Essays in International Economics

by

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À *ma maman*, to my wife.

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ABSTRACT

This dissertation studies three aspects of international economics and their effects on the internal economy.

The first chapter studies the effects of road and port infrastructure on international market access of different regions within a country, precisely in the context of India. I first show that comparable firms don't use the same port to reach the same destination, and that even on average, the port chosen by firms is not necessarily the closest. To quantify the welfare gains of improving ports or roads, I build a model of port choice that takes into account differential costs of reaching the port on different road types, and differences in port productivity. I embed this model in a general equilibrium model of intra- and inter-national trade across Indian districts and foreign countries and estimate that improving ports seems to have a larger aggregate effect on overall welfare than improving roads, but the effects are heterogenous across regions. Coastal districts benefit more from port improvements, while inland regions tend to benefit more from road improvements. Hence while the aggregate impact of port improvement is larger, there is scope for road investment to address unequal regional gains.

The second chapter studies the connection between international trade and international migration. I start from the observation that migration patterns potentially influence market access in two ways. First, as migrants relocate, overall demand for goods and services moves closer to the regions of immigration. Second, migrants act

as trade facilitators as they keep ties with their home countries. I estimate the causal impact of migrant on exports from the United States, and study the two mechanisms in a model of intra- and inter-national trade and migration. I simulate what would happen if the migrant share of the US fell back to 1980s level. US export trade costs would increase by 3.5% on average, and welfare would decrease by an average of 0.13%, with substantial variation across states. States who currently sell a larger portion of their output to migrants living in the US would suffer more as their customers move away, and states with higher export exposure would also suffer more from the rise in export costs.

The third chapter, co-authored with Andrei Levchenko and Raphael Auer, studies the impact of a hypothetical revocation of the North American Free Trade Agreement (NAFTA). We build a multi-sector, multi-country trade model and simulate an increase of tariffs between NAFTA countries and use the sectoral heterogeneity across US congressional districts combined with sectoral-level wage changes from the model to assess the district-level impact of the revocation of NAFTA. We then correlate the model implied changes with electoral outcomes to study whether districts that supported President Trump in the 2016 election stand to lose or gain from the revocation of NAFTA. We find that almost all districts lose in terms of real wage, and districts who voted more in favour of Trump actually tend to lose relatively more from NAFTA revocation. Losing districts tend to be more integrated in the world economy, not only because they suffer from a large import competition from abroad, but also because they export a large part of their output and use imported inputs. The results underscore the difficulty of making simple heuristic judgements about who gains and loses from trade policy changes in the global economy.

CHAPTER I

The Impact of Port and Road Infrastructure on International Market Access and Regional Inequality

1.1 Introduction

International trade relies on a network of infrastructures. Ports are at the center of this network, as around 80% of the world's trade in goods is seaborn (UNCTAD, 2018). Accordingly, port quality and easy access to ports are essential to participation in the global economy and investments in ports and port connectivity are large.[1] This paper seeks to address the following question: which part of the infrastructure network is the bottleneck?

I provide a framework to estimate the productivity of different ports and the relative importance of port infrastructure versus road infrastructure in shaping international market access and regional inequality. I build a simple model of port choice based on two key stylized facts derived from novel data on firm-port-destination data from India. First, while a given firm tends to use a unique port to reach a given destination, comparable firms in the same location and same sector use different ports to export to the same destination country. Second, the modal port within the same origin-sector-destination is not necessarily the closest port to the location, nor the closest to the destination. To build a model that rationalizes these facts, I assume

[1] For example, India's Sagarmala Project plans investments of over 15 billion USD for port modernization, and 30 billion USD for port connectivity between 2015 and 2035.

that firms have an idiosyncratic productivity shock for different port-routes. I also decompose the export cost into the cost of going to the port, a port specific productivity, and a cost of going from the port to the destination. A large port productivity induces firms to use a port that might require a longer route to the port.

Under a convenient assumption about the distribution of idiosyncratic route productivities, the model allows me to identify port quality differentials by observing firms' port choices. The estimation regresses port shares within an origin-destination pair on port fixed effects, after controlling for the origin-port cost and the port-destination cost. In this estimation, a key parameter governs the heterogeneity in idiosyncratic productivities and translates into a port-choice cost elasticity. I show how to estimate that parameter, and along the way I estimate parameters governing the costs of traveling to the port on different road types. I then incorporate the port choice model into a multi-region, multi-country model of intra- and inter-national trade and use it to conduct counterfactuals where roads and ports are separately improved to assess which component of the infrastructure network is the most important.

I apply my framework to India using a novel dataset of firm-level export transactions combined with various road and port data. I find that the port elasticity is around 15% higher than the trade elasticity. Using a trade elasticity of 5, this means that when the cost of using port increases by 1%, its share of use decreases by 5.7%. My estimates imply that quality varies significantly across Indian ports: the average port's iceberg trade cost is around 26 percentage points higher than the best port (weighted by value). My port quality estimates correlate well with observable measures of port productivity. I also estimate the cost of traveling to the port on a normal road and on an expressway and find that 100 kilometers (60 miles) on a normal road is equivalent to an ad-valorem trade cost of around 7.4%, while the same distance on an expressway is equivalent to an ad-valorem cost of 5.9%. According to my estimates, a firm is indifferent between shipping through the average port and driving an additional 350 km (215 miles) to ship through the best port.

I then construct a model of trade between Indian districts and foreign countries, where internal trade uses the road network, and international trade uses both the road and port infrastructures. Using the model, I estimate that bringing all ports to the best level increase real wages by close to 6% on average, with large heterogeneity across districts and a standard deviation of 5.3%. Inland districts gain less than coastal regions. Improving port access across regions by bringing all roads to the port to the same quality (while keeping internal costs constant) has a lower impact, with an increase in average real wages of 0.27%. In this case, inland regions with lower connectivity to the coast benefit more. When internal trade cost also improve with the road improvements, average wages increase by 2.3%. These results imply that port improvements have a larger potential than road improvements to increase overall welfare.

