and are mobile subject to frictions. Regions trade with each other subject to trade costs that are a function of migrant populations.

Preferences, demand and worker efficiency An agent of skill s born in region o and living in region d gets the following utility:

$$U_{od}^{s} = \frac{\left(C_{od}\right)^{\alpha}\left(C_{d}\right)^{1-\alpha}}{\kappa_{od}^{s}},$$

where C_{od} is a consumption bundle of a continuum of goods produced in o, C_d is a bundle of all available goods, and κ_{od}^{s} is a migration cost in term of utility. The consumption bundle C_{od} is a CES aggregator of a continuum of goods (indexed by ω) produced in origin country o and consumed at destination d:

$$C_{od} = \left[\int_{\omega\in\Omega_{od}} q_{od}\left(\omega\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where Ω_{od} is the set of available goods from o in d. C_d is in turn a CES aggregate over all bilateral bundles:

$$C_d = \left[\sum_i C_{id}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where the elasticity of substitution σ is the same across bundle from different countries as within a country's bundle.

This utility formulation extends the traditional Armington CES aggregator to allow for origin-bias in taste through the upper Cobb-Douglas nest. The origin-bias parameter α governs the share of spending on an agent's country of origin's goods. When $\alpha = 0$, the preferences collapse to those in the traditional Melitz (2003) model. The reasons to allow for origin-bias in preferences ($\alpha > 0$) is twofold. First, migrants spend less on domestic goods than natives (Albert and Monras, 2022). Hence, their presence might not increase local demand as much as if their tastes were the same as natives. Second, explicitly modeling origin-bias will allow me to estimate the impact of migrants on imports net of the taste channel.

Workers supply their endowment of labor inelastically in their location of residence, but have a different efficiency depending on where they were born and were they work. Specifically, worker μ of skill s born in region o and living in region d supplies $b_{od}^s(\mu)$ efficiency units of labor. The efficiency is distributed according to a Fréchet distribution, $F_{od}^s(b) = e^{-B_{od}^s b^{-\varepsilon}}$, where ε is the shape parameter governing the dispersion of efficiencies and B_{od}^s is a location parameter. Workers from region o are in general more efficient in regions d with higher B_{od}^s. 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 been used to model 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 The production side of the economy follows a Melitz (2003) structure. Each firm produces a differentiated product, and the market structure is monopolistic competition. The production function of firm ω in region o is given by $y(\omega) = A_o\psi(\omega)L(\omega)$, where A_o is region-specific productivity, $\psi(\omega)$ is the firm's idiosyncratic productivity, and $L(\omega)$ is the amount of a labor composite employed by the firm. Within a region, each firm is identical up to its productivity, so that the rest of the text refers to specific firms by their productivity ψ. The labor composite is a nested CES aggregate of labor. The upper nest aggregates low and high-skill labor composites with an elasticity of substitution ρ. The lower nest combines domestic labor and migrant labor with elasticity of substitution λ:

$$L = \left[\phi^L \left(L^L\right)^{\frac{\rho-1}{\rho}} + \phi^H \left(L^H\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{3}$$

where

$$L^s = \left[\phi^{sn} \left(L^{sn}\right)^{\frac{\lambda-1}{\lambda}} + \phi^{sm} \left(L^{sm}\right)^{\frac{\lambda-1}{\lambda}}\right]^{\frac{\lambda}{\lambda-1}}. \tag{4}$$

where L^{sn} and L^{sm} are the amount of labor from natives and migrants of skill s hired by the firm. Optimality implies that the cost of the labor bundle in a location o is a function of the wages of natives and migrants of different skills:

$$c_o = \left[\phi^L \left(c_o^L\right)^{1-\rho} + \phi^H \left(c_o^H\right)^{1-\rho}\right]^{\frac{1}{1-\rho}} \tag{5}$$

where

$$c_o^s = \left[\phi^{sd} \left(w_o^{sn}\right)^{1-\lambda} + \phi^H \left(w_o^{sm}\right)^{1-\lambda}\right]^{\frac{1}{1-\lambda}}$$

where w_o^{sn} and w_o^{sm} are the native and migrant wages in o, for $s \in \{L, H\}$.

There is a pool of ex-ante identical firms in country o. Firms productivity is given by $A_o\psi$, where A_o is common to all firms in o, and ψ is an idiosyncratic part of productivity that follows a Pareto distribution with parameter γ: $G(\psi) = 1 - \psi^{-\gamma}$.

A firm in region o needs to first pay a fixed cost of entry f_o^e/A_o expressed in units of composite labor to discover its productivity. It then needs to pay f_{od}/A_d units of the destination's composite labor as fixed overhead cost to enter a destination market d. Firms enter up to the point where expected profits equal fixed entry costs. After initial entry, the firm sells to a destination d if its market-specific profit is higher than the overhead cost. For firm ψ in region o, the variable cost to produce and deliver q_{od} units to destination d is given by $\frac{c_o \tau_{od}}{A_o \psi} q_{od}$, where c_o is the unit cost of composite labor and τ_{od} is an iceberg trade cost.

2.2 Trade and migration shares

Demand The agent maximizes utility subject to an income to be specified later. Given the homotheticity of the utility function and optimality conditions, total spending on good from firm ψ from o by all residents of country d is given by:

$$X_{od}(\psi) = \left[\frac{(1-\alpha)\sum_i E_{id}}{P_d^{1-\sigma}} + \frac{\alpha E_{od}}{P_{od}^{1-\sigma}} \right] (p_{od}(\psi))^{1-\sigma}, \tag{6}$$

where E_{id} is the total expenditure of natives from i in d. P_d and P_{od} are CES price indices:

$$P_d = \left[\sum_o (P_{od})^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \quad ; \quad P_{od} = \left[\int_{\psi \in \Psi od} p_{od}(\omega)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}}, \tag{7}$$

where Ψ_{od} is the set of firms exporting from o to d. The total value of trade from o to d is:

$$X_{od} = \alpha E_{od} + \frac{(P_{od})^{1-\sigma}}{P_d^{1-\sigma}} (1-\alpha) \sum_i E_{id} \tag{8}$$

The first term is the bilateral migrant origin-bias demand, while the second term is the traditional aggregate CES demand. It will prove useful to solve for the price index of the bundle of exports from o to d as a function of an adjusted trade share π_{od}^{adj}:

$$P_{od}^{1-\sigma} = \underbrace{\frac{X_{od} - \alpha E_{od}}{(1-\alpha)\sum_i E_{id}}}_{\pi_{od}^{adj}} P_d^{1-\sigma} \tag{9}$$

Residential choice shares A worker μ's indirect utility function can be written as:

$$V_{od}^{s}(\mu) = \frac{b_{od}^{s}(\mu) w_{od}^{s}}{P_{od}^{\alpha} P_{d}^{1-\alpha}} \frac{1}{\kappa_{od}^{s}},$$

where $b_{od}^{s}(\mu)$ is the labor efficiency draw of worker μ, w_{od}^{s} is the wage in region d received by the worker of skill s born in o (native or migrant wage), $P_{od}^{\alpha} P_{d}^{1-\alpha}$ is the price index the worker faces in d and κ_{od}^{s} is the migration cost. The worker chooses d to maximize his indirect utility. Usual steps using the Fréchet distribution yield the following residential choice shares:

$$\pi_{od}^{s,mig} = \frac{N_{od}^{s}}{\sum_{k} N_{ok}^{s}} = \frac{B_{od}^{s} \left(\frac{w_{od}^{s}}{(P_{od})^{\alpha} (P_{d})^{1-\alpha} \kappa_{od}^{s}} \right)^{\varepsilon}}{\sum_{k} B_{ok}^{s} \left(\frac{w_{ok}^{s}}{(P_{ok})^{\alpha} (P_{k})^{1-\alpha} \kappa_{ok}^{s}} \right)^{\varepsilon}}, \tag{10}$$

where N_{od}^{s} is the number of people of skill s born in o and living in d. Their corresponding amount of efficiency units of labor, denoted L_{od}^{s}, can be shown to be equal to:

$$L_{od}^{s} = (B_{od}^{s})^{\frac{1}{\varepsilon}} \left(\pi_{od}^{s,mig} \right)^{\frac{\varepsilon-1}{\varepsilon}} N_{o}^{s} \tilde{\gamma}, \tag{11}$$

where $N_{o}^{s} = \sum_{k} N_{ok}^{s}$ is the exogenous total population of skill s born in region o, and $\tilde{\gamma}$ is a constant. The expected welfare of an individual of skill s born in o is given by $W_{o}^{s} = \sum_{k} B_{ok}^{s} \left(\frac{w_{ok}^{s}}{(P_{ok})^{\alpha} (P_{k})^{1-\alpha} \kappa_{ok}^{s}} \right)^{\varepsilon}$.

Trade flows Given the CES individual demand (6) faced by the individual firm, the optimal price conditional on serving a market is given by a constant markup, so that

$$p_{od}(\psi) = \frac{\sigma}{\sigma - 1} \tau_{od} \frac{c_{o}}{A_{o} \psi},$$

where c_{o} is the cost of the labor bundle (3) in region o. Using similar steps as in the standard Melitz-Pareto model, one can solve for total exports from o to d by defining a cutoff firm productivity for which variable profits from exports exactly offset the overhead cost. Integrating firm-level exports from equation (6) over the set of exporting firms then gives the following expression for total exports from o to d:

$$X_{od} = \frac{\sigma}{\gamma - (\sigma - 1)} N_o^f \left(\tau_{od} \frac{c_o}{A_o}\right)^{-\gamma} (c_d f_{od})^{1-\frac{\gamma}{\sigma-1}} \left[\frac{(1-\alpha)\sum_i E_{id}}{P_d^{1-\sigma}} + \frac{\alpha E_{od}}{P_{od}^{1-\sigma}}\right]^{\frac{\gamma}{\sigma-1}},$$

where N_o^f is the (endogenous) mass of firms in o and E_{od} is the expenditure of agents born in o living in d. If $\alpha = 0$, this formula collapses to the standard Melitz-Pareto gravity equation.

Plugging the formula for $P_{od}^{1-\sigma}$ from equation (9) and rearanging gives:

$$\left(1 - \alpha \frac{E_{od}}{X_{od}}\right)^{\frac{\gamma}{\sigma-1}} X_{od} \propto \left(\frac{c_d}{A_d}\right)^{1-\frac{\gamma}{\sigma-1}} N_o^f \left(\frac{c_o}{A_o}\right)^{-\gamma} (d_{od})^{-1} \left((1-\alpha)\sum_i E_{id}\right)^{\frac{\gamma}{\sigma-1}} \left(P_d^{1-\sigma}\right)^{-\frac{\gamma}{\sigma-1}} \tag{12}$$

where I defined a composite trade cost $(d_{od})^{-1} = (f_{od})^{1-\frac{\gamma}{\sigma-1}} (\tau_{od})^{-\gamma}$. Equation (12) bears resemblance to a traditional gravity equation, where the left-hand side expression for exports is adjusted for the trade due to origin-bias. To ease intuition, consider the case where $\gamma/(\sigma - 1) \to 1$, which would be isomorphic to a standard Armington model rather than the Melitz-Pareto model. Then the expression can be written as

$$X_{od} - \alpha E_{od} \propto N_o^f \left(\frac{c_o}{A_o}\tau_{od}\right)^{1-\sigma} \frac{(1-\alpha)\sum_i E_{id}}{P_d^{1-\sigma}}.$$

The right side is a traditional gravity equation, but the left hand side is the trade flow net of the origin-bias consumption by migrants. In the actual formula (12), the exponent $\frac{\gamma}{\sigma-1}$ on the left side corrects not only for the spending by migrants, but also for the scale and additional entry into the destination d induced by the migrants' additional demand. Even in the absence of an impact of migrants on the physical trade costs d_{od}, trade would increase through two channels following an increase in migrants: the origin-bias that makes migrants import more, and the additional mass of exporters that now find it profitable to export.

Firm entry Similar steps to the traditional Melitz-Pareto model lead to the fact that the mass of firms entering in o is proportional so the labor force size:

$$N_o^f \propto \frac{A_o L_o}{f_o^e}, \tag{13}$$

where L_o is the total labor composite in o. An increase in the migrant population affects L_o and increases firm entry. This results in a lower price index of the bundle produced in region o because of love for variety from the CES demand. Hence, the endogenous firm entry due to migration has the same effect as an increase in the region's productivity A_o.

Labor demand While the labor supply is given by (11), the labor demand comes from cost minimization of (5) given wages w_d^{sn} and w_d^{sm} and implies that the wages paid to native workers of skill s in region d as a share of total wage bill is:

$$\frac{w_d^{sn} L_d^{sn}}{c_d L_d} = \frac{\phi^{sn} \left(w_d^{sn}\right)^{1-\lambda}}{\left(c_d^s\right)^{1-\lambda}} \frac{\phi^s \left(c_d^s\right)^{1-\rho}}{\left(c_d\right)^{1-\rho}}, \tag{14}$$

with an analog expression for the share of wages paid to migrant workers.

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

$$d_{od} = t_{od} \times \begin{cases} \left(\frac{N_{do}}{\sum_j N_{jd}}\right)^{-\eta_{exp}} \left(\frac{N_{od}}{\sum_j N_{jo}}\right)^{-\eta_{imp}} & \text{if } N_{od} \neq 0, \text{ and } o, d \text{ in diff. countries} \\ 1 & \text{otherwise} \end{cases}, \tag{15}$$

where t_{od} is an exogenous iceberg trade cost, and N_{od} is the total population born in location o and residing in d. η_{exp} is the elasticity governing the sensitivity of trade costs to destination-born migrants living in the origin location, and η_{imp} is the elasticity of trade costs to origin-born migrants living in the destination location. I assume that migration only matters for cross-border trade costs, and not for within-US flows (when both i and n are in the US).[3]

Balanced trade To close the model, I assume that trade is balanced so that:

$$\sum_d X_{od} = \sum_j X_{jo} \tag{16}$$

There is also no transfer within a region, so the total expenditures of migrants in a region is given by their labor income:

$$E^s_{od} = \begin{cases} w^{sm}_d L^s_{od} & \text{if } o,\, d \text{ in diff. countries} \\ w^{sn}_d L^s_{od} & \text{otherwise,} \end{cases} \tag{17}$$

and total labor payments are equal to total expenditures $c_o L_o = \sum_j X_{jo}$.

2.3 Equilibrium

In levels The equilibrium is a set of unit costs c_o, price indices P_{od} and P_d, migration shares $\pi^{s,mig}_{in}$, efficiency labor units L^s_{in}, trade flows X_{od}, firm mass N^f_o, wages w^{sn}_o and w^{sm}_o, trade costs d_{in} and expenditures E_{od} that satisfy equations (5), (9), (10), (11), (12), (13), (14), (15), (16) and (17).

In changes Is it convenient to solve the model using the so-called exact-hat algebra method (Dekle et al., 2008). Defining $\hat{X} = X^{new}/X^{old}$ as the proportional change in a variable X, the equilibrium change in all endogenous variables from an initial equilibrium to a counterfactual equilibrium can be obtained given changes in exogenous variables (migration costs $\hat{\kappa}^s_{in}$, productivity $\hat{A}_o$, exogenous trade costs $\hat{t}_{od}$) and observed values at the initial equilibrium of the wage bill shares $\Theta^s_{od} = \frac{w^s_{od} L^s_{od}}{X_d}$, trade flows X_{od} and migration shares $\pi^{s,mig}_{id}$.

[3]It would also be possible that the trade costs depend on whether there are more migrants from a third country in both regions. I explore this possibility empirically in appendix B.3 but leave it outside the scope of the model as I don't find robust evidence of the mechanism.

In the interest of space, the full system of equation is shown in Appendix A together with a description of the numerical algorithm used to solve the system. Appendix A.3 also presents a simplified version of the model that link the model to the motivating Figure (1) from the introduction.

3 Parameter estimation and calibration

To use the model, I need values of the demand and trade elasticities σ and γ, the migration elasticity ε, production elasticities λ and ρ, trade cost migrant elasticities η and the origin-bias α. The last two are still relatively understudied, so I estimate them in this section.

3.1 Trade cost elasticity of migration

3.1.1 Import costs

Using the pseudo-gravity equation 12 and absorbing all the origin- and destination-specific terms into fixed effects, one can rewrite:

$$\left(1-\alpha\frac{E_{od}}{X_{od}}\right)^{\frac{\gamma}{\sigma-1}} X_{od} = \gamma_o \mu_d d_{od}^{-1} \tag{18}$$

Parametrizing the trade cost as $\ln d_{od} = \ln z'_{od}\beta + \eta^{imp,H} \ln N_{od}^{high} + \eta^{imp,L} \ln N_{od}^{low} + \epsilon_{od}$ yields:

$$\ln\left[\left(1-\alpha\frac{E_{od}}{X_{od}}\right)^{\frac{\gamma}{\sigma-1}} X_{od}\right] = \gamma_o + \mu_d + \ln z'_{od}\beta + \eta^{imp,H} \ln N_{od}^{high} + \eta^{imp,L} \ln N_{od}^{low} + \epsilon_{od}, \tag{19}$$

where z'_{od} is a vector of bilateral gravity determinants (air and sea distance, common border), N_{od}^{s} is the number of migrants born in o living in d of skill s, and ϵ_{od} represents other unobservable determinants of the trade cost (including US-born from state d living in country o). These could be potentially correlated with migration costs and induce endogeneity, so I use an instrument for the number of migrants from origin o in destination d. I take values from the literature for $\sigma = 4$ and $\gamma = 4.25$, so that $\gamma/(\sigma - 1) = 1.41$ (Melitz and Redding, 2015) to compute the dependent variable based on data on imports and migrants' incomes. I run the estimation for various potential values of α. Note that all country-level determinants of trade costs common to all states, such as tariffs, are included in the country fixed effects.