I provide an estimate of the cost of improving all ports and improving all roads and show that the costs are of similar magnitude. I use data on investment in ports completed between 2015 and 2019 and changes in port shares to estimate that an additional billion dollar spent on port improvements reduces the iceberg trade cost at the port by around 6.5%. A placebo test using investments under completion and future investments shows that my estimates are not driven by correlation between investment targets and anticipated port growth. I approximate the cost of bringing all ports to the best level by multiplying the estimated marginal effect by the total improvements required to improve all ports. I also estimate the total cost of improving all roads by using data on cost per kilometer of highway improvement. These back of the envelope calculations indicate that improving all ports to the best level and improving all roads to the best level have a similar cost despite their relatively different welfare implications.

While the aggregate welfare impact of port infrastructure improvement seems larger than those of road infrastructure improvement for a comparable cost, their distributional impacts vary across regions. Hence policymakers might still be interested in using road improvements or a combination of road and port improvements if they have specific regions to target in mind. Improving specific ports can also provide a tool to address distributional concerns; I compute the bottleneck port for each Indian district, defined as the port which results in the highest gain in district-level welfare for an equal port-level improvement.

I contribute to the existing literature in several dimensions. First, while previous literature has mostly focused on each type of infrastructure separately, I adopt a more integrated view of infrastructures. Previous papers have highlighted the importance of road infrastructure (Asturias et al., 2019; Faber, 2014; Alder, 2019; Baldomero-Quintana, 2020), rail network (Donaldson, 2018) or ports (Ducruet et al., 2020; Ganapati et al., 2020) separately. A branch of the literature also studies how internal trade costs affects international trade and regional distributional impacts of trade liberalization (Atkin and Donaldson, 2015; Sotelo, 2020; Fajgelbaum and Redding, 2018). I contribute to this literature by giving a more prominent place to ports, which act as connecting points between internal and external trade costs. My paper is also related to the literature on optimal infrastructure investment, which has also focused on a single type of infrastructure (Fajgelbaum and Schaal, 2020; Santamaria, 2020). In this paper, I explicitly model road and port infrastructure, which allows me to assess which type of infrastructure is the bottleneck. A related paper is Van Leemput (2021), who estimates the gains from reducing internal and external trade costs in India. In the current paper, I specifically study the internal and external trade costs associated with infrastructure.

Second, I contribute to the growing literature on infrastructure and shipping networks that uses heterogeneous shipping costs for analytical convenience (Allen and Arkolakis, 2020; Ganapati et al., 2020). I provide stylized facts based on micro-data that justify the assumption of heterogenous shipping costs, and a novel estimate of the parameter estimating the shipping cost heterogeneity, based on firm-level data that can be useful in other settings. My framework is closely related to Allen and Arkolakis (2019), who estimate a related parameter, which is the elasticity of highway segment usage to the segment cost.[2] My estimation is grounded in disaggregated firm-level data, and applies more specifically to port choice. Thus my estimate is more suited for the the emerging literature on ports (Ducruet et al., 2020; Ganapati et al., 2020). The route choice model in Ganapati et al. (2020) is also closely related. In their model, producers in each potential sourcing location draw a random trade cost to other destinations for each variety of a continuum of goods, and offer a perfectly competitive price. Consumers then choose the least cost supplier for each variety in a similar fashion as in Eaton and Kortum (2002). In that framework, the parameter governing the route elasticity has the interpretation of a trade elasticity, while in my framework the trade elasticity and the port elasticity are allowed to differ. My estimate lends some support for their approach. While my estimate of the port-route elasticity is statistically significantly higher than the trade elasticity, it is close to it and inside the conventional range of trade elasticities.

[2] In a revision, Allen and Arkolakis (2020), the framework is modified and the elasticity is the trade elasticity. The original estimate is still used in other papers such as Ducruet et al. (2020) or Baldomero-Quintana (2020).

Finally, my paper provides a novel way of measuring port productivities and new estimates of road costs differential between expressways and normal roads. Blonigen and Wilson (2008) uses data on import charges to estimate port productivities. My framework only requires data on port shares, which is more commonly accessible through customs dataset than data on import or export charges. I also estimate the relative cost of distance on an expressway relative to normal roads which could be useful in the calibration in other research. As a contrast, other papers use theoretical relative speeds to infer the relative costs on expressways and normal roads (Asturias et al., 2019; Alder, 2019).

The remainder of the paper is organized as follows. Section 1.2 presents the data and stylized facts about port usage in India, section 1.3 builds the model of port choice, section 1.4 shows how to estimate the key parameters and port quality, section 1.5 shows the estimation results, section 1.6 builds the full model, and section 1.7 presents the results of the counterfactuals.

1.2 Basic facts

1.2.1 Data

The main data I use is a dataset of firm-level export transactions from India. The dataset covers a sample of around 16,300 firms. I observe every export transaction the firm makes between 2015 and 2019. For each transaction, I observe the value of the transaction, the port of exit and the destination port, which I use to infer the destination country. I also observe the list of a firm's branches with their address and merge the data with India's company register and Economics Census' list of establishments to obtain the firms' sectoral classification. For my purposes, I drop exports by air or land. In 2019, these constituted less than 5% of exports in terms of weight, and around 24% in terms of value.[3] I keep all ports used by at least 10 firms in my sample. The resulting sample covers 16,300 firms located in over 400 different Indian districts, 22 ports and over two hundred destinations. The 22 ports cover over 99% of Indian sea exports. The sample covers slightly less than 30% of India's total exports. Appendix A.1 shows that the sample is representative of the official aggregate figures for key statistics such as port and destination shares, and contains the details of the data construction.

1.2.2 Stylized facts

In this section, I show two stylised facts about port usage that are useful ingredients for modelling port choice.

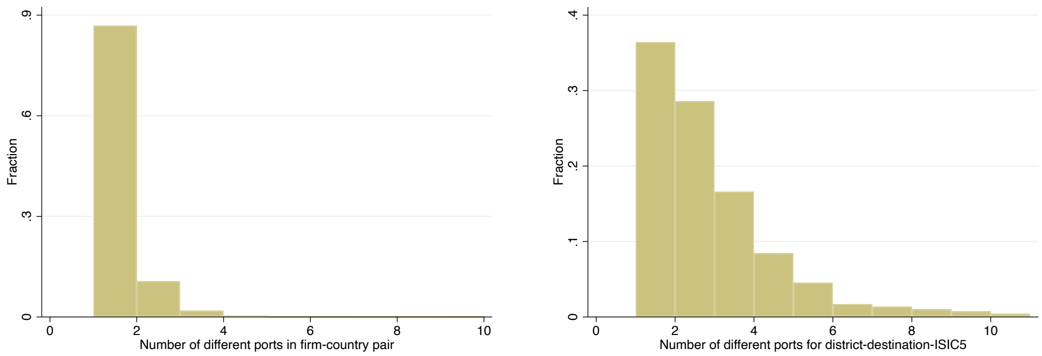
Heterogeneity in port choice First, I show that single firms tend to use only one port to reach a given destination. The left panel of Figure 1.1 shows the histogram of the number of port used within a firm-destination pair level. Close to 90% of firms use a unique port to reach a given destination.

I then look at how homogeneous the port choices are among comparable firms. To that end, I compute the number of different ports used by firms in the same sector and same origin region, to export to a same destination. I define a sector as an International Standard Industrial Classification (ISIC) 5-digit group, an origin region as an Indian district, and a destination as a country.[4] To classify each transaction to an origin district for firms that have many branches, I assume that the good was shipped from the branch closest to the observed port. This might introduce some

[3] Given India's border geography, the share of land exports is extremely low at 2.4% in value and 1.5% in weight. Exports by air are the main alternative to sea and account for around 21% of total exports in value and 1.5% in weight. Some transactions take place through inland port, used to transit towards actual ports. For these observations, I use the actual sea port of exit.

[4] An example of ISIC5 category is 17111 which corresponds to "Preparation and spinning of cotton fiber including blended cotton". Appendix A.2 explores narrower geographical classifications and shows that the patterns remain the same when using a postal code as an origin region, and discharge ports as destinations.

Figure 1.1: Number of ports used



Firm-destination

Origin-sector-destination

Notes: The left panel displays the histogram of the number of ports per firm-destination pair. The right panel displays the histogram of the number of ports per origin-sector-destination triplet. Only triplets with more than one firm are kept to avoid triplets where the number of ports is 1 simply due to small sample.

spurious heterogeneity in case of misclassification, and I repeat the same exercise using firms that only have one branch in Appendix A.2 with similar findings. The right panel of Figure 1.1 displays the histogram of the number of ports by sector-district-destination triplet. If all firms in the triplet were using the same port, the distribution would be a mass point at 1. However, it turns out that while the mode is a single port per triplet, more than one port is used in most cases. This indicates that firms have unobservable affinities for particular ports beyond their location, sectoral classification or destinations.

Closest port If some ports are better than others, firms might be willing to incur additional internal costs to reach a better port, even on average. In that case, the modal port in each triplet might not be the closest one available. Table 1.1 shows that indeed, the closest port to the origin is on average 17% closer to the origin than the modal port chosen by firms within a triplet, where the distance is the road distance. The modal port is also further away from the destination than the Indian

Table 1.1: Modal port distances

	origin-port distance		port-destination distance	
	modal port	closest port	modal port	closest port
Average	233	194	5,565	4,921
Median	93	81	5,337	4,299

Notes: This table shows the average and median road distance in kilometers between the origin district and three ports: the modal port within an origin-sector-destination triplet, the port closest to the origin (by road), and the port closest to the destination (by sea). The average and median are computed over triplets, weighted by number of transactions.

port closest to the destination by 11%, where the distance is the sea-distance. This implies that even on average, firms seem to either strike a balance between a port closer to their location, or a port closer to the destination, or they might simply chose to incur additional internal cost to reach a more productive port.

1.3 A model of port choice

In this section, I present a simple partial-equilibrium model of port choice that rationalizes the facts presented above. I will incorporate that model in a full general equilibrium later in section 1.6. For expositional purposes, I remove any sectoral dimension in this section, and add it later when moving to the data.

A firm i located in origin region o, faces the following iceberg trade cost to export to destination d through port ρ:

$$\tau_{io\rho d} = \frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}} \tag{1.1}$$

were $\tau_{o\rho}$ captures the cost of going from the origin region to the port, τ_{ρ} captures the cost of handling the shipment at the port, and $\tau_{\rho d}$ captures the cost of bringing the shipment from the port to the destination. $\varepsilon_{io\rho d}$ is a firm specific route $(o - \rho - d)$ productivity shifter that rationalizes the fact that different firms within the same sector-origin-destination use different ports. Differences in τ_{ρ} also explain why firms might not chose the closest port, even absent of firm heterogeneity.

I assume that the productivity shifter is Fréchet distributed, with the following cumulative distribution function:

$$F(\varepsilon) = \exp\left(-\varepsilon^{-\theta}\right),$$

where θ is a shape parameter that governs the dispersion of ε. High values of θ imply a low dispersion.