Instrument Migrants might choose to settle in a state because unobservable trade frictions between their origin country and the state are correlated with unobservable migration costs, leading to an upward bias in an OLS regression. Migrants could also target states that have low exports to their origin country, because that is where their country-specific skill would be especially beneficial in lowering export costs. In that case, OLS would be biased downward.

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

$$pull_{it}^{j} = \frac{\sum_{j' \notin continent_j} M_{j'i,t}}{\sum_{j' \notin continent_j} \sum_i M_{j'i,t}},$$

where $M_{j'i,t}$ is the number of migrants from country j' who migrated at time t to state i. I use the decadal censuses closest to the year of migration t to compute this pull factor. So for example, for $t = 1975$, I use the 1980 Census to compute $M_{j'i,t}$ as the number of people born in j' who migrated in 1975 and are living in state i as of 1980. This ensures that the instrument is not contaminated by movement within the US more than a decade after migration. This leave-out pull factor represents the attractiveness of state i to migrants from other continents at the year of migration t.

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 those from country j to state i ($M_{j,t}^{-i} = \sum_{i' \neq i} M_{ji',t}$). Multiplying the pull and push factors provides 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 over all years of migration provides an instrument for the stock of migrant population from country j in state i:

$$miginstr_{ji} = \sum_t pull_{it}^j M_{j,t}^{-i}$$

The main identifying assumption is that the shares ($pull_{it}^j$) 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 $miginstr_{ji}$ as an instrument for migrant stocks N_{ji}. In a robustness check, I also change the subset of countries used to compute the pull factor to leave out all other countries whose migration patterns are correlated with country j.[4] I also experiment with only using variation from migrants pre-2000 and pre-1990 in the instrument.

Other studies have dealt with endogeneity concerns by using natural experiments distributing the migrants of a single country across states (e.g. Parsons and Vézina, 2018). My estimation strategy uses many countries, which allows me to further include importer and exporter fixed effects in the regression to control for multilateral resistance terms.

Data sources for the estimation I use data from two sources to obtain a dataset of migrant stocks, incomes, as well as trade flows, for the 50 US states (and the District of Columbia) and foreign countries. Migrant stocks in US states come from the American Community Survey (ACS) 2012-16 sample. The ACS also contains the state of residence, country of birth, year of immigration, wage, total income, education and industry of work. I use the migrants' total income as my measure of their expenditure.[5] For trade flows at

[4]Formally, I compute the correlation across states of migrant population of any two country pairs. When I construct the pull factor for country j, I use only migrants from other countries where the correlation is lower than the median for that country.

[5]To ensure consistency between the trade and expenditure data constructed from the ACS, I rescale the state-level imports so that total imports to the US are equal to those in the OECD ICIO tables, and I rescale

the state-country level, I use US Census Bureau data on state-level imports and exports, using the average value between 2013 and 2016. I compute bilateral distance based on the geodistance of state and country capitals, and sea distance by finding the closest US international sea port to the state, and computing its average sea distance to the foreign destination's ports.[6] Additional details on the data are given in Appendix B.1.

Results I first present results with $\alpha = 0$ in the the top panel of Table 1, for comparability with other studies and to illustrate the instrumental variable diagnostics. The elasticity of imports to migrant population is around 0.2 when instrumented (column 2), slightly higher but not statistically different from the OLS results. Column 3 and 4 show that high skill migrants are driving the results, with an elasticity of 0.32 while the impact of low-skill migrants is not significant. There is an upward bias in the OLS results for low-skill migrants, consistent with positive correlation between unobserved trade and migration costs, and a downward bias for high-skill migrants, more in line with targeted migration towards high-trade costs states. All first-stage diagnostic tests are reassuring and Appendix XX displays the first-stage regression results where instruments are significant and have coefficients of the expected sign. Appendix Table B2 also displays a range of robustness checks, restricting migration before 1990 to construct the instrument, using only country with low migration correlation patterns to construct the instrument, preserving observations with 0 exports or migrants, or restricting to migrants who migrated after the age of 20. In all cases, the impact of migrants on trade survives. In the baseline, I cluster standard errors at both the state and country level. Appendix Table B3 shows alternative clustering with similar levels of statistical significance.

Figure 2 displays the coefficients on the migrant population from using regression specification (19) for different values of α, holding $\gamma / (\sigma - 1) = 1.41$.[7] The left panel pools

the incomes in the ACS so that the total income is equal to the total expenditure in the OECD ICIO tables. See Appendix B.1 for details.

[6] For landlocked countries, I pick the closest sea port to the country.

[7] In all regressions underlying Figure 2, instruments are strong and controls have the expected sign.

migrants of both skills together. The estimated impact of migrants decreases as α increases, consistent with origin-bias in tastes partially driving the correlation between imports and migrant population. The right panel plots $\eta^{imp,H}$ and $\eta^{imp,L}$ separately. There as well, the estimated impact of low-skill migrants decreases as α increases. However, the elasticity remains statistically and economically significant for high-skill migrants. As a result, I calibrate $\eta^{imp,H} = 0.3$ and $\eta^{imp,L} = 0$.

3.1.2 Export costs

To estimate the effect of migrants on exports, I use the same adjusted gravity equation (12) as for the import costs, but I don't observe the migrant population by state of birth in the foreign destination. Hence, I treat it as a potentially endogenous error term:

$$\ln X_{od} = \gamma_o + \mu_d + \ln z'_{od}\beta + \eta^{exp,H} \ln N_{do}^{high} + \eta^{imp,L} \ln N_{do}^{low} \underbrace{- \ln\left(1 - \alpha \frac{E_{od}}{X_{od}}\right)^{\frac{\gamma}{\sigma-1}} + \epsilon_{od}}_{\varepsilon'_{od}}, \quad (20)$$

where now o denotes a US state and d a foreign country. I use the same instrument for the the migrant population as before to address the endogeneity issue. The instrument is based on the attractiveness of the state when the importing country experienced outmigration. Hence, it is unlikely to be correlated with higher number of natives from the particular state in the country of destination.

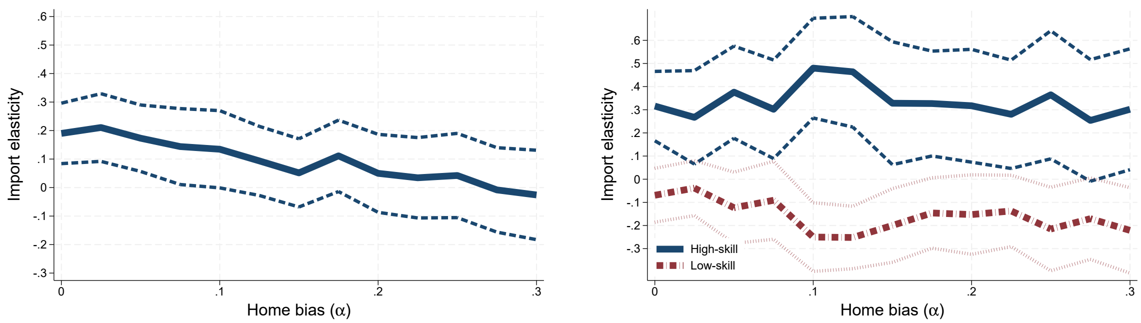
Results The lower panel of Table 1 displays the results of estimating equation (20). The elasticity of exports to total migrant population is around 0.15 when instrumented (column 2), slightly higher but not statistically different from the OLS results. When separating by skill, a similar story as for imports emerges: high-skill migrants are driving the positive impact of migrants on trade. As a result, I calibrate $\eta^{exp,H} = 0.15$ and $\eta^{exp,L} = 0$.

Table 1: Trade migrant elasticity

	OLS	IV	OLS	IV
	Imports ($\ln X_{od}$)			
$\ln N_{od}$	0.173***	0.190***		
	(0.0412)	(0.0541)		
$\ln N_{od}^{low}$			0.0791**	-0.0693
			(0.0390)	(0.0593)
$\ln N_{od}^{high}$			0.125**	0.316***
			(0.0515)	(0.0764)
KPF		479.4		202.6
AR F p-value		0.00	SW-F (low):	414.9
			SW-F (high):	434.6
N	5520	5520	4893	4893
	Exports ($\ln X_{od}$)			
	OLS	IV	OLS	IV
$\ln N_{do}$	0.117***	0.135***		
	(0.0295)	(0.0371)		
$\ln N_{do}^{low}$			0.0455*	0.020
			(0.0259)	(0.0504)
$\ln N_{do}^{high}$			0.0995***	0.147***
			(0.0351)	(0.0636)
KP-F		687.0		247.3
AR F p-value		0.000	SW-F (low):	508.5
			SW-F (high):	517.1
N	5988	5988	5165	5165

Notes: results from estimating equation 19, using the instrument described in the text and with $\alpha = 0$ for the import panel, and from equation 20 for the export panel. Standard errors in parenthesis, twoway clustered at the state and country-level. All regressions include state and country fixed effects and trade costs controls (distance, sea distance from the nearest port and common border). "KP-F" refers to the first stage Kleibergen-Paap F-statistic, "AR F p-value" refers to the p-value of the Anderson-Rubin test for significance of the endogenous regressors, and "SW-F" to the Sanderson-Windmeijer first stage F statistic. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

Figure 2: Import migrant elasticity



Notes: The figure plots the estimates of $\eta^{imp,s}$ from equation (19). The left panel pools migrants of both skill level together. The right panel separates by high- and low-skill migrants.

3.1.3 Robustness

I interpret the impact of migrants on trade flows as a reduction in trade costs. In this section, I provide some results on heterogeneous effects and additional regressions that support this interpretation. In the interest of space, I present only regressions on exports.

Language and heterogenous effects The first column of Table 2 shows that the impact of migrants is higher for countries whose language is the most different from English, using the measure of linguistic distance from Spolaore and Wacziarg (2016). This lends credit to the interpretation that migrants can reduce trade frictions, as their native language is more likely to be useful for those countries. The second column shows that the effect is present for all continents, so that no particular region is driving the results. The third column displays results by income category of the migrants' country. The effect is the strongest in low income countries, decreasing slightly for high income countries. Given the strong correlation of income per capita and institutional quality, a plausible interpretation is that migrants are especially helpful in institutional settings difficult to navigate.

Industry-level regressions I also run the regression at the industry-level, regressing industry specific exports on the migrant population working in the industry as well as the total migrant population in the state. In Table 3, the results show that both migrants working in the industry and overall migrant population have an impact (columns 1 and 2). The first result is reassuring for the interpretation, while the second also justifies modelling the impact of migrants on trade costs as an externality. The OLS bias is negative for migrants working in the industry as in the baseline regressions, but positive for other migrants, consistent with a positive correlation between unobserved migration and trade costs.

When regressing the industry-level exports on industry-working migrants, the results also survive a demanding specification with a state-country fixed effect and an industry-specific coefficient on distance and common border (columns 3). Columns 4 uses Nunn (2007)'s

Table 2: Heterogeneity of export-migrants elasticity

	Language	Continent		Income level	
$\ln N_{do}$	0.0839	Africa	0.180***	Low	0.206***
	(0.0508)		(0.0652)		(0.0685)
$\ln N_{do}$	0.0930**	Asia	0.161***	Low-mid	0.148***
$\times lingDist_{od}$	(0.0440)		(0.0476)		(0.0384)
		Europe	0.162***	Up-mid	0.135***
			(0.0596)		(0.0428)
		N.America	0.0950*	High	0.137**
			(0.0489)		(0.0570)
		S.America	0.0815		
			(0.0672)		
		Oceania	0.0962		
			(0.0829)		
Bil. controls	✓	✓		✓	
KP-F	167.6	83.65		129.7	
SW-F	306.8	844; 1672; 561		740; 1589	
	395.8	1078; 1599; 457		1016; 811	
N	4603	5985		5954	

Notes: All regressions include bilateral controls, state and country fixed effects. The dependent variable is exports from o to d, $\ln X_{od}$. Standard errors in parenthesis, twoway clustered at the state and country level. Migrant population is instrumented using the same instrument as the baseline regressions. The center panel displays the continent-specific coefficient on $\ln N_{do}$ and the right panel displays the category-specific coefficients on $\ln N_{do}$. "KP-F" refers to the first stage Kleibergen-Paap F-statistic. "SW-F" refers to the Sanderson-Windmeijer first stage F statistic, where the F-statistics are reported in the order of the endogenous variables.

measure of contract intensity to show that the impact of migrants on industries with low contracting intensity is lower. Columns 5 and 6 also regress the number of NAICS 4-digit industry for which there are positive exports on the migrant population. The results show that migrants also have an impact on this extensive margin of trade.

Migration vs ancestry Burchardi et al. (2019) show that there is no effect of ancestry on trade flows, which appear at odds with my findings. However, ancestry also includes US-born population that might have never lived in their country of ancestry. In Appendix B.3, I contrast the effect of migrants and ancestry. I replicate the finding that ancestry doesn't seem to have a causal impact on trade flows when the instrument captures the totality of variation in ancestry. However, I show that instrumenting ancestry with my instrument results in a positive and significant impact of ancestry. Since IV estimates capture local average treatment effects (Imbens and Angrist, 1994), it is likely that the impact of ancestry is positive only when the variation comes from migrants who lived in their country of origin as is the case for my instrument.

Table 3: Industry-level regressions and extensive margin

	NAICS 3-digits export (log)				# of NAICS 4-digit	
	OLS	IV	IV	IV	OLS	IV
$\ln N_{do}^{NAICS}$	0.0420***	0.0647***	0.0496*	0.0843***		
	(0.0121)	(0.0230)	(0.0267)	(0.0267)		
$\ln N_{do}^{total}$	0.142***	0.118**			6.854***	6.626***
	(0.0527)	(0.0466)			(1.161)	(2.116)
$\ln N_{do}^{NAICS} \times$				-0.384*		
$FracHomog.$				(0.198)		
State-country FE			✓	✓		
KP-F		641.2	587.6	290.5		718.3
SW-F (first):		1500.8		800.7		
SW-F (2^{nd}):		2065.7		992.0		
AR-F p-val.:			0.055			0.003
N	20917	20917	19864	19864	4170	4170

Notes: All regressions include bilateral controls, state and country fixed effects (industry-specific coefficients and industry-state/industry-country fixed effects for columns 1-4). In columns 1-4, the dependent variable is log exports from o to d in a given NAICS 3-digit industry. In columns 5-6, the dependent variable is the number of 4-digit NAICS industries with positive exports. Standard errors in parenthesis, twoway clustered at the state and country level. Migrant population is instrumented using the same instrument as the baseline regressions. "KP-F" refers to the first stage Kleibergen-Paap F-statistic, "AR F p-val" refers to the p-value of the Anderson-Rubin test for significance of the endogenous regressors, and "SW-F" to the Sanderson-Windmeijer first stage F statistic. "SW-F (first)" refers to the SW-F of the first endogenous variable, and "SW-F (2^{nd})" refers to that of the second one. $FracHomog$ measures the (inverse) complexity, measured as the fraction of input in the NAICS industry that is sold on an organized exchange.

3.2 Origin-bias parameter

Estimation strategy To estimate the origin bias parameter α, it is useful to show that the expected (or average) wage received by natives from o in region d is given by:[8]

$$\frac{w_{od}^s L_{od}^s}{N_{od}^s} = \kappa_{od}^s \left(P_{od}\right)^\alpha P_d^{(1-\alpha)} W_o^s,$$

where $W_o^s = \sum_k B_{ok}^s \left(\frac{w_{ok}^s}{(P_{ok})^\alpha (P_k)^{1-\alpha}\kappa_{ok}^s}\right)^\varepsilon$ is the expected welfare of an agent of skill s born in o. Intuitively, the average worker needs to be compensated for migration costs or for a higher price index in the destination of migration. Further using the fact that $P_{od} = \left(\pi_{od}^{adj}\right)^{\frac{1}{1-\sigma}} P_d$ (Equation 9), and parameterizing the migration costs κ_{od}^s as a function of a vector of covariates z_{od} (e.g. distance, common border) yields the following estimating equation for α:

$$\ln \frac{w_{od}^s L_{od}^s}{N_{od}^s} = \gamma_o^s + \psi_d^s + z_{od}'\beta - \frac{\alpha}{\sigma - 1} \ln \left(X_{od} - \alpha \sum_s w_{od}^s L_{od}^s \right) + \varepsilon_{od}^s \tag{21}$$

where γ_o^s and ψ_d^s are fixed effects and ε_{od}^s captures other bilateral migration costs that are unrelated to the distance. Equation (21) cannot be directly estimated since it requires α to compute the regressor. To overcome this issue, I take a first order Taylor expansion of equation (21) around $\alpha_0 = 0$ to get the following estimating equation:

$$\ln \frac{w_d L_{od}}{N_{od}} = \gamma_o^s + \psi_d^s + z_{od}'\beta - \frac{\alpha}{\sigma - 1} \ln X_{od} + \alpha \frac{\sum_s w_{od}^s L_{od}^s}{X_{od}} + \varepsilon_{od}^s \tag{22}$$

where ε_{od}^s now also contains high-order terms which should be small since $\alpha < 1$.[9] Hence, regressing the average wage on imports, while controlling for the share of total income of bilateral migrants into bilateral import flows, will produce an estimate of $\frac{\alpha}{\sigma-1}$.Since the above

[8] See Appendix B.4 for a derivation.

[9] One can even add a second order approximation, where the regression will feature an extra term $\left(\frac{\sum_s w_{od}^s L_{od}^s}{X_{od}}\right)^2$. In unreported results, adding additional orders doesn't affect the estimate of α. Appendix B.4 reports simulations showing that the first order approximation estimation performs well.

expression is also equal to the expected wage of any individual, it is also possible to regress the wage at the individual level which allows me to add additional controls.