The firm chooses the port ρ^* that minimizes the export cost, so the effective esport cost for firm i is given by $\tau_{iod} = \min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{i\rho d}}$. Using the properties of the Fréchet distribution, standard steps show that the probability of choosing port ρ is given by:

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}}{\sum_k \left(\tau_{ok}\tau_k\tau_{kd}\right)^{-\theta}}, \tag{1.2}$$

so that θ can also be interpreted as the port elasticity. For large values of θ (corresponding to small heterogeneity in idiosyncratic productivities), the share of firms that react to a change in the port-specific cost is larger because the draw of ε is more concentrated and more firms' optimal choice changes.

The expected export cost between o and d is given by:

$$\tilde{\tau}_{od} = E\left[\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{i\rho d}}\right] = \kappa\left[\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{1}{\theta}}, \tag{1.3}$$

where κ is a constant involving the Gamma function and θ. Notice that the expected trade cost depends on the same term $\Phi_{od} = \sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}$ as the denominator of the share equation (1.2), with an exponent of $1/\theta$. I will use this fact below to estimate the parameter θ.

Equation (1.2) makes it apparent how the port (inverse) quality τ_ρ is related to the observable left-hand side share. With an estimate of θ and controlling for the costs from the origin to the port, and from the port to the destination, one can recover an estimate of τ_ρ. The value of θ is key in that estimation: a large θ implies that small deviations in port quality lead to high changes in shares, while a low θ leads to muted changes. Similarly, equation (1.3) shows that θ also governs how the expected trade cost depends on the range of port costs. A large θ implies smaller heterogeneity, so that all firms use the same port and the expected cost is close to the smallest ($\tau_{o\rho}\tau_\rho\tau_{\rho d}$). Finally, it is clear that export costs depend on the cost along the two "domestic" main segments of the route and their corresponding infrastructure: road quality affects $\tau_{o\rho}$ and port quality affects τ_ρ.

The model is related to Allen and Arkolakis (2019), with the following departure. That paper introduces an intermediary trader who incurs an idiosyncratic trade cost shifter along different routes and assume that firms match randomly with the traders. I instead assume that the route productivity shifter is firm specific, which fits the firm-level stylised fact showed in Section 1.2 better, and can be incorporated in a standard trade model with firm heterogeneity as shown below in Section 1.6. It is also related to the framework of Ganapati et al. (2020) and Allen and Arkolakis (2020). There, the producers in an origin location draw a random trade cost to other destinations for each good in a continuum of varieties, and offer a perfectly competitive price. Consumers then choose the least cost supplier for each variety in a similar fashion as in Eaton and Kortum (2002). In that framework, the dispersion parameter θ has the interpretation of a trade elasticity. In the present paper, the dispersion parameter in trade costs draws θ is allowed to be different from the trade elasticity.

1.4 Estimation strategy

In this section, I show how to identify θ under standard assumptions in the trade literature, and how to recover estimates of infrastructure quality.

1.4.1 Port elasticity

To estimate θ, I make two additional assumptions on pricing and demand, and show how to combine export value data with port shares to estimate θ.

The first assumption is that firms set constant markup prices. The price that firm i in origin o would charge to destination d if it sent through the port ρ is given by:

$$p_{iod} = \mu c_i \tau_{io\rho d} = \mu c_i \min_{\rho} \frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}, \tag{1.4}$$

where μ is the markup and c_i is the firm's marginal cost. This assumption is consistent with a variety of common market structures, including perfect competition and monopolistic competition. I still allow for firm-level heterogenous marginal cost c_i.

The second assumption I make is that the demand satisfies constant elasticity of substitution, so the spending on each firm's output in destination d is given by:

$$X_{iod} = (p_{iod})^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}}, \tag{1.5}$$

where σ is the elasticity of substitution in demand, X_d is total spending at destination d and P_d is the price index. Under assumptions (1.4) and (1.5), the total exports of firm i to destination d are given by:

$$X_{iod} = (\mu c_i p_{iod})^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}},$$

To eliminate μ and c_i, it will be convenient to work with the ratio of a same firm's sales to different destinations:

$$\frac{X_{iod}}{X_{io\delta}} = \left(\frac{p_{iod}}{p_{io\delta}}\right)^{(1-\sigma)} \frac{X_d P_d^{\sigma-1}}{X_\delta P_\delta^{\sigma-1}}$$

To further remove the destination pair specific term, take the same ratio with that of an other firm located in an other origin destination o':

$$\frac{X_{iod}}{X_{io\delta}} / \frac{X_{jo'd}}{X_{jo'\delta}} = \left(\frac{p_{iod}}{p_{io\delta}} / \frac{p_{jo'd}}{p_{jo'\delta}} \right)^{(1-\sigma)} .$$

Using the fact that the Fréchet draws are independent across destinations and firms, one can show that the expectation of this ratio conditional on observing the firms export value through their optimal port is given by (see Appendix A.3.1 for the proof):

$$\begin{aligned} E\left[\frac{X_{iod}}{X_{io\delta}} / \frac{X_{jo'd}}{X_{jo'\delta}}\right] &= \Gamma\left(1+\frac{1-\sigma}{\theta}\right)^2 \Gamma\left(1-\frac{1-\sigma}{\theta}\right)^2 \\ &\quad * \left(\frac{\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho\delta}\right)^{-\theta}}{\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}} / \frac{\sum_\rho \left(\tau_{o'\rho}\tau_\rho\tau_{\rho\delta}\right)^{-\theta}}{\sum_\rho \left(\tau_{o'\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}} \right)^{\frac{1-\sigma}{\theta}} , \end{aligned} \tag{1.6}$$

where Γ is the gamma function and the expectation is taken over all firm pairs in origin o and o' exporting to the same destination pair (d, δ). Notice that the summation terms inside the parenthesis are equal to the multilateral resistance term Φ_{od} on the denominator of the port share equation. As a consequence, the previous equation can be rewritten in terms of observable port shares as:

$$E\left[\frac{X_{iod}}{X_{io\delta}} / \frac{X_{jo'd}}{X_{jo'\delta}}\right] = \Gamma\left(1+\frac{1-\sigma}{\theta}\right)^2 \Gamma\left(1-\frac{1-\sigma}{\theta}\right)^2 \left(\frac{\pi_{o\rho d}}{\pi_{o\rho\delta}} / \frac{\pi_{o'\rho d}}{\pi_{o'\rho\delta}} \right)^{\frac{1-\sigma}{\theta}} , \tag{1.7}$$

which provides a useful moment condition to estimate the ratio $\frac{1-\sigma}{\theta}$. That estimating strategy uses the fact that the expected trade cost is a function of the multilateral resistance term Φ_{od} to the power of $1/\theta$.

Two elements of the moment condition (1.7) work together to estimate the ratio $\frac{1-\sigma}{\theta}$. The first part is the product of the Gamma functions $\Gamma(1+x)^2 \Gamma(1-x)^2$, which is equal to 1 at $x = 0$ and is strictly increasing until $x = 1$ where it tends to infinity. The second part is the ratio of port shares that controls for average trade costs. Absent of any heterogeneity across firms, the ratio of values on the left-hand side would be completely captured by the ratio of the trade costs, and the first part would tend to 1, consistent with $x = 0$ and $\theta = \infty$ (remember that a high θ implies low dispersion in the Fréchet draws). As the Fréchet draws become more disperse, the expectation of the value ratio increases, which implies a higher x and lower θ.

Note that until this point, the specific multiplicative form of the cost $\tau_{o\rho d}$ hasn't been used. I use it now to link the moment condition to the data. The value I observe is *freight-on-board* (FOB), which means that it only includes the cost up to the port, but not the cost of transportation from the port to the final destination. Hence the observed value is $X^*_{io\rho d} = \tau_{\rho d}^{-1} X_{iod}$. As a result, when going to the data, I take the ratios conditioning on the two firms using the same port pair to reach the destination pair, so that the $\tau_{\rho d}$ terms cancel out:

$$E\left[\frac{X^*_{io\rho d}}{X^*_{io\rho'\delta}} / \frac{X^*_{jo'\rho d}}{X^*_{jo'\rho'\delta}}\right] = E\left[\frac{X_{iod}}{X_{io\delta}} / \frac{X_{jo'd}}{X_{jo'\delta}}\right]. \tag{1.8}$$

Note that conditioning on a particular *observed* port pairs (ρ, ρ') has no impact on the expectation, since the observed port pairs are the optimal ones.

For exposition purposes, I dropped the sectoral component in the notation. When moving to the data, I will also allow for different trade costs by sector, by simply computing the port shares at the origin-sector-destination pair level, and the sales ratio restricting to firms in the same sector.

1.4.2 Infrastructure quality

As mentioned above, the share of firms within an origin-destination pair using a given port is informative on the underlying trade cost and specific port quality. As a reminder, taking logs of the equation of port shares (1.2) gives:

$$\ln \pi_{o\rho d} = -\theta \ln \tau_{o\rho} - \theta \ln \tau_\rho - \theta \ln \tau_{\rho d} - \ln \Phi_{od}$$

While the previous section focused on estimating θ and didn't need to identify τ_ρ for that purpose, I now show how to recover estimates of τ_ρ given an estimate of θ.

The strategy is to parametrize $\tau_{o\rho}$ and $\tau_{\rho d}$ and estimate $\ln \tau_\rho$ using a port fixed effect. Specifically, the cost between o and ρ is the product of the cost over each segment k used to get from o to ρ on least-cost path on the road network:

$$\tau_{o\rho} = \prod_k t_{k(o\rho)} \tag{1.9}$$

I then assume that the cost on the segment is a function of time, given by:

$$t_k = \exp\left(\beta^{time} time_k\right). \tag{1.10}$$

The exponential form is has the convenient property that the iceberg cost tends to 1 as the time spent on the segment tends to 0. Splitting a segment in two parts also doesn't affect the cost, because the product of the two subsegment iceberg trade costs will equal the the iceberg cost of the main segment and only depend on the total time spent on the segment. To link the time with observable road infrastructure, I assume that the time on segment k depends on the types of road of the segment:

$$time_k = \tilde{\beta}^{c(k)} dist_k, \tag{1.11}$$

where $c(k)$ is the road category of segment k and $dist_k$ is the distance travelled on the segment. In practice, c will be either a normal road (typically with two lanes in total, and no separation), or an expressway separated in the middle (typically with two lanes per direction). The parameter $\tilde{\beta}^c$ captures the (inverse) average speed on a particular type of road. This parametrization will allow me to easily run counterfactual such as replacing a given segment of infrastructure from normal road to expressway.