In the regression, the error term ε^s_{od} incorporates unobservable migration costs that are potentially correlated with trade costs, and hence with import flows. To address this issue, I instrument imports with the sea distance between the closest port to state d and the origin country o. The idea behind this instrument is that while most goods are transported by sea, virtually all migration happens by air or land. Hence, sea distance is a determinant of trade costs but not migration costs. Of course, this is true today and not historically. Accordingly, I also control for the migrant population in 1960 from o in state d in the regression. Air passenger travel for large distance overtook sea in the 1960s, so that conditional on migration population in 1960, the sea distance is exogenous to migration costs.[10]

It is worth noting that the estimation of α doesn't rely on the supply part of the model. The key assumptions are the Cobb-Douglass aggregator between origin-good and the international bundle, and the fact that the elasticity of substitution σ is the same across varieties within the origin-good bundle and the international bundle. Appendix B.4 illustrates the small bias of the estimator despite the Taylor approximation using Monte Carlo simulations.

Results Table 4 presents the results of the estimation, using distance and time zone difference as measures of migration costs. The estimates are consistent with a positive origin-bias. Column 1 regresses the average wage at the country-state pair level on bilateral imports, while column 2 regresses an individual migrant's wage on imports from their origin country. In all specifications, there is a negative effect of imports on income. Through the lenses of the model, this result is explained by the fact that lower import costs increase imports and decrease the price index faced by migrants, so that they need a lower wage compensation. Using a value of $\sigma = 4$ (Melitz and Redding, 2015), the last column implies an origin bias parameter $\alpha \approx 3 * 0.039 \approx 0.12$, meaning that migrants spend around 10% of their budget on

[10] One drawback of this strategy is that I have to drop observations from Mexico and Canada, as most the their trade with the US is not done through sea, which renders the instrument weak.

goods from their country of origin. This value is consistent with Albert and Monras (2022) who estimate that migrants spend 15% less on domestic goods.

Bounds on α An alternative approach is to bound α by using the condition that $X_{od} \geq \alpha E_{od}$, because the total spending of migrants on their country of origin's good cannot be greater than total imports. In the model, the inequality should hold for every *od* pair. However, this might not be the case in the data.[11] Hence I sum over states and compute the ratio between imports and migrants income from that country. For countries that are included in the full quantitative model, the minimum ratio is around 0.03 and the tenth percentile is around 0.1. Hence, the point estimate of 0.12 found above seems reasonable given the fact that α should be thought of as an average origin-bias. In fact, when weighing by import size, the first percentile of the import-migrant expenditure ratio is around 0.11.

3.3 Calibration

I calibrate the model to 50 US states (+DC), 56 countries, and a composite "Rest of the World" (ROW).[12] Table 5 summarizes the parameter values and the data shares needed to solve the model (trade, migration and wage shares).

Data sources I build measures of migrant stock in every region by combining data from the World Bank's Bilateral Migration Matrix for 2013 with the American Community Survey (ACS). International trade data comes from the OECD Inter-Country Input-Output table for 2013, and within-US trade data from the Commodity Flow Survey (CFS).[13] I calibrate wage bill shares using survey data from the ACS for the US, and other national surveys for other countries obtained through IPUMS-International (MPC, 2019). Appendix C provides details on the sources and an exact mapping between data and model objects.

[11] For example, there is a sizeable Cuban population in the US, but there is no trade relationship between the US and Cuba. There might also be measurement error in the data.

[12] 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.

[13] See Appendix C.2 for a discussion of the data in the CFS, and a robustness check for its limitations.

Parameter values I calibrate the trade and migration elasticitiy from the literature. I set the $\sigma = 4$ and $\gamma = 4.25$ following Melitz and Redding (2015), and the migration elasticity ε to 2.3 as in Caliendo et al. (2021). For production elasticities, I set the elasticity of substitution between natives and migrants $\lambda = 20$ and the substitutability between skill $\rho = 3.3$ following Ottaviano and Peri (2012). For the elasticity of composite trade costs to migration, I use my estimates from above and set $\eta^{imp,H} = 0.3$, $\eta^{exp,H} = 0.15$ and $\eta^{imp,L} = \eta^{exp,L} = 0$. I set the origin-bias parameter $\alpha = 0.1$. In section 4.2 and appendix D, I explore different values of elasticities, with no significant differences in the interpretation of the results.

4 Counterfactual simulations

To quantify the effect of migration, I conduct the following counterfactual: I increase migration costs to US states for all foreign countries ($\kappa^s_{o,US}$) such that the share of the population of migrants of skill s from origin o in the total US population is equal to that of 1980. It is also broadly consistent with proposed legislation that aim to reduce legal annual immigration flows by half.[14] Any potential change in migration costs can be simulated, but this simulation can help us understand what would the economy look like now if the US nation-wide migration policy was more similar to that of 1980.

[14]In 1980, the share of migrant population in the US was 6.2%, around half of what it is in my baseline year. 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 for details of the proposed bill: https://www.congress.gov/bill/115th-congress/senate-bill/354

Table 4: Origin-bias parameter estimation

	$\ln avgWage_{od}$	$\ln wage_{i,od}$
$\ln X_{od}$	-0.0545*	-0.0399**
	(0.0289)	(0.0186)
Migration cost controls	✓	✓
Individual controls		✓
Twoway cluster	✓	✓
KP-F	28.91	29.77
AR F p-value	0.049	0.066
N	4344	570019

Notes: Results from estimating equation 22, using the instrument described in the text. The coefficient on $\ln X_{od}$ has the structural interpretation of $\frac{\alpha}{1-\sigma}$. All regressions include the share of income of migrants in bilateral imports as well as skill-state and skill-country fixed effects. Standard errors in parenthesis, twoway clustered at the state and country-level. The migration cost controls refer to distance, migrant population in 1960 and time zone difference. Individual controls include age, age squared, education level fixed effects, and industry (NAICS 4-digit) fixed effects. Observations are weighted using the survey weight. "KP-F" refers to the first stage Kleibergen-Paap F-statistic and "AR F p-value" refers to the p-value of the Anderson-Rubin test for significance of the endogenous regressors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

Table 5: Link between the model and the data

	Description	Value	Source
Parameter			
α	origin-bias	0.1	own estimates
$\eta^{imp,H}$, $\eta^{exp,H}$	migration-elasticity of trade costs	0.3, 0.15	own estimates
ε	migration elasticity	2.3	Caliendo et al. (2021)
γ and σ	trade and demand elasticity	4.25 and 4	Melitz and Redding (2015)
ρ, λ	subst. between skills, subst. between native and migrant	3.3, 20	Ottaviano and Peri (2012)
Exog. objects			
$\hat{A}_n$, $\hat{B}^s_{in}$,$\hat{t}_{od}$		1	keep constant
$\hat{\kappa}^s_{in}$	migration costs		increased to target 1980 migrant shares of pop.
Data			
N_{od}	population data		ACS, World Bank
X_{od}	trade data (including services)		Census data on state level exports and imports, OECD ICIO, Commodity Flow Survey
Θ_{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.

To further understand the role of migration in shaping market access of each state, I also run four additional counterfactuals for each state:[15]

1. The first increases migration costs in the particular state keeping firm entry and trade costs constant. It captures the net effect of the decrease in the state's labor supply and of the decrease in the aggregate demand fuelled by the migrants in the state. I refer to this scenario as the "labor supply and own-state MA" effect.

2. The second keeps migration and trade costs fixed but changes the state's firm mass exogenously as would have happened if the migration costs to the state had increased. It captures the fact that migrants contribute to gains from scale. I refer to this scenario as the "firm exit" effect.

3. The third increases migration costs in all other states except the state of interest. It captures the change in within-US market access, leaving the labor supply and trade costs in the state unaffected. I define wage changes from this counterfactual as the "intra-national market access effect".

4. The fourth leaves migration costs unchanged but increases the export trade costs to the level they reach in the main counterfactual. I further decompose it into import and export costs. I refer to this scenario as the "international market access effect".

4.1 Results

I present first aggregate US results, before turning regional impacts and their decomposition.

[15] Precisely, for each state s I first store the change in migration costs κ^s_{od}, firm mass $\hat{N}^f_o$ and trade cost $\hat{d}_{od}$ from the main conterfactual. I construct the first additional counterfactual by setting $\hat{\kappa}^s_{i\sigma}, \forall i \notin US$ as in the main counterfactual for state σ, and $\hat{\kappa}_{is'} = 1, \forall s' \neq s$, and no effect of migrants on trade costs ($\eta = 0$), forcing firm entry to remain fixed. The second keeps all migration and trade costs fixed, but exogenously changes $\hat{N}^f_s$. The third additional counterfactual uses $\hat{\kappa}^s_{i\sigma} = 1, \forall i \notin US$ for state σ, and $\hat{\kappa}_{is'}$ as in the main counterfactual,$\forall s' \neq s$, and no effect of migrants on trade costs ($\eta = 0$). The fourth is constructed using $\hat{\kappa}_{ij} = 1$ and $\hat{t}_{ij} = \hat{d}_{ij}$.

Aggregate results The top panel of Table 6 shows the average percentage change in real wages of a state's natives by skill, decomposed into own-state labor supply and MA, firm exit, intra-national MA and international MA effects, as well as the change in exports as share of state output. While the sum of decompositions is not exactly 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.[16] Standard deviations across states are also shown in parentheses. The drop in average wage is 2.5% and 2.4% for low- and high-skill natives respectively, indicating that migrants have a positive impact on welfare. Firm exit accounts for more than half of the change (around 1.4% in both cases), while the combination of internal and international market access effects accounts most of the rest (around 0.8% for low-skill and 0.9% for high-skill). The combined effect of the change in labor supply and own-state market access is responsible for only a small fraction of the overall change, but accounts for most of the difference between high- and low-skill. The change in relative skill wage is explained by the fact that the current migrant population is more skill-intensive than the 1980 migrant population. Hence, to match 1980 migrant shares, there is a stronger drop in high-skill migrants than low-skill migrants, which translates into a larger decrease of the high-skill labor supply relative to the low-skill labor supply.

The bottom panel of Table 6 displays the change ad-valorem tariff equivalent of the changes in import and export costs under the assumed trade elasticity of 4. The rise in import cost increase of 7%, is much higher than the trade-weighted import tariffs imposed by the US (around 1.6%). The export ad-valorem tariff equivalent is 2.4%, about half of the 4.9% current ad valorem export tariffs faced by US exporters (WEF, 2016). Trade as a share of output decreases (-14%) due to the increase in costs, but also when trade costs are

[16]The correlation between the sum of the decompositions and the main counterfactual is 0.999, and the average absolute difference is around 0.07 percentage points, out of an average of 2.2 percentage points. 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 as it is easier to interpret its reaction to migrant demand and export exposure through the lens of the model. Change in state's native welfare is highly correlated with the change in the state's welfare because the initial share of native population in the state is high (see Equation A.11 in the appendix).

Table 6: Average changes

Average wage changes

	Low-skill	High-skill
Total	-2.46	-2.36
	(1.27)	(1.21)
Labor supply and own-state MA	-0.19	-0.01
	(0.32)	(0.36)
Firm exit	-1.44	-1.41
	(1.13)	(1.10)
Intra-national MA	-0.40	-0.53
	(0.40)	(0.39)
Exporter MA	-0.11	-0.10
	(0.07)	(0.07)
Importer MA	-0.26	-0.24
	(0.18)	(0.16)

Average trade changes

	Endogenous trade costs	Constant trade costs
Change in import costs	7.00	0
	(1.28)	
Change in export costs	2.49	0
	(0.44)	
Change in trade as share of output	-14.14	-1.40
	(1.45)	(1.01)

Notes: The top panel shows the average percentage changes in real wages across US states, weighted by native population, after reducing the share of migrants by country and skill in the US population to 1980s levels. The bottom table shows the average trade-weighted change in trade costs (under the assumed trade elasticity of 4). Standard deviation across states are in parenthesis.

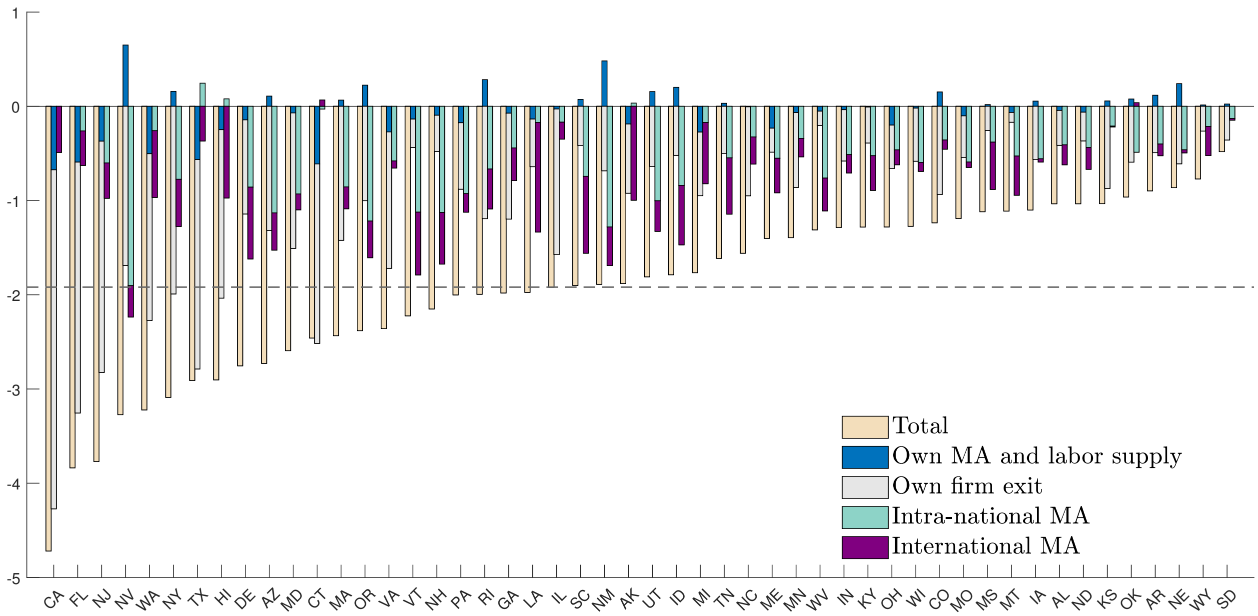
left unchanged (-1.4%). In the later case, this is a result of the migrants' origin-bias. Since migrants consume disproportionally more of international good than natives, they increase imports - and exports since trade is balanced.[17]

Regional heterogeneity and decomposition This section investigates what drives the heterogenous response to the drop in migrant population across states, focusing on explaining the variation in real wage changes across US states for the state's natives. Figure 3 plots the percentage change in a state's real wage for the main counterfactual as well as the four additional counterfactuals. The first bar (in beige) displays the change in the real wage for the main counterfactual. The second bar (in grey) displays the own-state effect, decomposed into the combined labor supply and own-state market access effect and the firm exit effect. The third bar displays the intra-national market access effect (defined as the change in real wage when other-state migrant population is reduced, in blue), and the international market access effect (defined as the change when only export trade costs are changed, in purple).

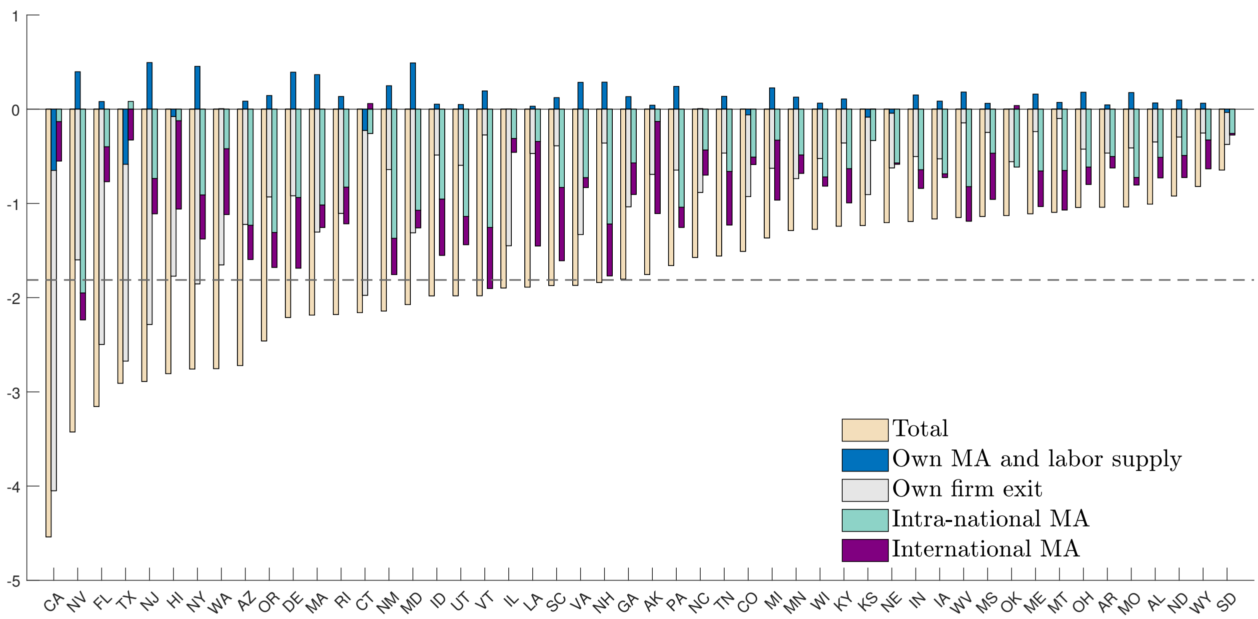
The state-level results reveal several interesting patterns. First, there is a substantial heterogeneity across states. The total impact on the low-skill wage ranges from a larger than 5% decline in California to less than half a percent in South Dakota. The high-skill changes reveal a similarly large dispersion. Second, the change in the wage is not always driven by the same component. For example, consider the change in low-skill wage for Nevada and Washington (fourth and fifth group of bars). Both states experience an overall similar drop in real wage. The impact of firm exit is also similar for both states. However, Nevada has a smaller share of output sold within the state than Washington. As a consequence, the net effect of removing migrants in Nevada is positive (blue bar) because the increase in wages due to the drop in labor supply in Nevada is not compensated by a decrease in aggregate demand faced by Nevada's producers. Instead, Nevada is hurt the most when migrant population in the rest of the country is lowered (light green bar for intra-national

[17] The same counterfactual setting the origin-bias parameter $\alpha = 0$ results in an increase in export, as overall demand moves abroad.