I also parametrize the cost between the port and the destination as the sea distance between the port and destination:

$$\ln \tau_{\rho d} = \lambda \ln seadist_{\rho d} + u_{\rho d}.$$

Combining the parametrizations leads to the following estimating equation:

$$\ln \pi_{o\rho d} = \sum_{c} \underbrace{\beta^{c}}_{-\theta\beta^{time}\tilde{\beta}^{c}} dist^{c}_{o\rho} + \beta^{sea} \ln seadist_{\rho d} + \underbrace{\alpha_{\rho}}_{-\theta\tau_{\rho}} + \Phi_{od} + u_{o\rho d},$$

where $dist^{c}_{o\rho}$ is the total distance travelled on roads of type c, to go from o to ρ on the least-cost route. Because the least-cost route is itself a function of unknown parameters β^{c}, the parameters can be estimated using the following non-linear least-square problem:

(1.12)
$$\min_{\{\beta^{c}\},\beta^{sea},\{\alpha_{\rho}\},\{\Phi_{od}\}} \left[\ln \pi_{o\rho d} - \min_{r \in R_{o\rho}} \left\{ \sum_{c} \beta^{c} dist^{c}_{o\rho}(r) \right\} - \beta^{sea} \ln seadist_{\rho d} - \alpha_{\rho} - \Phi_{od} \right]^{2},$$

where $R_{o\rho}$ is the set of routes on the road network that go from origin o to port ρ. A necessary condition for the vector $\beta^{*} = \{\beta^{*c}\}$ to be a solution to this problem is that:

$$\beta^{*} = arg \min_{\{\beta^{c}\}} \left\{ \ln \pi_{o\rho d} - \sum_{c} \beta^{c} dist^{c}_{o\rho}(\beta^{*}) - \beta^{sea} \ln seadist_{\rho d} - \alpha_{\rho} - \Phi_{od} \right\}^{2}, \tag{1.13}$$

where $dist^{c}_{o\rho}(\beta^{*})$ is the total length on category c in the solution of the least cost route given β^{*}. In other words, regressing the port shares on the distances computed conditional on β^{*} and other covariates needs to result in the same vector β^{*}, so that β^{*} is a fixed point to the mapping defined by the $arg \min$ function in (1.13). Note that given β^{c}, the least-cost route problem is well defined and easily solved using standard routing optimization algorithms. Hence one can solve the fixed-point problem in (1.13) using the following steps:

1. Guess $\{\beta^c\}$,

2. Solve for the optimal route for all $o\rho$ pairs given β^c,

3. Solve for $\{\beta^c\}, \beta^{sea}, \{\alpha_\rho\}, \{\Phi_{od}\}$ given $dist^c_{o\rho}$ by Poisson pseudo-maximum likelihood estimation,

4. Go back to step 1 with the new value of $\{\beta^c\}$.

In practice, I use the Dijkstra algorithm to solve for the least cost route. I use some initial values for β^c (for example based on the maximal speeds on each type of road), and the algorithm only takes few iterations to converge because the optimal route using my initial guess is very close to the one using the final β^c.

Being a solution to the fixed point problem (1.13) is only a necessary condition to being a solution to the minimization problem (1.12), unless the fixed point is unique. While I am not able to prove this, I check that the solution is unique by starting from different initial guesses, and all converge to the same point.[5]

The advantage of this estimation procedure is that is provides an estimate of port quality (τ_ρ) and the effect of different road types on trade costs (β^c) from the same estimating procedure, up to a common scale equal to θ. Estimating the β^cs directly instead of relying on preset values of $\tilde{\beta}^c$ (the average speed per road category) and a calibrated value of β^{time} ensures that the parameters are identified using the same framework as the measure of port quality, and that they are consistent with the context of India.

One might be concerned about the fact that the port qualities are estimated using a fixed effect, and that fixed effects are usually not consistently estimated. In my case, this is not a concern because the number of ports is fixed and does not grow

[5] In particular, I also try starting points where the order of β^c is counterintuitive (e.g. cost on normal roads is lower than cost on expressways). All initial guesses converge to the same point.

with sample size.

1.5 Estimation Results

This section presents the estimation results.

1.5.1 Port elasticity

I run the estimation at different levels of regional and sectoral aggregation. I compute the port shares as the share of firms that use a port within a sector-origin-destination group. Table 1.2 displays the results.

Table 1.2: Elasticity estimation results

	District level			Postal code level		
	Pooled	ISIC3	ISIC5	Pooled	ISIC3	ISIC5
$\frac{\sigma-1}{\theta}$	0.886	0.889	0.878	0.890	0.876	0.876
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
N	2,587,540	289,036	134,536	262,597	686,531	219,800
Cluster	destination pair					

Notes: This table shows the results of estimating the elasticity parameter using the strategy outlined in section 1.4.

All results estimates point toward a port elasticity that is slightly higher than the trade elasticity. With a trade elasticity of 5 (e.g. Costinot and Rodríguez-Clare, 2014) corresponding to $\sigma - 1 = 5$, the port elasticity would be around $5/0.88 \approx 5.7$. This implies that if a port's cost increases by 1%, its share would decrease by around 5.7%.

Appendix A.3.1 displays similar results when computing the port shares by numbers of transactions or by value. In all cases the ratio is between 0.7 and 1.

1.5.2 Infrastructure quality

I use the national highway network extracted from Open Street Map (OSM) to compute the fastest routes.[6] I keep all roads tagged as national highways or state highways with more than two lanes, and allow the trade cost to differ by road category, where I create two categories: expressway (two or more lanes per direction, physical separation in the middle), and normal roads (typically, on the National Highway, these would have two lanes in total, shared for both directions). Expressways constitute around 25% of the total National Highway length. I take the OSM data as of January 2020 and estimate equation (1.12) using the average 2018-19 origin-port-destination shares. Appendix A.1.3 discusses the potential issues with the road data and compares it with official statistics to show that the user-generated OSM data matches official statistics well. Table 1.3 displays the results.

Table 1.3: Road parameters and port quality estimation

	$\ln \pi^s_{o\rho d}$
Normal road	-.00422
	(.0001)
Expressway	-.00339
	(.0001)
$\ln seadist_{\rho d}$	-.808
	(.096)
Same state port	.683
	(.032)
Port FE	yes
sector-origin-dest FE	yes
Cluster	sector-origin-dest
N	242,528

Notes: The table shows the estimates of the PPML estimation using the least-cost route after convergence of the cost parameters.

[6] Open Street Map is a crowd-sourced map of the world, where users can add or modify roads, including details about the road such as number of lanes, oneway, and road names.

Roads As one would expect, distance on the expressway has a smaller negative impact on the probability of choosing a port than distance on normal roads. The difference between $\beta^{expressway}$ and β^{road} is both statistically and economically significant: the cost associated with traveling on a normal road is about 25% higher than that of traveling on an expressway. If only time spent on the road matters, and given a highway speed of 70km/h, the estimate would imply a speed of around 55km/h on a normal road, which is of the right order of magnitude. The distance of the port to the final destination also has the expected negative impact on the choice of the port, with an elasticity of around 0.81. The coefficient has the structural interpretation of $\theta * \eta$, where η is the elasticity of trade costs with respect to sea distance. Using my estimate $\frac{\sigma-1}{\theta} \approx 0.88$, this results implies an elasticity of trade to sea-distance of around $0.81 * 0.88 \approx 0.7$. This is in the range of the review of values for the elasticity of trade to distance by Disdier and Head (2008).[7]

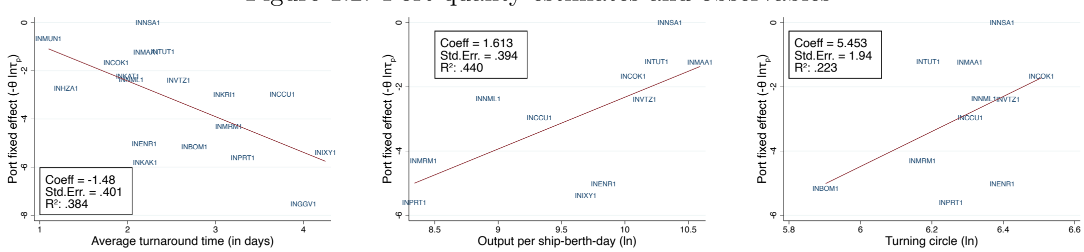
Interpreting $\tilde{\beta}^c$ as the (inverse) average speed on the category, using $\theta = 5.7$ consistent with usual trade elasticity values and the estimate above, and assuming a speed of 70km/h on the expressway ($\tilde{\beta}^c = 1/70$) implies that the semi-elasticity of trade cost to time of travel in hours is around 0.042 ($.00339 * 70/5.7$). This implies that an additional hour of travel time is equivalent to a 4.2% ad-valorem trade cost. This is lower, but in the same order of magnitude, as the estimate of 0.07 from Allen and Arkolakis (2019) for the US. It is to be expected that the cost would be lower in India due to lower labor cost.

Ports To ensure that the estimated fixed effect really captures changes in costs, Figure 1.2 displays the scatterplot of the estimated port fixed effect estimates against

[7] Disdier and Head (2008) find an average value of 0.9, and report that 90% of published estimates lie between 0.28 and 1.5. Feyrer (2009) estimates sea-distance elasticity in particular, based on the closure of the Suez Canal, and finds a long run elasticity of around 0.5.

three types of measures of port quality, for port for which the measures are available. The left panel compares the fixed effect to the average turnaround time taken between the ship entrance in the port and its exit. A longer turnaround time is associated with a lower port productivity. The center panel compares the estimate to the output handled at the port by ship-berth-day. The higher the output per ship-berth-day, the higher the productivity. Finally, the right panel shows that the fixed effect also correlates with the port's topography: larger ships need a wider turning circle, and ports with higher fixed effect are able to accommodate larger ships.

Figure 1.2: Port quality estimates and observables



Turnaround time | Output per ship-berth-day | Turning circle diameter

Notes: The left panel plots the estimated port fixed effect against the average turnaround time it takes between when the ship enters and exists the port. The center panel displays the port fixed effect against the average port output per ship-berth-day, which is the total tonnage handled at the port divided by the number of days a ship was docked at the berth. The right panel plots the fixed effect against the turning circle diameter of the port. Larger ships need a wider turning circle.

Table 1.4 shows the estimates of $-\ln \tau_\rho$ relative to the best port for the 10 largest Indian ports and some summary statistics over the 22 ports in my sample. The variation across ports is large: the standard deviation across ports is between 28% and 16% depending on the port elasticity value, which can be interpreted as differences in ad-valorem trade costs. To put some perspective on this number, compare it to the cost of traveling by road. The standard deviation of the port fixed effect (1.6) is equivalent to $1.6/.00422 \approx 380$ kilometers travelled on the road. In other words, a firm would be indifferent (up to the idiosyncratic costs) between using a port, or using a better port one standard deviation less costly but 380km further away. Using the same computation, a firm is indifferent between using the median port and driving an additional 280km to the best port.

Turning to observables, the standard deviation in turnaround times across ports is around 1.48 days. Using the coefficient of -1.42 when regressing the port fixed effect on turnaround time, a one standard deviation improvement in the turnaround time is associated with an improvement of 2.1 in the port fixed effect, the same order of magnitude as the actual standard deviation of the port fixed effects or higher (1.6). In other words, the standard deviation of the estimated port qualities roughly matches the standard deviation of observed turnaround times. How realistic is the coefficient of -1.42? Using $\theta = 5.7$, this is equivalent to a 25% ad-valorem trade cost for every 24 hours of turnaround time ($1.42/5.7 \approx 0.25$). Given the estimated semi-elasticity of 4.2% ad-valorem trade cost per each additional hour of driving from above, this is equivalent to around 6 hours of driving. Given the truck would stay idle during the 24 hours, it makes sense that the cost of an additional day of waiting for the ship to be ready would be lower than what the driving time implies.