Figure 3: Decomposition of the change in real wage



Low-skill



High-skill

Notes: The figure plots the counterfactual real wage change in each state in the main counterfactual and the four decompositions. The top panel shows results for non-college educated, and the bottom for college-educated.

MA effect). While Nevada has large trade flows with its high-migrant neighbour California, Washington doesn't rely as much as the demand from migrants because it is located further away from high-migrant states.

To clearly illustrate the mechanisms at play, Figure 4 plots the value of each decomposition bar or the high skill wage changes against the relevant heuristic measures mentioned in Section A.3, further decomposing the own-state effect into a labor supply and an own-state market access channel.[18] The blue dots in Panel (a) plot the labor supply effect against the migrant share. As expected, the relationship is positive. States with a higher migrant share benefit from the removal of migrants in their state in partial equilibrium, because the labor supply drops. However, the red dots show that the own-state market access is more negative for states with a high migrant share, because the decrease in migrant population leads to a decrease in aggregate demand. The net effect depends on the state's openness. If most of the state's consumption is its own output, the two effects would cancel out to a large extent. However, because of trade linkages, there is a disconnect between the increase in the labor supply in the state and the change in market access faced by the state. Panel (b) plots the overall own-state effect against the state's openness (both towards other states and towards the rest of the world). States with a low openness suffer relative to those with a higher openness, because their aggregate demand is more severely affected for a given change in their migrant population.[19] Panel (c) plots the change in wage due to firm exit against the initial migrant population share. States with larger migrant population loose more because they lose their scale economies and have lower firm entry. Panel (d) plots the intra-national market access effect on exposure to migrants from other states. The relationship is negative: states who sell a larger share of their output to migrants in other states experience a larger decline in market access. Finally, panels (e) and (f) plot the export and import international market access effect against the export and import exposure. States with a higher export ex-

[18]The same figure for low-skill is relegated to appendix D.

[19]Note that the fit of the scatterplot would be improved even further if instead of overall openness, the horizontal axis was plotting the difference between the high-skill migrant population as a share of the state's population and the share of the state's output consumed by those migrants.

posure suffer more from the increase in trade costs as their exports become more expensive. States with larger import exposure suffer the most, as their price index increases the most. The slope of the importer market access effect is larger because the calibrated elasticity of import-cost to migrants is larger, so import costs increase more than export costs.

4.2 Robustness of counterfactuals and additional exercies

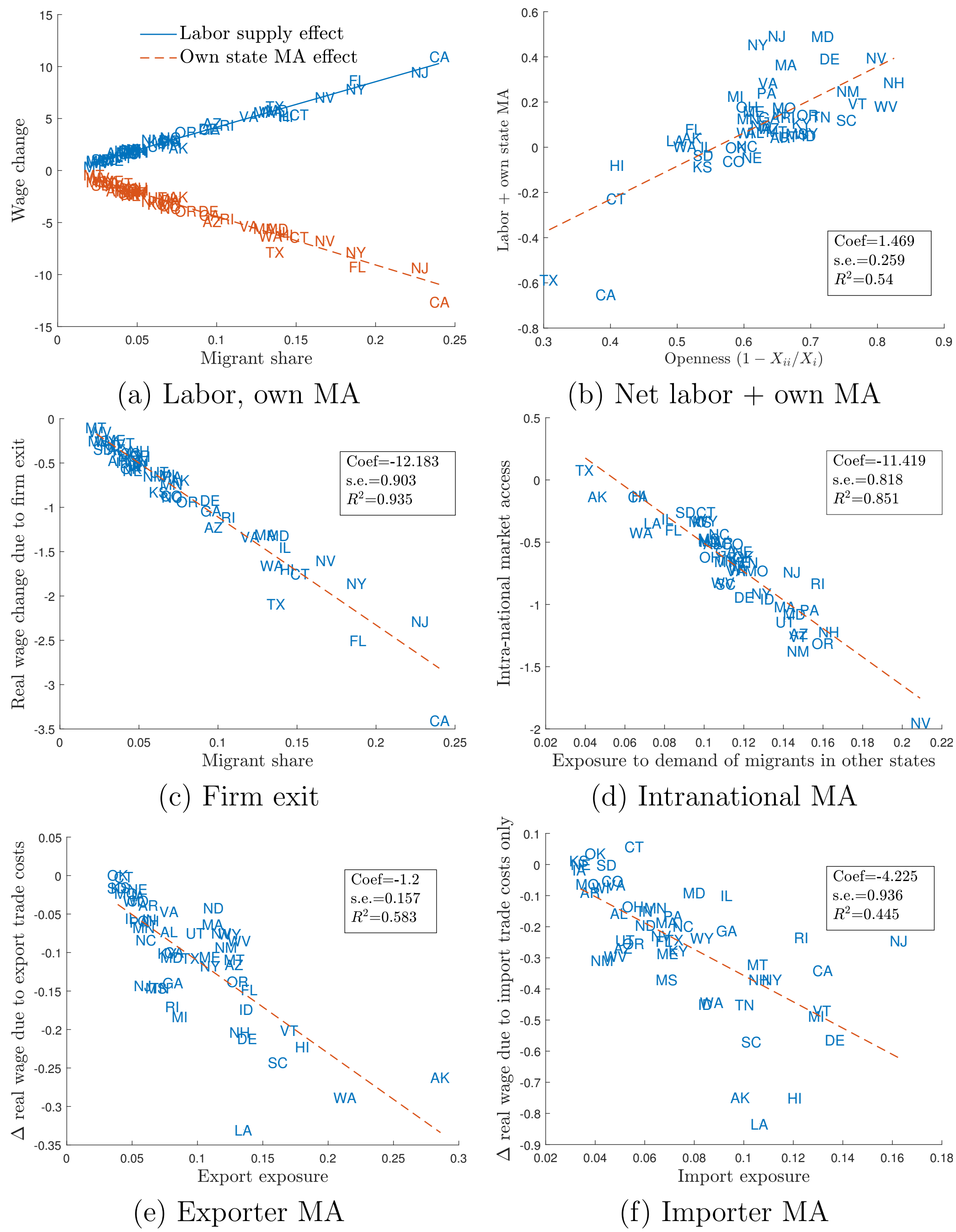
To gauge the robustness of the model's prediction, I provide several robustness checks in appendix D and summarize the results in Table 7. For each robustness check, I feed the same change in migration costs, and report the average change in real wages by skill, changes in trade costs and the change in the Trade/GDP ratio, as well as the correlation of wage changes with the baseline. Appendix Figure D3 displays the decompositions.

Varying parameter values I first remove origin-bias. A lower α implies that migrants consume more in the US and less abroad. When $\alpha = 0$, removing migrants depresses local demand more, so the wage drop is slightly more severe. On the other hand, the trade to GDP ratio falls by one percentage point less. I then vary the production elasticities (skill substitutability ρ or migrant/native substitutability λ). By and large, the correlation with the baseline is high. A low γ implies that native wages fall by more and migrants wage increase, leading to a smaller outmigration, so that the Trade/GDP ratio falls by less.

Additional counterfactuals I increase the migration costs only for high-skill or low-skill migrants individually. The first two columns of the bottom panel of Table 7 show that the impact low-skill migrant reduction is less severe, since they have no direct impact on trade costs. In fact, decreasing low-skill migration would benefit low-skill natives. On the other hand, high-skill migrants bring about decreases in trade costs. Hence, even when lowering only high-skill migrant population, both native skills experience a drop in real wages.

I also simulate an exercise keeping total migrant population constant, but allowing additional migrants from countries currently subject to a cap at the expense of other migrants

Figure 4: Heuristic measures (high-skill)



(a) Labor, own MA

(b) Net labor + own MA

(c) Firm exit

(d) Intranational MA

(e) Exporter MA

(f) Importer MA

Notes: The left panel plots the change in real wage in the own-state counterfactual, where only migration costs to the specific state are increased, against the difference between own-migrant share and own-migrant demand exposure. The middle panel plots the change in real wage when migration costs in other states increase, against the exposure to migrants from other states. The right panel plots the change in real wage when only export costs increase, against export exposure. Own migrant exposure is defined as $shmig_i X_{ii}/X_i$, exposure to demand from other stated is defined as $\sum_{j \neq i} shmig_j X_{ij}/X_i$, and export exposure is defined as X_{iRW}/X_i.

Table 7: Sensitivity and alternative counterfactuals

	Baseline	No bias	Skill subst.		Migrant/native subst.	
		$\alpha = 0$	$\rho = 1.6$	$\rho = 50$	$\lambda = 5$	$\lambda = 100$
Low-skill	-2.46	-2.52	-2.58	-2.34	-2.89	-2.32
High-skill	-2.36	-2.46	-2.30	-2.42	-2.94	-2.18
Exp. costs	2.49	2.99	2.51	2.47	1.88	2.69
Imp. costs	7.00	7.61	6.98	7.02	5.65	7.46
Trade/GDP	-14.14	-13.14	-14.13	-14.14	-10.71	-15.21
Corr with base		0.97	0.99	0.98	0.98	1.00

	Reduction by skill		Less	Only	Only	TFP as
	Low	High	diverse	India	Mexico	fun. of mig.
Low-skill	0.22	-2.66	-0.05	-0.36	-0.19	-8.35
High-skill	-1.00	-1.35	-0.03	-0.20	-0.66	-8.96
Exp. costs	-0.12	2.63	0.09	0.04	0.36	1.88
Imp. costs	0.05	6.91	0.13	0.51	1.40	7.69
Trade/GDP	-0.28	-13.67	-0.43	-0.58	-1.79	-12.47

Notes: The top panel repeats the baseline counterfactual migration changes, changing parameter values. "Low-skill" refers to the average (population-weighted) change in low-skill real wage of a state's native. "High-skill" refers to the average (population-weighted) change in high-skill real wage of a state's native. "Export/GDP" refers to the change in the US export/GDP ratio. The bottom panel shows the result of alternative counterfactual. "Reduction by skill" applies the increase in migration cost from the baseline separately by skill. "Less diverse" keeps migration population constant, but increases migration from countries currently subject to the 7% immigrant flow cap in the US at the expense of other countries. "Only India" and "Only Mexico" apply the change in migration costs from the baseline only for those countries. "TFP as func. of mig." uses the baseline change in migration costs, but adds an additional impact of birthplace diversity on TFP (A_n).

(third column).[20] In that case, overall welfare would decrease and trade-weighted trade costs would increase because larger trade partners are also those subject to the cap.

Appendix Figure D1 shows the results of increasing the migration costs for one country at a time. Table 7 shows the results for India and Mexico. The differential impact by skill mostly depends on whether the country's migrants are low or high-skill intensive. The impact on aggregate exports depend on the skill composition of the migrants, since only high-skill migrants have an impact on trade costs, and on the size of the country as a trading partner.

Impact of migrants on productivity The model can easily accommodate additional effects of migration on productivity identified in the literature (Ottaviano and Peri, 2006; Alesina et al., 2016). I rerun the counterfactuals with the added channel that productivity A_n is a function of the population's birthplace diversity to match Ottaviano and Peri (2006)'s empirical results (see Appendix D for details). The last column of the bottom panel of Table 7 shows the results. The drop in wages is more pronounced as the removal of migrants lowers birthplace diversity and thus TFP. The predictions for trade are however similar.

5 Conclusion

This paper explores and quantifies an underappreciated mechanism through which migrants affect the welfare of natives: market access. Migrants shape market access through two channels. They reduce trade frictions, thereby easing access of their host country to their origin country's market, and they change the geographical location of demand, thereby benefiting regions close to the migration destination.

The evidence shows that migrants have a causal impact on exports and import from and to their origin country, particularly high-skill migrants. Using a model of intra- and inter-national trade and migration with origin-bias in tastes calibrated to the US states, I

[20] No country can represent more than 7% of total immigrant flow to the US in a year, a cap that binds for China, India, Mexico and the Philippines. I simulate a counterfactual where I increase their combined migrant stock by 1 million (consistent with current backlogs) while keeping total migrant population constant.

show that a nationwide reduction in migrant population produces heterogeneous responses in wage through different effects on intra- and inter-national market access. In addition to the already studied impacts on scale effects, states with a high exposure to migrants inside the US relative to their own migrant population are hurt more by the removal of migrants. Those with a high international trade exposure are hurt more by the increase in trade costs. While policy discussions typically emphasize the effect of migrants' labor supply, this paper shows that their effect on labor demand through increased market access is also important.

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ONLINE APPENDIX
(NOT FOR PUBLICATION)

A Model Appendix

A.1 Equilibrium in changes

To ease the formulation of the equilibrium, it will be convenient to define an "adjusted trade share":

$$\pi_{od}^{trade} = \frac{X_{od} - \alpha E_{od}}{\sum_k X_{kd} - \alpha E_{kd}} = \frac{\left(N_o^f\right)^{\frac{\sigma-1}{\gamma}} \left(\frac{c_o}{A_o}\right)^{-(\sigma-1)} (d_{od})^{-\frac{\sigma-1}{\gamma}} (X_{od})^{1-\frac{\sigma-1}{\gamma}}}{\sum_k \left(N_k^f\right)^{\frac{\sigma-1}{\gamma}} \left(\frac{c_k}{A_k}\right)^{-(\sigma-1)} (d_{kd})^{-\frac{\sigma-1}{\gamma}} (X_{kd})^{1-\frac{\sigma-1}{\gamma}}},$$

An equilibrium in changes is a set of changes in trade adjusted trade share $\hat{\pi}_{od}^{adj}$, trade flows $\hat{X}_{od}$, trade cost changes $\hat{d}_{od}$, migration shares $\hat{\pi}_{od}^{s,mig}$, price indices $\hat{P}_d^{1-\sigma}$, unit costs $\hat{c}_o$, wages $\hat{w}_n^{sm}$ and $\hat{w}_n^{sd}$, firm entry $\hat{N}_o^f$, effective labor $\hat{L}_{od}^s$ that satisfy the following system of equations given initial equilibrium data on trade share π_{od}^{adj}, wage bill shares $\Theta_{od}^s = \frac{w_{od}^s L_{od}^s}{X_d}$, trade flows X_{od}, migration shares $\pi_{id}^{s,mig}$ and given exogenous shocks $\hat{\kappa}_{in}^s$, $\hat{\tau}_{od}$, $\hat{D}_n$:

$$\hat{\pi}_{od}^{adj} = \frac{\left(\hat{N}_o^f\right)^{\frac{\sigma-1}{\gamma}} \left(\frac{\hat{c}_o}{\hat{A}_o}\right)^{-(\sigma-1)} \left(\hat{d}_{od}\right)^{-\frac{\sigma-1}{\gamma}} \left(\hat{X}_{od}\right)^{1-\frac{\sigma-1}{\gamma}}}{\sum_k \pi_{kd}^{adj} \left(\hat{N}_k^f\right)^{\frac{\sigma-1}{\gamma}} \left(\frac{\hat{c}_k}{\hat{A}_k}\right)^{-(\sigma-1)} \left(\hat{d}_{kd}\right)^{-\frac{\sigma-1}{\gamma}} \left(\hat{X}_{kd}\right)^{1-\frac{\sigma-1}{\gamma}}} \tag{A.1}$$

$$\hat{d}_{od} = \hat{\tau}_{od} \prod_s \left(\hat{\pi}_{do}^{s,mig}\right)^{\eta_{exp}^s} \left(\hat{\pi}_{od}^{s,mig}\right)^{\eta_{imp}^s} \tag{A.2}$$

$$\begin{aligned} \hat{X}_{od} \quad &= \quad \hat{\pi}_{od}^{adj} \frac{\sum_{i,s} \Theta_{id}^s \hat{\Theta}_{id}^s \left(\sum_l X_{dl} \hat{X}_{dl} + \hat{D}_d D_d\right)}{X_d + D_d} \underbrace{\frac{X_{od} - \alpha \sum_s \Theta_{od}^s (X_d + D_d)}{X_{od}}}_{shAdj_{od}} \\ &+ \frac{\sum_s \Theta_{od}^s \hat{\Theta}_{od}^s \left(\sum_l X_{dl} \hat{X}_{dl} + \hat{D}_d D_d\right)}{\sum_s \Theta_{od}^s (X_d + D_d)} \underbrace{\frac{\alpha \sum_s \Theta_{od}^s (X_d + D_d)}{X_{od}}}_{shHome_{od}} \end{aligned} \tag{A.3}$$

$$\hat{\pi}_{id}^{s,mig} = \frac{\left(\frac{\hat{w}_{id}^s}{\hat{\kappa}_{id}^s \left(\hat{\pi}_{id}^{adj}\right)^{\alpha} \hat{P}_d}\right)^{\varepsilon} \hat{B}_{id}^s}{\sum_n \pi_{in}^{s,mig} \left(\frac{\hat{w}_{in}^s}{\hat{\kappa}_{in}^s \left(\hat{\pi}_{in}^{adj}\right)^{\alpha} \hat{P}_d}\right)^{\varepsilon} \hat{B}_{in}^s} \tag{A.4}$$

$$\hat{P}_d^{1-\sigma} = \left(\frac{\hat{c}_d}{\hat{A}_d}\right)^{\frac{\sigma-1}{\gamma}-1} \sum_o \pi_{od}^{tr} \left(\hat{X}_{od}\right)^{1-\frac{\sigma-1}{\gamma}} \left(\hat{N}_o^f\right)^{\frac{\sigma-1}{\gamma}} \left(\frac{\hat{c}_o}{\hat{A}_o}\right)^{1-\sigma} \left(\hat{d}_{od}\right)^{\frac{1-\sigma}{\gamma}} \tag{A.5}$$

$$(\hat{c}_d)^{1-\rho} = \left[\Theta_d^L \left(\hat{c}_d^L\right)^{1-\rho} + \Theta_d^H \left(\hat{c}_d^H\right)^{1-\rho}\right] \qquad (\hat{c}_d^s)^{1-\lambda} = \left[\Theta_d^{sn} \left(\hat{w}_d^{sn}\right)^{1-\lambda} + \Theta_d^{sm} \left(\hat{w}_d^{s,m}\right)^{1-\lambda}\right] \tag{A.6}$$

$$\hat{w}_n^{sd}\hat{L}_{nn}^s = \frac{\left(\hat{w}_n^{sd}\right)^{1-\lambda}}{\left(\hat{c}_n^s\right)^{1-\lambda}}\frac{\left(\hat{c}_n^s\right)^{1-\rho}}{\left(\hat{c}_n\right)^{1-\rho}}\frac{\sum_d \hat{X}_{nd}X_{nd}}{\sum_d X_{nd}} \tag{A.7}$$

$$\hat{w}_n^{sm}\sum_{i\neq n}\hat{L}_{in}^s\frac{\Theta_{in}^s}{\Theta_n^{sm}} = \frac{\left(\hat{w}_n^{sm}\right)^{1-\lambda}}{\left(\hat{c}_n^s\right)^{1-\lambda}}\frac{\left(\hat{c}_n^s\right)^{1-\rho}}{\left(\hat{c}_n\right)^{1-\rho}}\frac{\sum_d \hat{X}_{nd}X_{nd}}{\sum_d X_{nd}} \tag{A.8}$$

$$\hat{c}_n\hat{N}_n^f = \frac{\hat{A}_n\frac{\sum_d \hat{X}_{nd}X_{nd}}{\sum_d X_{nd}}}{\hat{f}_n^e} \tag{A.9}$$

$$\hat{L}_{in}^s = \left(\hat{B}_{in}^s\right)^{\frac{1}{\varepsilon}}\left(\hat{\pi}_{in}^{s,mig}\right)^{\frac{\varepsilon-1}{\varepsilon}} \tag{A.10}$$

The change in expected welfare is given by:

$$\hat{U}_o^s = \left[\sum_d \hat{B}_{od}^s\left(\frac{\hat{w}_{od}^s}{\hat{P}_d\left(\pi_{od}^{adj}\right)^{\alpha}\hat{\kappa}_{od}}\right)^{\varepsilon}\pi_{od}^{mig,s}\right]^{\frac{1}{\varepsilon}} \tag{A.11}$$

A.2 Solution algorithm

1. Guess for changes in migration shares: $\hat{\pi}_{in}^s$
2. Solve for changes in trade costs ($\hat{d}_{od}$), effective labor supply ($\hat{L}_{in}^s$) and productivity:

$$\hat{L}_{in}^s = \left(\hat{B}_{in}^s\right)^{\frac{1}{\varepsilon}}\left(\hat{\pi}_{in}^{s,mig}\right)^{\frac{\varepsilon-1}{\varepsilon}}$$

$$\hat{d}_{od} = \prod_{s\in L,H}\left(\hat{\pi}_{od}^{s,mig}\right)^{-\eta_{exp,s}}\left(\hat{\pi}_{do}^{s,mig}\right)^{-\eta_{imp,s}}$$

3. Solve for wages $\hat{w}_n^{sd}$ and $\hat{w}_n^{sm}$
   (a) Guess $\hat{w}_n^{sd}$ and $\hat{w}_n^{sm}$
   (b) Solve for the change in unit cost $\hat{c}_n$ using:

$$\left(\hat{c}_n\right)^{1-\rho} = \left[\Theta_n^L\left(\hat{c}_n^L\right)^{1-\rho} + \Theta_n^H\left(\hat{c}_n^H\right)^{1-\rho}\right] \qquad \left(\hat{c}_n^s\right)^{1-\lambda} = \left[\Theta_n^{sd}\left(\hat{w}_n^{s,d}\right)^{1-\lambda} + \Theta_n^{sm}\left(\hat{w}_n^{s,m}\right)^{1-\lambda}\right]$$

   (c) Solve for firm mass $\hat{N}_d^f$ by using:

$$\hat{N}_n^f = \frac{\hat{A}_n\left(\sum_{i,s}\Theta_{in}^s\hat{w}_{in}^s\hat{L}_{in}^s + \hat{D}_nD_n\right)}{\hat{c}_n\hat{f}_n^e}$$

   (d) Solve for $\hat{X}_{od}$ by solving:

i. Guess $\hat{X}_{od}$ and compute $\hat{\pi}^{adj}_{od}$

$$\hat{\pi}^{adj}_{od} = \frac{\left(\hat{N}^f_o\right)^{\frac{\sigma-1}{\gamma}} \left(\hat{c}_o\right)^{-(\sigma-1)} \left(\hat{d}_{od}\right)^{-\frac{\sigma-1}{\gamma}} \left(\hat{X}_{od}\right)^{1-\frac{\sigma-1}{\gamma}}}{\sum_k \pi^{adj}_{kd} \left(\hat{N}^f_k\right)^{\frac{\sigma-1}{\gamma}} \left(\hat{c}_k\right)^{-(\sigma-1)} \left(\hat{d}_{kd}\right)^{-\frac{\sigma-1}{\gamma}} \left(\hat{X}_{kd}\right)^{1-\frac{\sigma-1}{\gamma}}}$$

ii. Update $\hat{X}_{od}$ using

$$\hat{X}_{od} = \hat{\pi}^{adj}_{od} \frac{\sum_{i,s} \Theta^s_{id} \hat{\Theta}^s_{id} \left(\sum_l X_{dl} \hat{X}_{dl} + \hat{D}_d D_d\right)}{X_d + D_d} \underbrace{\frac{X_{od} - \alpha \sum_s \Theta^s_{od} \left(X_d + D_d\right)}{X_{od}}}_{shAdj_{od}}$$
$$+ \frac{\sum_s \Theta^s_{od} \hat{\Theta}^s_{od} \left(\sum_l X_{dl} \hat{X}_{dl} + \hat{D}_d D_d\right)}{\sum_s \Theta^s_{od} \left(X_d + D_d\right)} \underbrace{\frac{\alpha \sum_s \Theta^s_{od} \left(X_d + D_d\right)}{X_{od}}}_{shHome_{od}}$$

iii. Go back to i with the updated guess until convergence

(e) Update $\hat{w}^{sd}_n$ and $\hat{w}^{sm}_n$ and go back to (a) until convergence:

$$\hat{w}^{sd}_n \hat{L}^s_{nn} = \frac{\left(\hat{w}^{sd}_n\right)^{1-\lambda}}{\left(\hat{c}^s_n\right)^{1-\lambda}} \frac{\left(\hat{c}^s_n\right)^{1-\rho}}{\left(\hat{c}_n\right)^{1-\rho}} \frac{\sum_d \hat{X}_{nd} X_{nd}}{\sum_d X_{nd}}$$

$$\hat{w}^{sm}_n \sum_{i \neq n} \hat{L}^s_{in} \frac{\Theta^s_{in}}{\Theta^{sm}_n} = \frac{\left(\hat{w}^{sm}_n\right)^{1-\lambda}}{\left(\hat{c}^s_n\right)^{1-\lambda}} \frac{\left(\hat{c}^s_n\right)^{1-\rho}}{\left(\hat{c}_n\right)^{1-\rho}} \frac{\sum_d \hat{X}_{nd} X_{nd}}{\sum_d X_{nd}}$$

4. Solve for the migrant relevant price index

$$\hat{\Pi}_{od} = \left(\frac{1}{\frac{\sum_{i,s} \hat{w}^{sm}_d \hat{L}^s_{id} E^s_{id}}{\sum_{i,s} E^s_{id}}} \frac{\hat{X}_{od} X_{od} - \alpha \sum_s \hat{w}^s_{od} \hat{L}^s_{od} E^s_{od}}{X_{od} - \alpha \sum_s E^s_{od}} \right)^{\alpha} \hat{P}_d.$$

5. Update the migration shares $\hat{\pi}^{s,mig,+1}_{id}$ and go back to 1 until convergence ($\max |\hat{\pi}^{s,mig,+1}_{id} - \hat{\pi}^{s,mig}_{id}| < \delta$)

$$\hat{\pi}^{s,mig,+1}_{id} = \frac{\left(\frac{\hat{w}^s_{id}}{\hat{\kappa}^s_{id} \hat{\Pi}_{id}}\right)^{\varepsilon} \hat{B}^s_{id}}{\sum_n \pi^{s,mig}_{id} \left(\frac{\hat{w}^s_n}{\hat{\kappa}^s_{in} \hat{\Pi}_{id}}\right)^{\varepsilon} \hat{B}^s_{in}}$$

A.3 A simpler model to illustrate the market access mechanisms

To illustrate the market access mechanisms at play, consider a simpler version of the model without skill differences and without imperfect substitutability between migrants and natives (this is equivalent to setting ρ and γ to infinity). Shut down the scale effects by setting

$\sigma - 1 = \gamma$ and assume that the number of firms is fixed. Suppose that migration is exogenous as well, letting ε go to 0, so the migration shares are entirely driven by B^s_{od}.

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^{US}, each attributed to a state i in a fixed and exogenous proportion β_i. There is a total rest of the world native population equal to L^{RW}. Define the overall fraction of migrants in the US as μ, so that the total migrant population is in the US is equal to $\frac{\mu}{1-\mu} L^{US}$. Suppose that each migrant is attributed to a state i in a fixed and exogenous proportion γ_i, so that a state population is equal to $\frac{\mu\gamma_i + (1-\mu)\beta_i}{1-\mu} L^{US}$. This would be achieved in the full model by letting the migration elasticity ε go to 0, and setting $B_{RWi} = \frac{\gamma_i \mu}{L^{RW}}$ for $i \in US$ and $B_{RWRW} = \frac{L^{RW}}{\mu} - 1$. For simplicity, assume there is no migrants from the US into the rest of the world (RW).

We are interested in the reaction of wages in different states as the national fraction of migrant μ varies.[21]

The labor market clearing implies that:

$$\underbrace{w_n \frac{\mu\gamma_n + (1-\mu)\beta_n}{1-\mu} L^{US}}_{\text{labor payment in } n} = \underbrace{\sum_{i \in US} \left\{ \pi^{trade}_{ni} w_i \frac{(1-\alpha)\mu\gamma_i + (1-\mu)\beta_i}{1-\mu} L^{US} \right\}}_{\text{output sold in the US}} + \underbrace{\pi^{trade}_{nRW} (1-\alpha) w_{RW} \left(R - \frac{\mu}{1-\mu} L \right)}_{\text{exports}}$$

Subsection A.3.1 below shows that differentiating the previous equation with respect to μ, keeping β_i and γ_i constant, the elasticity of state n's wage with respect to μ, denoted ξ_n, satisfies:

$$\left(\xi_n - \sum_i \frac{X_{ni}}{X_n} \xi_i \right) + (\sigma - 1) \left(\xi_n - \sum_{k,i} \frac{X_{nk}}{X_n} \pi_{ik} \xi_i \right) =$$
$$\frac{1}{1-\mu} \left(\underbrace{(1-\alpha) \sum_{i \in US, i \neq n} \frac{shm_i (1 - \alpha\, shm_i) X_{ni}}{X_n}}_{\text{other states mig. expos.}} - \underbrace{\left(1 - \frac{(1-\alpha)(1-\alpha\, shm_n) X_{nn}}{X_n} \right) shmig_n}_{\text{own mig. share - own mig. expos.}} \right)$$
$$+ \underbrace{\frac{X_{nRW}}{X_n}}_{\text{export expos.}} \frac{1}{1-\mu} \left\{ (\sigma - 1) \eta^{exp} \left[\underbrace{1 - shm_n}_{\text{cost decrease}} - \underbrace{\sum_{k \in US} \pi^{trade}_{kRW} (1 - shm_k)}_{\text{price index}} \right] - \frac{MIGPOP}{RWPOP} \right\}, \tag{A.12}$$

[21] Because in the full model, the change in B_{in} is equivalent to a change in κ^s_{in}, 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.

where RW denotes rest of the world and shm_i is the share of migrants in i's population. Consider the case without origin-bias ($\alpha = 0$). This expression implies that the deviation of state n's elasticity (ξ_n) from a weighted average of other regions' elasticities (the left-hand side) depends on the exposure to migrants in other states ($\sum_{i \in US, i \neq n} \frac{X_{ni} shm_i}{X_n}$), and the difference between own migrant share and own-migrant demand exposure ($\left(1 - \frac{X_{nn}}{X_n}\right) shm_n$), and on the export exposure term on the last row. When $\alpha > 0$, the increase in market access from migrants' demand is dampened, and only the increase in labor supply remains if $\alpha = 1$.

A state with a high exposure to migrants in other states benefits more from an overall increase in migrant population, as its internal market access increases with additional migrants. When the own absorption share (X_{nn}/X_n) is low, the state is worse off when its own migrant share increases, because the increased labor supply is not fully compensated by an increase in own expenditure. However, a low absorption share also implies a higher exposure to other states as well, so the two terms in the middle row are correlated. When $\alpha = 0$, the two terms add up to the total migrant demand exposure ($\sum_{i \in US} \frac{X_{ni} shm_i}{X_n}$) minus the share of migrant in the state. These are the two quantities depicted in the right panel of Figure 1 in the introduction. When overall migrant demand exposure is higher than the migrant share, the wage reacts positively to the influx of migrants because market access increases by more than labor supply.

The term on the last row shows how the reaction of wage depends on export exposure. The first term inside the curly bracket captures the effect of the decrease in export trade costs. It is increasing in the trade elasticity ($\sigma - 1$), and the migration trade cost elasticity η^{exp}: a change in migrant population affects trade costs which in turn affects exports. State n's export trade cost elasticity with respect to the aggregate migrant share μ is equal to η multiplied by 1 minus the share of migrant shm_n.[22] Hence the first term in the square brackets represents the decrease in trade costs and subsequent increase in trade share. The second term in the square brackets, labeled "price index", captures the effect of the decrease in all the states' trade costs, which lower the RW price index and dampen the increase in state n's trade share. The second term in the curly brackets ($MIGPOP/RWPOP$) illustrates the loss in revenue from exports, as demand moves towards the US. One might expect this loss of export market access to be compensated by the increased demand in the US. However the increased demand in the US is offset by the increased labor competition from migrants. The offset is broken down when states are not identical and trade with each other, and the middle row in equation (A.12) governs the relative gains and losses.

Of course, these analytical results only hold for a simplified case where migration shares are exogenous and ignore the change in the price index, which is likely to fall as labor supply increases and import trade costs decrease. To estimate the full effect of migration changes, I now turn to the calibration of the quantitative model required to conduct counterfactuals.

[22] The share of migrants in state n is given by $\frac{\mu\gamma_n}{\mu\gamma_n + (1-\mu)\beta_n}$. The elasticity of the share of migrants with respect to μ is equal to $\frac{\beta_n}{[\mu\gamma_n + (1-\mu)\beta_n]}$, which is equal to $1 - shm_n$.

A.3.1 Simplified model derivation

Start from the labor market clearing equation:

$$w_n\left[\frac{\mu}{(1-\mu)}\gamma_n+\beta_n\right]=\sum_{i\in US}\pi_{ni}w_i\left[\frac{(1-\alpha)\,\mu}{(1-\mu)}\gamma_i+\beta_i\right]+\pi_{nRW}\,(1-\alpha)\,w_{RW}\left(\frac{R}{L}-\frac{\mu}{1-\mu}\right)$$

Define P_n as the total population of region n: $P_n=\frac{\mu\gamma_n+(1-\mu)\beta_n}{1-\mu}L$ and $P_n^{bias}=\frac{(1-\alpha)\mu\gamma_n+(1-\mu)\beta_n}{1-\mu}L=P_n-\frac{\alpha\mu\gamma_n}{1-\mu}L=P_n-\alpha migpop_n=P_n\,(1-\alpha migsh_n)$ if $n\in US$, and $P_{RW}^{bias}=(1-\alpha)\left(R-\frac{\mu}{1-\mu}L\right)$.

We have that:

$$w_nP_n=\sum_i\pi_{ni}w_iP_i^{bias} \tag{A.13}$$

Before taking the derivative of equation (A.13), consider first the partial derivatives with respect to μ of P_n and π_{ni}.

$$\frac{\partial P_n}{\partial\mu}=\frac{1}{(1-\mu)^2}\gamma_nL,$$

$$\frac{\partial P_n^{bias}}{\partial\mu}=\frac{(1-\alpha)}{(1-\mu)^2}\gamma_nL=(1-\alpha)\,\frac{\partial P_n}{\partial\mu}$$

when $n\in US$, and for the rest of the world:

$$\frac{\partial P_{RW}}{\partial\mu}=-\frac{1}{(1-\mu)^2}L$$

Regarding the trade shares, we have:

$$\frac{\partial\pi_{ni}}{\partial\mu}=\pi_{ni}\left[-\frac{(\sigma-1)}{w_n}\frac{\partial w_n}{\partial\mu}+(\sigma-1)\sum_k\pi_{ki}\frac{\partial w_k}{\partial\mu}\frac{1}{w_k}\right],i\in US$$

And when i is the rest of the world, we also have to take into account changes in export trade costs from the US:

$$\begin{aligned}\frac{\partial\pi_{ni}}{\partial\mu}=\pi_{ni}\Bigg[&-\frac{(\sigma-1)}{w_n}\frac{\partial w_n}{\partial\mu}+(\sigma-1)\sum_k\pi_{ki}\frac{\partial w_k}{\partial\mu}\frac{1}{w_k}\\&+(\sigma-1)\,\eta\frac{1}{\mu}\frac{1-migsh_n}{1-\mu}-(\sigma-1)\,\eta\frac{1}{\mu}\sum_{k\in US}\pi_{ki}\frac{1-migsh_k}{1-\mu}\Bigg],i=RW\end{aligned}$$

Take the derivative of the labor market clearing condition with respect to μ:

$$\frac{dw_n}{d\mu}P_n+w_n\frac{dP_n}{d\mu}=\sum_i\frac{d\pi_{ni}}{d\mu}w_iP_i^{bias}+\pi_{ni}\frac{dw_i}{d\mu}P_i^{bias}+\pi_{ni}w_i\,(1-\alpha)\,\frac{dP_i}{d\mu}$$

Plug in for trade share change:

$$
\begin{aligned}
\frac{dw_n}{d\mu}P_n + w_n\frac{dP_n}{d\mu} = \sum_i \Bigg(& -\frac{(\sigma-1)}{w_n}\pi_{ni}\frac{dw_n}{d\mu} + (\sigma-1)\,\pi_{ni}\sum_k \pi_{ki}\frac{dw_k}{d\mu}\frac{1}{w_k}\Bigg) w_i P_i^{bias} \\
&+ \pi_{ni}\frac{dw_i}{d\mu}P_i^{bias} + \pi_{ni}w_i\,(1-\alpha)\,\frac{dP_i}{d\mu} \\
&+ (\sigma-1)\,\eta\frac{1}{\mu}\pi_{nRW}\,(1-\alpha)\,w_{RW}P_{RW}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right),
\end{aligned}
$$

and rearange:

$$
\begin{aligned}
\frac{dw_n}{d\mu}P_n + (\sigma-1)\,\frac{dw_n}{d\mu}\frac{1}{w_n}\sum_i \pi_{ni}w_iL_i + w_n\frac{dP_n}{d\mu} = \sum_i \Bigg(&(\sigma-1)\,\pi_{ni}\sum_k \pi_{ki}\frac{dw_k}{d\mu}\frac{1}{w_k}\Bigg) w_i P_i^{bias} \\
&+ \pi_{ni}\frac{dw_i}{d\mu}P_i^{bias} + \pi_{ni}w_i\,(1-\alpha)\,\frac{dP_i}{d\mu} \\
&+ (\sigma-1)\,\eta\frac{1}{\mu}X_{nRW}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right)
\end{aligned}
$$

Plug in for change in population:

$$
\begin{aligned}
\frac{dw_n}{d\mu}P_n + (\sigma-1)\,\frac{dw_n}{d\mu}\frac{1}{w_n}\sum_i X_{ni} + w_n\frac{1}{(1-\mu)^2}\gamma_n L = (\sigma-1)\sum_i X_{ni}\left(\sum_k \pi_{ki}\frac{dw_k}{d\mu}\frac{1}{w_k}\right) - \\
\pi_{nRW}w_{RW}\,(1-\alpha)\,\frac{1}{(1-\mu)^2}L + \sum_i \pi_{ni}\frac{dw_i}{d\mu}P_i^{bias} + \sum_{i\in US}\pi_{ni}w_i\,(1-\alpha)\,\frac{\gamma_i L}{(1-\mu)^2} \\
+ (\sigma-1)\,\eta\frac{1}{\mu}X_{nRW}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right)
\end{aligned}
$$

Multiply by μ and rewrite as an elasticity, with $\xi_n = \frac{dw_n}{d\mu}\frac{\mu}{w_n}$:

$$
\begin{aligned}
\xi_n w_n L_n + (\sigma-1)\,\xi_n\sum_i X_{ni} + w_n\frac{\mu\gamma_n L}{(1-\mu)^2} = (\sigma-1)&\sum_i X_{ni}\left(\sum_k \pi_{ki}\xi_k\right) \\
&+ \sum_i \pi_{ni}\xi_i w_i P_i^{bias} + \sum_{i\in US}\pi_{ni}w_i\,(1-\alpha)\,\frac{\mu}{(1-\mu)^2}\gamma_i L \\
&- \pi_{nRW}w_{RW}\,(1-\alpha)\,\frac{\mu}{(1-\mu)^2}L \\
&+ (\sigma-1)\,\eta X_{nRW}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right)
\end{aligned}
$$

Divide by $w_n L_n = X_n$ and rearange (using $X_{ni} = \pi_{ni} w_i P_i^{bias}$):

$$\left(\xi_n - \sum_i \frac{X_{ni}}{X_n}\xi_i\right) + (\sigma-1)\left(\xi_n - \sum_{i,k}\pi_{ki}\frac{X_{ni}}{X_n}\xi_k\right) = -\frac{w_n}{X_n}\frac{\mu\gamma_n L}{(1-\mu)^2}$$
$$+\sum_{i\in US}\pi_{ni}\frac{w_i}{X_n}\frac{(1-\alpha)\mu}{(1-\mu)^2}\gamma_i L - \pi_{nRW}\frac{w_{RW}}{X_n}\frac{(1-\alpha)\mu}{(1-\mu)^2}L$$
$$+(\sigma-1)\eta\frac{X_{nRW}}{X_n}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right)$$

Realize that $\frac{\mu\gamma_n L}{(1-\mu)}$ is equal to the migrant population in state n, and $\frac{\mu L}{1-\mu}$ is equal to the total migrant population in the US (MIGPOP):

$$\left(\xi_n - \sum_i \xi_i\frac{X_{ni}}{X_n}\right) + (\sigma-1)\left(\xi_n - \sum_{i,k}\pi_{ki}\xi_k\frac{X_{ni}}{X_n}\right) = -\frac{w_n}{X_n}\frac{migpop_n}{(1-\mu)} + \sum_{i\in US}\pi_{ni}\frac{w_i}{X_n}(1-\alpha)\frac{migpop_i}{(1-\mu)}$$
$$-(1-\alpha)\pi_{nRW}\frac{w_{RW}}{X_n}\frac{MIGPOP}{(1-\mu)}$$
$$+(\sigma-1)\eta\frac{X_{nRW}}{X_n}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right)$$

Realize that $migpop_i = migsh_i P_i = migsh_i(1-\alpha migsh_i)P_i^{bias}$:

$$\left(\xi_n - \sum_i \xi_i\frac{X_{ni}}{X_n}\right) + (\sigma-1)\left(\xi_n - \sum_{i,k}\pi_{ki}\xi_k\frac{X_{ni}}{X_n}\right) = -\frac{migsh_n}{(1-\mu)} + \frac{1-\alpha}{1-\mu}\sum_{i\in US}\frac{X_{ni}}{X_n}migsh_i(1-\alpha migsh_i)$$
$$-(1-\alpha)\pi_{nRW}\frac{w_{RW}}{X_n}\frac{MIGPOP}{(1-\mu)}$$
$$+(\sigma-1)\eta\frac{X_{nRW}}{X_n}\left(\frac{1-migsh_n}{1-\mu} - \sum_{k\in US}\pi_{kRW}\frac{1-migsh_k}{1-\mu}\right)$$

Finally $(1-\alpha)\pi_{nRW}w_{RW}MIGPOP = X_{nRW}\frac{MIGPOP}{RWPOP}$:

$$\left(\xi_n - \sum_i \xi_i\frac{X_{ni}}{X_n}\right) + (\sigma-1)\left(\xi_n - \sum_{i,k}\pi_{ki}\xi_k\frac{X_{ni}}{X_n}\right) = -\frac{migsh_n}{(1-\mu)} + \frac{1-\alpha}{1-\mu}\sum_{i\in US}\frac{X_{ni}}{X_n}shmig_i(1-\alpha migsh_i)$$
$$+\frac{1}{1-\mu}\frac{X_{nRW}}{X_n}\left[(\sigma-1)\eta\left(1-shmig_n - \sum_{k\in US}\pi_{kRW}(1-shmig_k)\right) - \frac{MIGPOP}{RWPOP}\right]$$

which is equation (A.12).

B Regression data and additional results

B.1 Data details

Migration data To run the regressions, I need data on migrant population by country of origin and US state, as well as their education attainment, year of entry in the US, income, and industry of work. All these variables are readily available from the American Community Survey and the decadal censuses. I gather the 2012-16 5-year ACS as well as the 1960, 70, 80, 90 and 2000 census from IPUMS (MPC, 2019). I compute the total migrant population by country and state (N_{od}) by summing the total person weights *perwt* in the 12-16 ACS, and use the individual's wage income (*incwage*) as my measure of income (w_{od}) and total expenditure (E_{od}) when estimating the origin-bias parameter.

When constructing the instrument pull factors, I compute the number of migrants of a given country j' to a state i at time t ($M_{j'i,t}$) as the total migrants born in j', whose year of migration is t and who reside in state i, from the closest decadal Census.[23]

Trade data I use the US Census data on imports and exports by state of destination/origin, as well as by NAICS industry.

Consistency between the migration and trade data The estimation of the origin-bias parameter relies on computing the share of total expenditure by migrants in the total import from their origin-country. To ensure consistency, I use the OECD ICIO table for 2013 that provides consistent data on total expenditure in the US and total imports from the US. I scale the state-level data on imports so that the US total imports are equal to the one in the OECD data, and I scale the income data in the ACS data so that the US total income is equal to the total spending in the OECD data.

Bilateral controls I manually construct a common border dummy for states on the Canadian and Mexican border, and I compute the geodistance between a state's capital and a country's capital. To compute the sea distance, I first take the list of all cargo ports from the UNLOCODE and use Eurostat's SEAROUTE program to compute the shortest sea distance between all US ports and all foreign ports.[24] I then manually assign a US port to each state, and take the average sea distance to the ports in foreign countries to compute the state-country sea distance.

B.2 Robustness checks

Table B1 displays the first stage regressions corresponding to Table 1. Table B2 displays robustness checks varying the instrument construction, preserving observations with 0 migrations, and using PPMLE. Table B3 displays alternative clustering. The positive impact of migration on trade flows and the instrument relevance survive in all cases.

[23]For example, to predict the pull factor for year 1985, I used the 1990 Census.
[24]See `https://github.com/eurostat/searoute`.

Table B1: First stage regressions

	Imports			Exports		
	$\ln N_{od}$	$\ln N_{od}^{low}$	$\ln N_{od}^{high}$	$\ln N_{do}$	$\ln N_{do}^{low}$	$\ln N_{do}^{high}$
ln(1+instr)	0.773***			0.771***		
	(0.0353)			(0.0294)		
ln(1+instrLS)		0.676***	0.209***		0.686***	0.221***
		(0.0278)	(0.0150)		(0.0273)	(0.0163)
ln(1+instrHS)		0.166***	0.571***		0.161***	0.551***
		(0.0301)	(0.0264)		(0.0263)	(0.0249)
KP-F	479.4	202.6		687.0	247.3	
SW-F		414.9	434.6		508.5	517.1
N	5520	4893	4893	5988	5165	5165

Notes: The table displays the first stage results of regressions from Table 1. The first-stage for imports and exports differ slightly due to the different samples with positive imports and exports. All regressions include importer and export fixed effects as well as bilateral controls. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

B.3 Additional results

Ancestry and migration Table B4 contrasts the impact of migration and ancestry. Specifically, I take the data on ancestry from Burchardi et al. (2019) (BCH) as well as their instrument and compare their regression specification to mine. BCH use a similar instrument in spirit, but not exactly the same. They also rely on a push-pull approach, but rather than constructing the predicted stock of migrant (or population with a given ancestry) by summing over past years of migration, they use all past decade predicted flows as joint instruments for ancestry.[25] Furthermore, their regression uses $\ln(1 + ancestry_{od})$ with ancestry computed in thousands of people, but use the past predicted flows in thousands (without log).

Instead, my approach uses $\ln(migrants_{od})$ as independent variable, and uses ln(1 + sum of past pred. flows) as an instrument. Two differences can explain why one would find an impact in the latter approach but not in the former. First, the variable is different: while ancestry and migration are correlated, ancestry also includes people that have never lived in their country of ancestry, which might dampen the effect. Second, the instruments are not exactly the same. An other potential explanation is that I use the log instead of log(1+migrants), but I show that Burchardi et al. (2019)'s results are similar when using log ancestry.

In Table B4, I first show that both migration and ancestry don't have an impact on

[25] To map it to the description from section 3.1, they compute $\hat{flow}_{ijt} = pull^j_{it} M^{-i}_{j,t}$ for each decade, and use all $\hat{flow}_{ijt}$ as instruments in addition to other additional terms that I leave out for exposition purposes.

Table B2: Robustness for trade migrant elasticity

	Imports						
	Baseline	Pre 1990	Low corr.	1+mig	Age 20	PPMLE	
$\ln N_{od}$	0.190***	0.316***	0.174***			0.332***	
	(0.0541)	(0.0663)	(0.0584)			(0.0583)	
$\ln(1 + N_{od})$				0.166***			0.311***
				(0.0433)			(0.0534)
$\ln(N_{od}^{age20})$					0.182***		
					(0.0478)		
KP-F	479.4	207.5	123.8	774.3	776.4		
AR-F p.	0.000	0.000	0.005	0.001	0.000		
N	5520	5520	5520	8280	5289	6077	10550

	Exports						
	Baseline	Pre 1990	Low corr.	1+mig	Age 20	PPMLE	
$\ln(N_{do})$	0.135***	0.151***	0.104***			0.353***	
	(0.0371)	(0.0472)	(0.0391)			(0.0738)	
$\ln(1 + N_{do})$				0.0744***			0.310***
				(0.0267)			(0.0678)
$\ln(N_{do}^{age20})$					0.121***		
					(0.0328)		
KP-F	687.0	230.6	146.3	770.4	881.6		
AR-F p.	0.001	0.003	0.011	0.009	0.001		
N	5988	5988	5988	9681	5664	6127	10650

Notes: results from estimating equation 19, using the instrument described in the text and with $\alpha = 0$ for the import panel, and from equation 20 for the export panel. Standard errors in parenthesis, twoway clustered at the state and country-level. All regressions include state and country fixed effects and trade costs controls (distance, sear distance and common border). "Baseline" is the baseline specification, "Pre 1990" uses only migration before 1990 to construct the instrument, "Low corr." leaves out countries with migration patterns correlation higher than median in the instrument construction, and "Age 20" uses migrants who entered the US after age 19 as independent variable. "KP-F" refers to the first stage Kleibergen-Paap F-statistic, "AR F p-value" refers to the p-value of the Anderson-Rubin test for significance of the endogenous regressors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

Table B3: Clustering robustness for trade migrant elasticity

Imports

	Twoway		State-level		Country-level	
$\ln N_{od}$	0.190***		0.190***		0.190***	
	(0.0541)		(0.0473)		(0.0449)	
$\ln N_{od}^{low}$		-0.0693		-0.0693		-0.0693
		(0.0593)		(0.0657)		(0.0633)
$\ln N_{od}^{high}$		0.316***		0.316***		0.316***
		(0.0764)		(0.0817)		(0.0812)
KP-F	479.41	203.6	969.9.2	319.1	757.8	205.5
AR-F p.	0.001	0.000	0.000	0.000	0.000	0.000
N	5520	4893	5520	4893	5520	4893

Exports

	Twoway		State-level		Country-level	
$\ln N_{do}$	0.135***		0.135***		0.135***	
	(0.0371)		(0.0339)		(0.0288)	
$\ln N_{do}^{low}$		0.0196		0.0196		0.0196
		(0.0504)		(0.0444)		(0.0502)
$\ln N_{do}^{high}$		0.147**		0.147**		0.147**
		(0.0636)		(0.0592)		(0.0636)
KP-F	687.0	247.3	1430.3	405.6	1009.9	219.4
AR-F p.	0.001	0.001	0.000	0.000	0.000	0.000
N	5988	5165	5988	5165	5988	5165

Notes: results from estimating equation 19, using the instrument described in the text and with $\alpha = 0$ for the import panel, and from equation 20 for the export panel. Standard errors in parenthesis, clustered at the level in the column name. All regressions include state and country fixed effects and trade costs controls (distance, sear distance and common border). . "KP-F" refers to the first stage Kleibergen-Paap F-statistic, "AR F p-value" refers to the p-value of the Anderson-Rubin test for significance of the endogenous regressors. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

exports when using the Burchardi et al. (2019) specification (columns 1 and 2 of the first panel). Second, I show that both have an impact when using my instrument (columns 3 and 4 of the first panel). A potential explanation for this result is that my instrument is capturing variation in *recent* waves of migration: even in the robustness above where I only use migrants from before 1990, the time frame is much more recent than the 19th century that is also included in the ancestry instrument. Instrumenting ancestry with my more recent instrument captures the local average treatment effect of the variation induced by recent migrants rather than overall ancestry. Indeed, in the bottom panel of table B4, I repeat the regressions, but only using the variation in the BCH instruments from the 1990 and 2000 waves. Columns 1 and 2 again show insignificant effects, and weak instruments. However, when using the log of the instruments rather than the instrument itself, I do find positive and significant impact of both migration and ancestry on exports.[26] I conclude that the difference from BCH's results probably come from the fact that migrants have a more recent exposure to their origin country relative to ancestry. Further, the differences in the regression specification and log of instrument can also explain the different coefficients.

Impact of migrants on within-US trade It might be possible that migrants also facilitate trade within the US by increasing trade between two states if the two states have a similar migrant composition. I explore this possibility in Table B5, regressing the value of the Commodity Flow Survey's inter-state flows on bilateral distance as well as a measure of "migrant distance". To compute this distance, I take the euclidian distance between the vector of migrant population in two states.[27] I use the same instrument as above for migrant stock to compute an instrument for the distance between state's migrant composition. When pooling skills together (columns 1 and 2), there is no impact of migrant composition similitude on interstate-flow. When separating by skill, the OLS results show a decrease in trade flows when the high-skill migrant composition are more dissimilar. However, the result doesn't survive instrumenting.

B.4 Origin bias estimation details

Derivation of the expected wage To show that the wage satisfies equation (3.2), first compute the expected value of the labor productivity shock conditional on choosing the optimal destination. To do that, note that the CDF of the maximized indirect utility is

[26] As a reminder, the instruments are the predicted migrant flow in the decade before 1990 and the decade before 2000. It makes sense to log them since we want to instrument for the log of the migrant or ancestry stock.

[27] For state s_1 and s_2, I compute $dist^{mig}_{s_1,s_2} = \left(\sum_c (N_{cs_1} - N_{cs_2})^2\right)^{1/2}$.

Table B4: Effect of Immigration vs ancestry

	BCH instrument		Pre 1990 instrument	
$\ln migrant_{od}$	0.253		0.205***	
	(0.387)		(0.0461)	
$\ln ancestry_{od}$		-0.0222		0.287***
		(0.167)		(0.0639)
KP-F	33.33	54.17	450.9	210.3
N	4603	4603	4603	4603

	More recent waves of BCH instrument			
	BCH instr. (recent)		BCH instr. (recent, log)	
$\ln migrant_{od}$	3.441		0.408***	
	(4.555)		(0.0942)	
$\ln ancestry_{od}$		3.956		0.308***
		(6.018)		(0.0816)
KP-F	1.677	1.449	33.87	85.07
N	4603	4603	4603	4603

Notes: All regressions include bilateral controls for distance and common border, as well as state and country fixed effects. Standard errors in parenthesis, clustered at country level. Ancestry data is taken directly from Burchardi et al. (2019). BCH instrument refers to the Burchardi et al. (2019)'s instruments used in their export regression. Pre 1990 instrument refers to the same instrument as the robustness from Table B2. "BCH instr. (recent)" restricts the instruments from Burchardi et al. (2019) to the census wave 1990 and 2000 predicted migrant flows. "BCH instr. (recent, log)" uses the same instruments, but uses $\ln(1 + instrument)$ as an IV.

Table B5: Inter state flows and migrant similarity

	State-to-state flow			
	OLS	IV	OLS	IV
$\ln dist^{mig}_{s_1,s_2}$	-0.0685	0.173		
	(0.0415)	(0.113)		
$\ln dist^{mig,high}_{s_1,s_2}$			-0.341***	-0.143
			(0.0904)	(0.190)
$\ln dist^{mig,low}_{s_1,s_2}$			0.113**	0.247
			(0.0496)	(0.148)
$\ln distance_{s_1,s_2}$	-1.259***	-1.315***	-1.238***	-1.308***
	(0.0754)	(0.0795)	(0.0736)	(0.0762)
KP-F		70.29		22.02
AR F p-val.		0.112		0.154
N	2539	2539	2539	2539

Notes: All regressions include an importer and exporter state fixed effect. Standard errors in parenthesis, twoway clustered at the importer and exporter level. $\ln dist^{mig}_{s_1,s_2}$ refers to the difference in migrant population composition between the two states.

given by

$$
\begin{aligned}
P\left(\max_d \frac{w_{id}^s}{\kappa_{id}^s P_{id}^f} b_{id}^s(\mu) < x\right) &= \prod_d P\left(\frac{w_{id}^s}{\kappa_{id}^s P_{id}^f} b_{id}^s(\mu) < x\right) \\
&= \prod_d P\left(b_{id}^s(\mu) < x\frac{\kappa_{id}^s P_{id}^f}{w_{id}^s}\right) = \prod \exp\left\{-B_{id}^s \left(x\frac{\kappa_{id}^s P_{id}^f}{w_{id}^s}\right)^{-\varepsilon}\right\} \\
&= \exp\left\{-\sum_d B_{id}^s \left(\frac{\kappa_{id}^s P_{id}^f}{w_{id}^s}\right)^{-\varepsilon} x^{-\varepsilon}\right\}
\end{aligned}
$$

where I distorted the notation slightly to denote the wage received by the individual born in i in destination d as w_{id}^s, and the price index they face as P_{id}^f (where in the model $P_{id}^f = P_d^{1-\alpha} P_{od}^{\alpha}$). From there, the expectation of the maximized indirect utility can be solved as

$$
E\left[\max_d \frac{w_{id}^s}{\kappa_{id}^s P_{id}^f} b_{id}^s(\mu)\right] = \left(\sum_d B_{id}^s \left(\frac{w_{id}^s}{\kappa_{id}^s P_{id}^f}\right)^{\varepsilon}\right)^{\frac{1}{\varepsilon}} \Gamma\left(1 - \frac{1}{\varepsilon}\right)
$$

where Γ is the Gamma function, so that $E\left[b_{id}^s(\mu)|d\right] = \frac{\kappa_{id}^s P_{id}^f}{w_{id}^s} \left(\sum_d B_{id}^s \left(\frac{w_{id}^s}{\kappa_{id}^s P_{id}^f}\right)^{\varepsilon}\right)^{\frac{1}{\varepsilon}} \Gamma\left(1 - \frac{1}{\varepsilon}\right)$. Hence:

$$
\begin{aligned}
E\left[w_{id}^s(\mu)|d\right] &= E\left[w_{id}^s b_{id}^s(\mu)|d\right] = w_{id}^s E\left[b_{id}^s(\mu)|d\right] \\
&= \kappa_{id}^s P_{id}^f \underbrace{\left(\sum_d B_{id}^s \left(\frac{w_{id}^s}{\kappa_{id}^s P_{id}^f}\right)^{\varepsilon}\right)^{\frac{1}{\varepsilon}}}_{W_i^s} \Gamma\left(1 - \frac{1}{\varepsilon}\right)
\end{aligned}
$$

In the model, we have that $P_{id}^f = P_d^{1-\alpha} P_{id}^{\alpha}$, so that the expected wage of any individual of skill s born in i, living in d is given by:

$$
E\left[w_{id}^s(\mu)|d\right] = \kappa_{id}^s P_{id}^{\alpha} P_d^{1-\alpha} W_i^s
$$

which is equation (3.2) in the main text since we assume a large enough pool of individual so that the law of large number holds. It also means that we can use the same equation at the individual level, since the expectation is the same for any individual.

Small bias from Taylor approximation To assess the performance of my estimation method, I provide the following Monte Carlo simulation. First, I use the baseline regression (22)

$$
\ln \frac{w_d L_{od}}{N_{od}} = \gamma_o^s + \psi_d^s + z_{od}'\beta - \frac{\alpha}{\sigma - 1} \ln X_{od} + \alpha \frac{\sum_s w_{od}^s L_{od}^s}{X_{od}} + \varepsilon_{od}
$$

to recover estimates of the fixed effects γ_o^s, ψ_d^s, β, and α (instrumenting for imports with sea distance). I also compute the variance of the residual. Then, I compute the adjusted imports $X_{od} - \hat{\alpha} E_{od}$ and regress them:

$$\left(1 - \alpha \frac{E_{od}}{X_{od}}\right)^{\frac{\gamma}{\sigma - 1}} X_{od} = \gamma_o \mu_d d_{od}^{-1}$$

to recover estimates of the trade costs d_{od} (parametrized as a function of distance, sea distance and common border).

Then, I assume a value of α to construct a simulated value of wages:

$$\ln\left(\frac{w_d L_{od}}{N_{od}}\right)_{sim} = \hat{\gamma}_o^s + \hat{\psi}_d^s + z'_{od}\hat{\beta} + \alpha \hat{d}_{od} + \varepsilon_{od}$$

where I sample ε_{od} from a Normal distribution with the same variance as the residuals from above. And I also construct simulated values of imports as

$$(X_{od})_{sim} = \hat{\gamma}_o \hat{\mu}_d \hat{d}_{od}^{-1} + \alpha E_{od}$$

I then run the same regression as equation (22) on the simulated wage and import data. I do this using three regressions. First without any approximation term (only regressing the wage on imports), then with a first-order approximation (as in my baseline) and finally with a second-order approximation. I run 1000 simulations for values of α between 0 and 0.4 and compute the bias in each case. Figure B1 displays the results. The blue dashed line shows the bias with no Taylor expansion, the solid red line shows the bias when using a first-order approximation, and the dash-dotted green line shows the bias when using a second-order approximation. In both the first and second order approximation cases, the bias is negligible until $\alpha \approx 0.25$ and then increases slightly. I take this as evidence that my estimation strategy for α is sound.

C Data and calibration

C.1 Population data

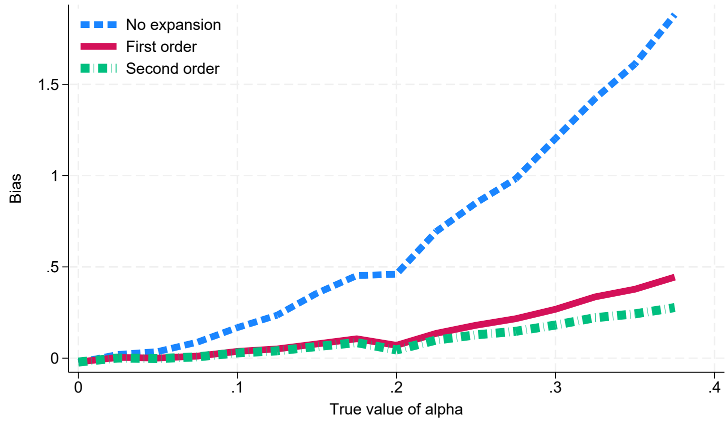
Total migrant stock To get the total number of migrants born in i and living in j, I combine the American Community Survey 2013 data that provides information on place of birth of residents in each US states with estimates from the World Bank on residing population in each country (POP_i), and estimates of Bilateral Migration Matrix for 2013 (MIG_{ij} for $i \neq j$, which translates directly into N_{ij} in the model).[28] 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:

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

[28]http://www.worldbank.org/en/topic/migrationremittancesdiasporaissues/brief/migration-remittances-data

Figure B1: Bias of the origin-bias parameter estimate



Notes: Monte Carlo simulations of the estimation strategy for α. The horizontal axis represents the "true" value of α used in the 1000 simulations. The red solid line plots the bias of using a first-order expansion in the regression equation (as in the baseline estimation). The dot-dash green line uses a second-order expansion, and the dashed blue line doesn't use the Taylor approximation.

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 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 ≥ 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: $shskill_{ij}^s = \frac{ACS_{ij}^s}{ACS_{ij}}$.

When $j \in \{CAN, MEX\}$, I use survey data from IPUMS-International (corresponding to the 2011 Census for Canada and 2010 Census for Mexico[29]) and compute the skill share:

[29]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

$shskill^s_{ij} = \frac{IPUMS^s_{ij}}{IPUMS_{ij}}$. 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: $shskill^s_{ij} = \frac{\frac{ACS^s_{iUS}}{\sum_{n\in US} ACS^s_{nUS}} IPUMS^s_{USj}}{\frac{ACS_{iUS}}{\sum_{n\in US} ACS_{nUS}} IPUMS_{USj}}$.

When $j \notin \{US, CAN, MEX\}$ and $i = j$, I impute $shskill^s_{jj}$ as the overall skill share in the country, using data from the OECD's World Indicators of Skills for Employment database.[30]. 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^s_{ij} using the average skill shares of natives from i in countries where I have data: $shskill^s_{ij} = \overline{shskill}^s_{i,REST}$.

Finally I compute N^s_{ij} as: $N^s_{ij} = shskill^s_{ij} * N_{ij}$.

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.

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 $i, j \notin US$, I simply use the total ICIO exports from i to j:

$$X_{ij} = X^{ICIO}_{ij}$$

If $i \in US, j \notin US$:

$$X_{ij} = X^{ICIO}_{US,j} \frac{X^{census,EX}_{ij}}{\sum_{n\in US} X^{census,EX}_{nj}},$$

where $X^{census,EX}_{ij}$ 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 $i \notin US, j \in US$:

$$X_{ij} = X^{ICIO}_{i,US} \frac{X^{census,IM}_{ij}}{\sum_{n\in US} X^{census,IM}_{nj}},$$

where $X^{census,IM}_{ij}$ 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 $i, j \in US$:

$$X_{ij} = X^{ICIO}_{US,US} \frac{X^{CFS}_{ij}}{\sum_{n,m\in US} X^{CFS}_{nm}},$$

between the migration data and the skill shares.

[30] https://stats.oecd.org/Index.aspx?DataSetCode=WSDB

where X_{ij}^{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.[31] I check the robustness of my results to this assumption by assuming that the same fraction of service output that is internationally traded is also traded within the US. More precisely, define the share of tradable in services as $\sigma^{serv} = X_{US,ROW}^{SERVICE}/X_{US}^{SERVICE}$, computed from the ICIO. Then when computing X_{ij} for $i \neq j$, $i, j \in US$, I use that same share to compute trade flows:

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

where I use sectoral employment data to attribute the service production to each state. For own-state flow, I use:[32]

$$\begin{aligned} X_{ii} = & (1-\sigma^{serv}) X_{US,US}^{ICIO,SERVICES} \frac{emp_i^{SERVICES}}{emp_{US}^{SERVICES}} \\ & + \left(X_{US,US}^{ICIO,NOSERVICE} + \sigma^{serv} X_{US,US}^{ICIO,SERVICES} \frac{emp_i^{SERVICES}}{emp_{US}^{SERVICES}} \right) \frac{X_{ii}^{CFS}}{\sum_{n,m \in US} X_{nm}^{CFS}}. \end{aligned}$$

Table C1 shows the result in the baseline calibration and the alternative service trade calibration. They are of similar magnitude, and the correlation across states is high.

Table C1: Results with alternative services calibration

	Baseline	Alt. Service
Low-skill	-2.46	-2.32
High-skill	-2.36	-2.18
Exp trade costs	2.49	2.69
Imp trade costs	7.00	7.46
Trade/GDP	-14.14	-15.21
Corr with baseline		0.99

Notes: The table displays the average change in high and low-skill native wages as well as the change in export and import costs for the baseline, and the alternative service trade calibration.

[31] In the ICIO data, the share of US exports in US service output is around 5%, while it is around 15% for non-services.

[32] This is probably an underestimation of within US service trade flows, as services are probably more tradable domestically than internationally.

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 (Θ^s_{in}) directly from the survey data also used to construct the migration shares.[33] 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 imputes 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 Model calibration

A final hurdle to use the data in the model is to ensure that it is consistent with all initial market clearing equations. However, the presence of trade deficits and origin bias might not fully fit the data. The first potential issue is that trade flows adjusted for origin bias need to be positive: $X_{od} - \alpha \sum_s \Theta^s_{od} \left(\sum_k X_{dk}\right) \geq 0$, or expressed in shares: $\frac{X_{od}}{\sum_k X_{kd}} - \alpha \sum_s \Theta^s_{od} \geq 0$. For a small fraction of pairs, this inequality doesn't hold after calibrating X_{od} and Θ^s_{od} as outlined above. To construct a new vector X^{cal}_{od} consistent with this condition, I solve the following problem:

$$\min_{X^{cal}_{od}} \sum_{o,d} \left(X^{cal}_{od} - X_{od}\right)^2 \quad \text{s.t.} \quad \frac{X^{cal}_{od}}{\sum_k X^{cal}_{dk}} - \alpha \sum_s \Theta^s_{od} \geq 0$$

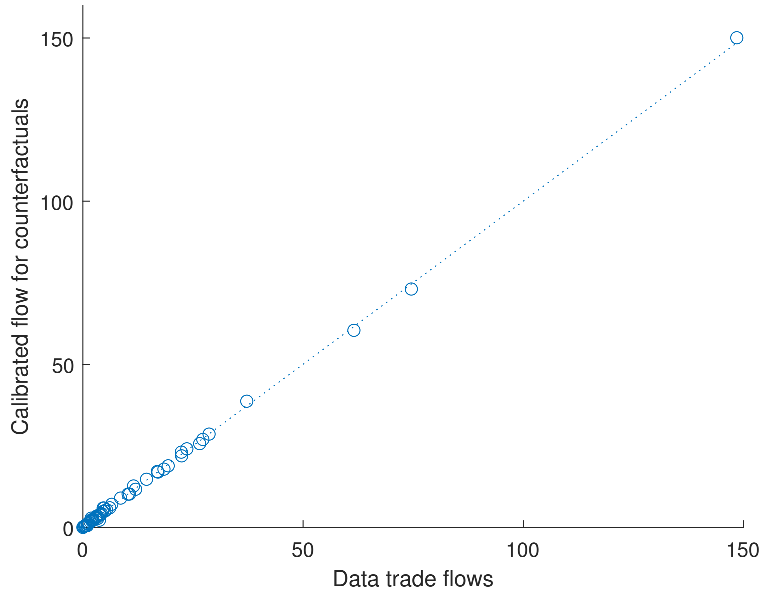
and use the resulting X^{cal}_{od} as my baseline values. The second issue to be solved is that the model doesn't feature trade deficits, while these appear in the data. To address this issue, I solve the system described in A.2, setting $\hat{\kappa}^s_{in} = 1$, to remove any trade deficit from the data and build a baseline set of trade flows X_{od}, migration patterns N^s_{od} and wage bill shares Θ^s_{od} that are fully consistent with the model. I then use this baseline as the initial equilibrium when computing the counterfactual solutions. Figure C1 plots the final trade flow values X^{cal}_{od} against the data X_{od}. All dots lie very close to the 45 degree line. Only very small values of trade are affected by the adjustment.

C.5 List of regions in the model

Table C2 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 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

[33] I use the average wage of migrants fo skill s from i in n, multiplied by the total number of migrants N^s_{in}, to get the total wage bill paid to migrants from i in n, and compute the shares from there.

Figure C1: Fit of the calibrated trade flows



Notes: The figure plots the calibrated trade flows against the raw data trade flows. The solid line is a 45 degree line.

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.

Table C2: List of regions in the model

US States		Countries	
Alabama		Argentina	Iceland
Alaska	Nebraska	Australia	Israel
Arizona	Nevada	Austria	Italy
Arkansas	New Hampshire	Belgium	Japan
California	New Jersey	Bulgaria	Kazakhstan
Colorado	New Mexico	Brazil	Korea
Connecticut	New York	Canada	Lithuania
Delaware	North Carolina	Switzerland	Latvia
Dist. of Columbia	North Dakota	Chile	Morocco
Florida	Ohio	China	Mexico
Georgia	Oklahoma	Colombia	Malaysia
Hawaii	Oregon	Costa rica	Netherlands
Idaho	Pennsylvania	Cyprus	Norway
Illinois	Rhode Island	Czech Republic	New Zealand
Indiana	South Carolina	Germany	Peru
Iowa	South Dakota	Denmark	Philippines
Kansas	Tennessee	Spain	Poland
Kentucky	Texas	Finland	Portugal
Louisiana	Utah	France	Romania
Maine	Vermont	United Kingdom	Russia
Maryland	Virginia	Greece	Saudi Arabia
Massachusetts	Washington	Hong Kong	Singapore
Michigan	West Virginia	Croatia	Slovakia
Minnesota	Wisconsin	Hungary	Sweden
Mississippi	Wyoming	Indonesia	Thailand
Missouri		India	Vietnam
Montana		Ireland	South Africa

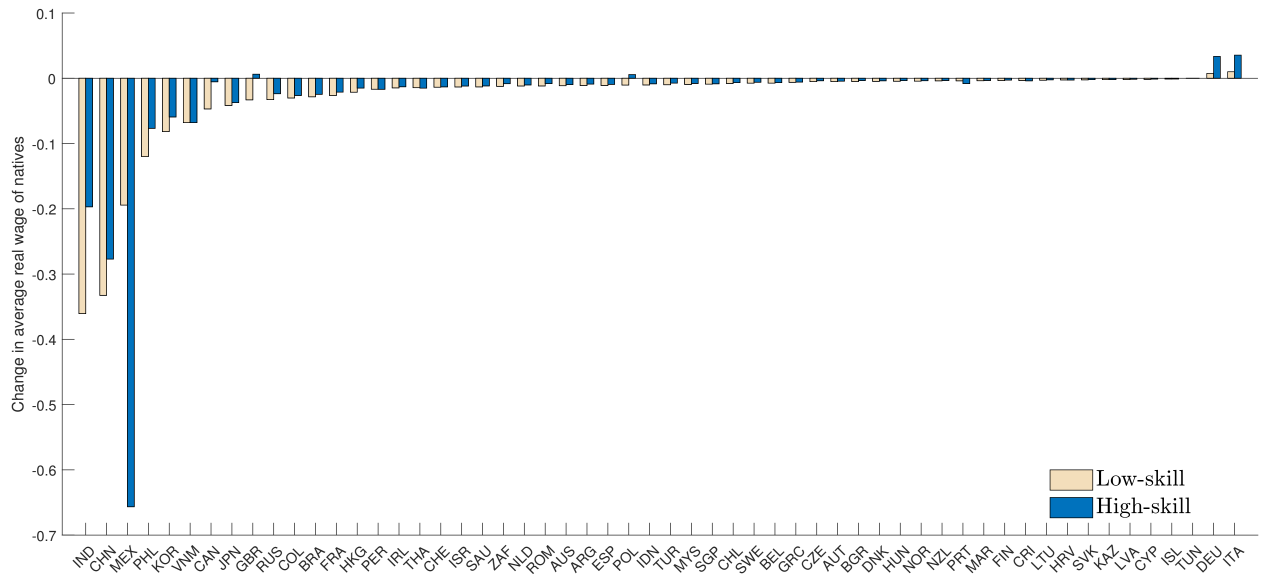
D Additional counterfactuals and robustness checks

Impact of migrants on productivity Ottaviano and Peri (2006) estimate the effect of place-of-birth diversity on US-native wages. They measure diversity as $Div_n = 1 - \sum_i (\frac{N_{in}}{pop_n})^2$. Regressing log native wages on Div_n, they find a coefficient of around 1.27 (Ottaviano and Peri, 2006, Table 1). I match their estimate by rerunning my counterfactual while assuming that $\hat{A}_n = \exp(\zeta \Delta Div_n)$. I set ζ such that when I regress the counterfactual log-wage change of US natives (taking the average over low and high-skill) on ΔDiv_n, I replicate the coefficient of 1.27. To do that, I need to set $\zeta \approx 0.8$ (with $\zeta = 0$, as in my baseline model, the coefficient is around 0.2, so the model accounts for around 15% of that channel already). The last column of the bottom panel of Table 7 display the results of the counterfactual in that case.

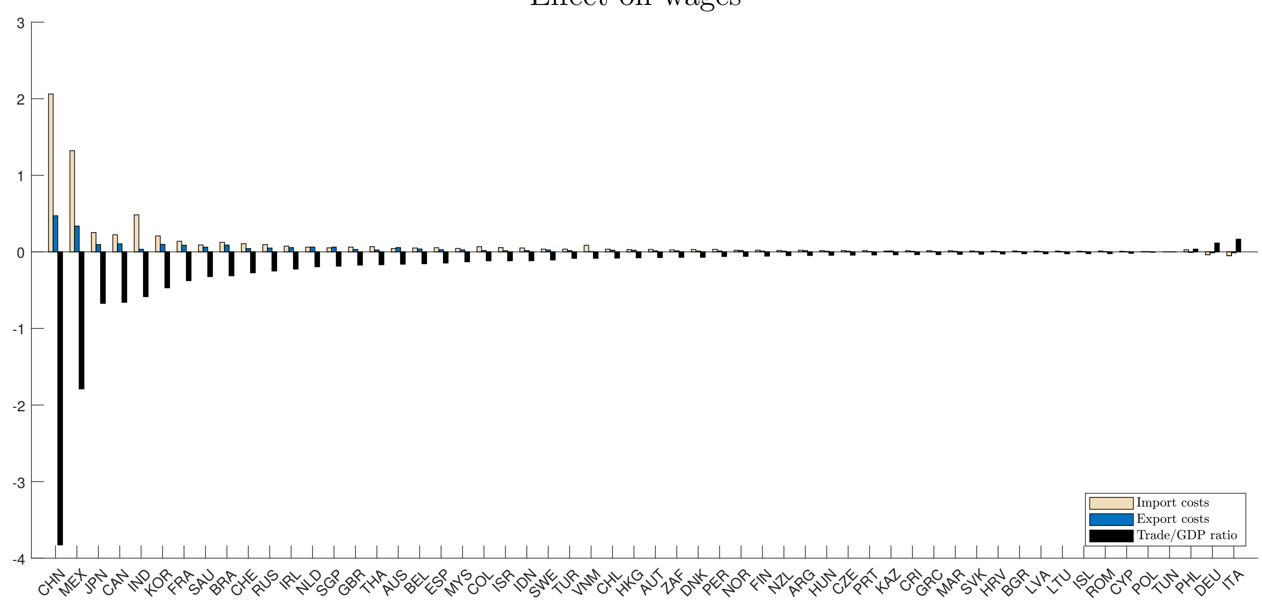
Individual country effects In Figure D1, I show the results of increasing the migration costs of one country at a time. Large immigrant countries such as Mexico, China and India have the largest impact. The impact by skill is very different, depending on the skill composition of the migrant population of a given country. Indian-born migrants in the US are relatively high-skilled, so that their removal hurts low-skill natives relatively more. On the contrary, Mexican-born migrants in the US are relatively low-skill, so that their removal disproportionately hurts high-skill natives. Turning to the impact on aggregate exports, the impact is more pronounced for large trading partners, as the increase in trade costs for that specific country depresses aggregate exports more.

D.1 Additional figures

Figure D1: Effect of removing migrants by country



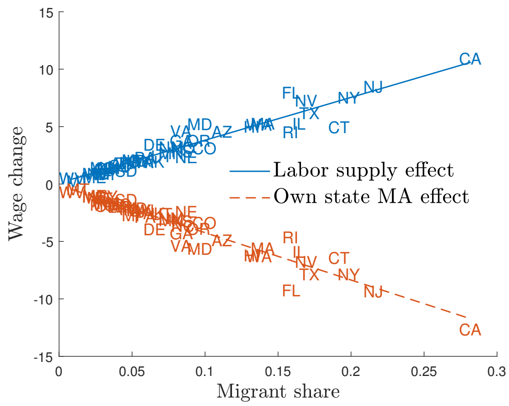
Effect on wages



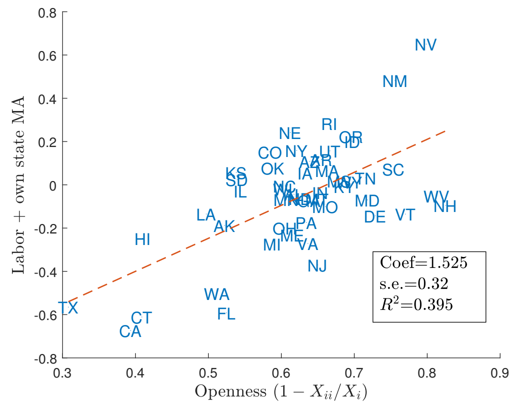
Effect on trade

Notes: Change in real wages of US natives (in percents) and changes in international trade as a share of output, if migration costs for individual countries are changed as in the baseline counterfactual.

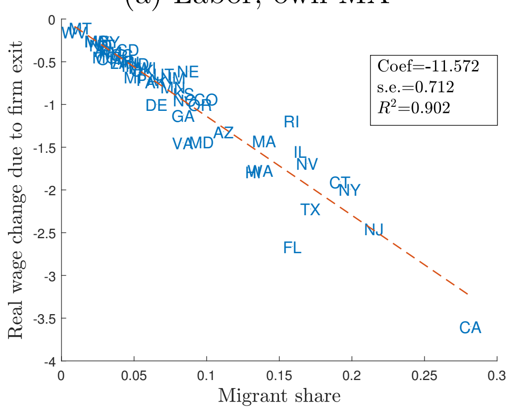
Figure D2: Heuristic measures (low-skill)



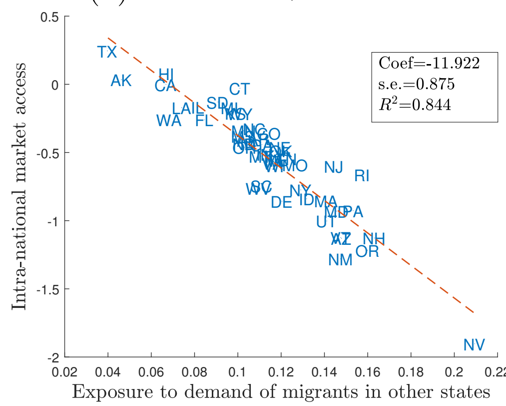
(a) Labor, own MA



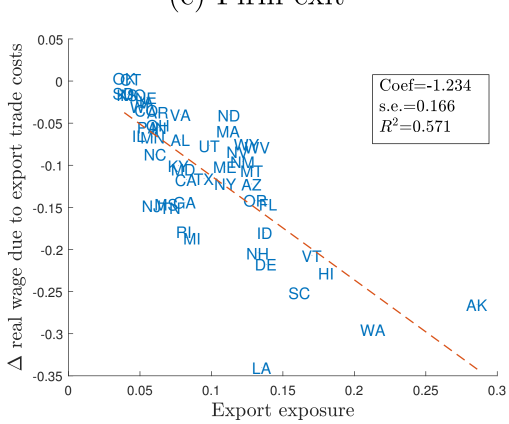
(b) Net labor + own MA



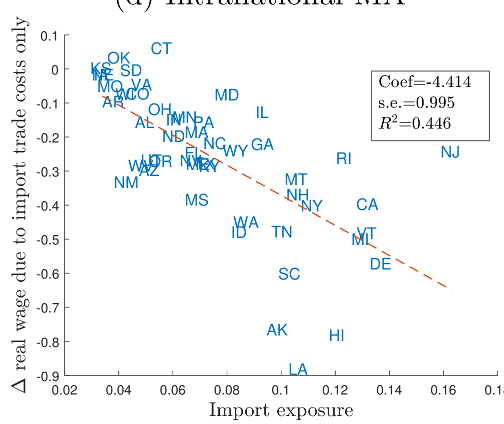
(c) Firm exit



(d) Intranational MA



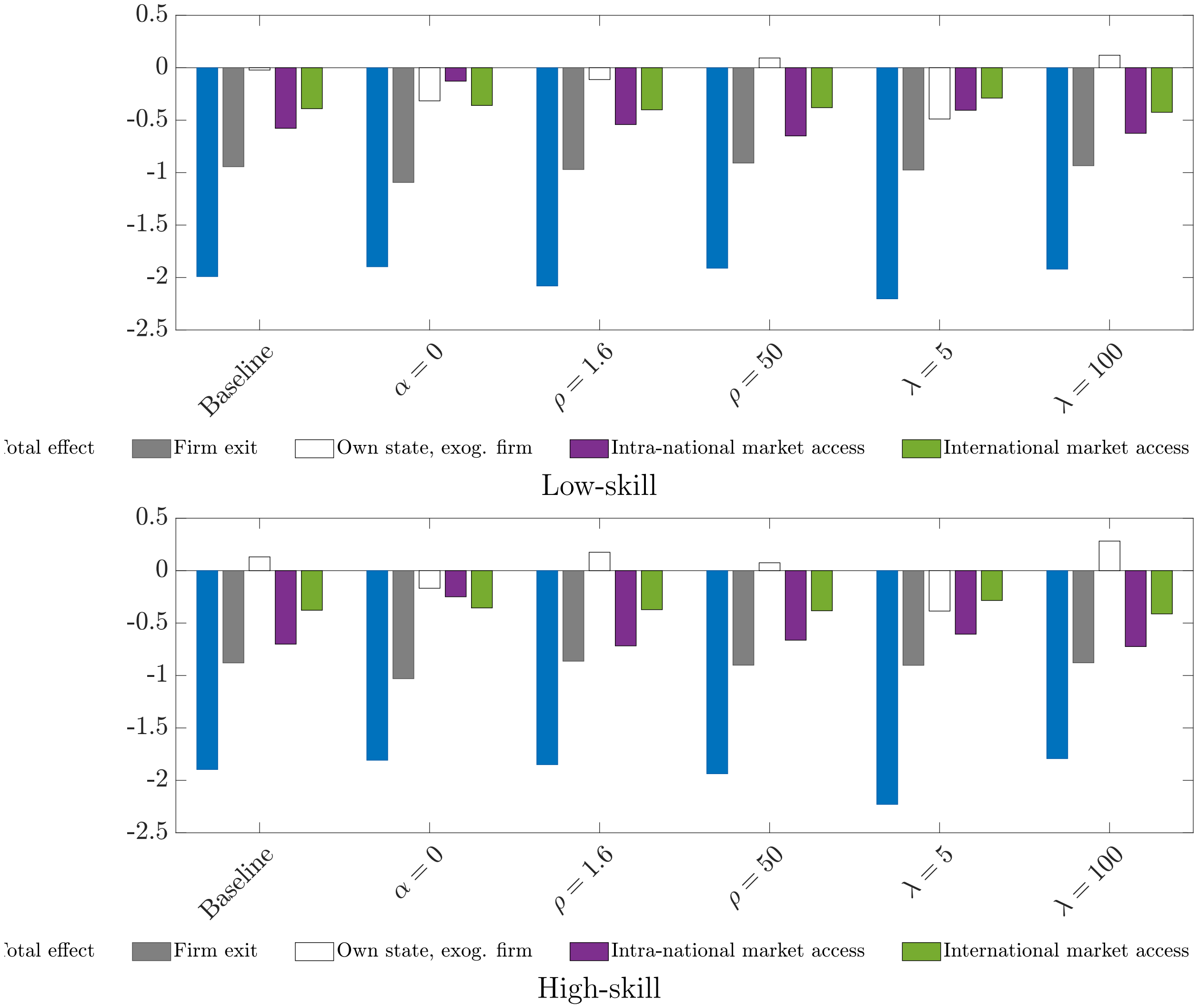
(e) Exporter MA



(f) Importer MA

Notes: The left panel plots the change in real wage in the own-state counterfactual, where only migration costs to the specific state are increased, against the difference between own-migrant share and own-migrant demand exposure. The middle panel plots the change in real wage when migration costs in other states increase, against the exposure to migrants from other states. The right panel plots the change in real wage when only export costs increase, against export exposure. Own migrant exposure is defined as $shmig_i X_{ii}/X_i$, exposure to demand from other stated is defined as $\sum_{j \neq i} shmig_j X_{ij}/X_i$, and export exposure is defined as X_{iRW}/X_i.

Figure D3: Decomposition of the change in real wage (robustness)



Notes: The figure plots the average decomposition of each of the robustness described in the top panel of Table 7.