The left panel of Figure 1.3 displays the ports on the Indian map, where the size of each port is proportional to its estimated quality (a larger circle represents a lower cost). It is apparent that while the geographical distribution of port location is fairly balanced, the geographical distribution of port quality isn't and regions in the North-East are further aways from ports with low costs. The right panel of Figure 1.3 shows the road network, with expressways displayed as bold red solid lines and normal roads displayed as dashed blue lines. Historically, the first large scale expressway build in India was the Golden Quadrilateral, connecting Delhi, Mumbai, Chennai and Kolkota. The North-South (going from North of Delhi to the southern

Table 1.4: Estimated port quality

Port Name	Port fixed effect	Implied quality	
	$(-\theta\ ln\hat{\tau}_\rho)$	$(\theta = 5.7)$	$(\theta = 10)$
Nava Sheva	0.00	0.00	0.00
Mundra	-0.65	0.11	0.06
Chennai	-1.22	0.21	0.12
Tuticorin	-1.20	0.21	0.12
Kolkata	-2.96	0.52	0.30
New Mangalore	-2.36	0.41	0.24
Vishakhapatnam	-2.39	0.42	0.24
Kochi	-1.66	0.29	0.17
Kattupalli	-2.22	0.39	0.22
Mumbai	-5.16	0.90	0.52
Average	-1.46	0.26	0.15
Median	-1.20	0.21	0.12
Standard dev.	1.60	0.28	0.16

Notes: This table displays the estimated port qualities, defined as the negative of $\ln \tau_\rho$. The largest 10 ports in my dataset are displayed, and they account for around 75% of total shipments through sea. The Kolkata port includes both the Haldia dock complex and Kolkota dock system. The summary statistics are weighted by total value transiting through the ports.

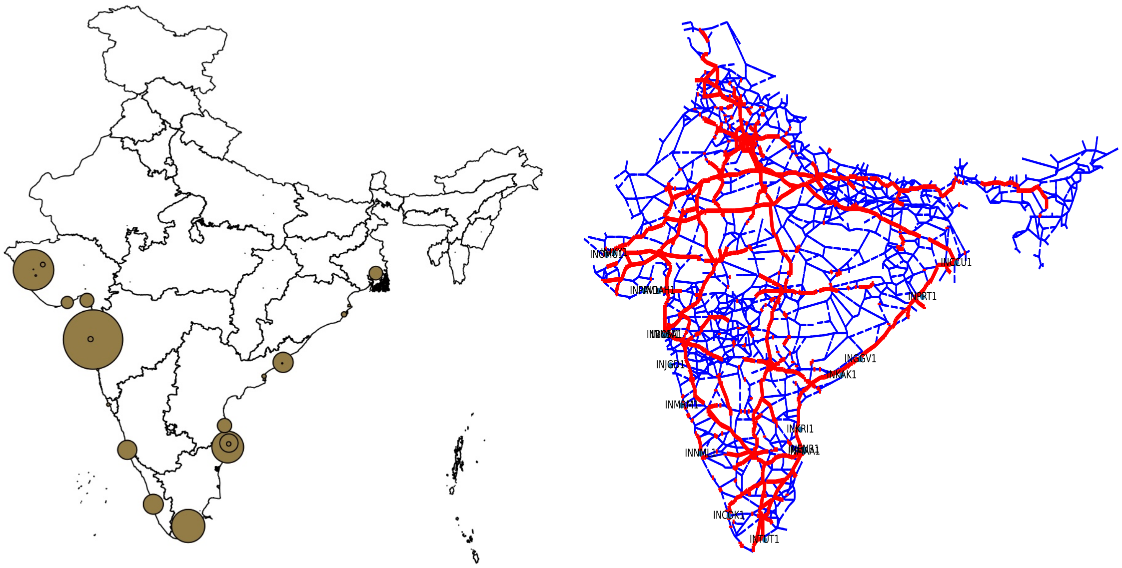
tip of India, passing through the center of India) and East-West corridor (from the western state of Gujarat to the eastern state of Assam) were build afterwards. The graph shows that other segments of the road network are also expressways, but that a substantial part is made of roads with only two lanes for both directions. For example, the central region is linked with Dehli and the south by an expressway, but its connectivity to the east and west coasts requires passing through patches of normal roads.

To assess how the heterogeneity in export costs due to road or to ports translates into regional output and welfare disparities, I next incorporate the port choice model into a full quantitative model to conduct counterfactuals.

1.6 Full quantitative model

The quantitative model I develop here is very similar to the Krugman (1980) model, with modified trade costs. There are N regions, which can be either Indian

Figure 1.3: Estimated ports quality and road network



Notes: This left panel displays the ports on the map of India, where the size of the circle represents the estimated quality of the port. The right panel displays the road network, where "expressways" are displayed in red and "normal roads" are displayed in blue.

districts or foreign countries, and two sectors (non-tradable services and tradable goods).

1.6.1 Preferences

Each region d has a representative consumer whose utility is Cobb-Douglass over goods (G) and services (S):

$$U_d = (G_d)^{\alpha_d} (S_d)^{1-\alpha_d},$$

where S_d is the quantity of services consumed and G_d is a CES aggregate of a continuum of goods, with an elasticity of substitution σ:

$$G_d = \left[\int_i c_{id}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}.$$

Optimality implies that consumers spend $X_d^G = \alpha_d X_d$ on manufacturing goods, and $X_d^S = (1 - \alpha_d) X_d$ on services, where X_d is region d's total spending. Within the goods composite, expenditure on each variety is given by:

$$X_d^G(i) = p_d(i)^{1-\sigma} \frac{X_d^G}{\left(P_d^G\right)^{1-\sigma}},$$

where $\left(P_d^G\right)^{1-\sigma} = \sum_i p_d(i)^{1-\sigma}$ is the ideal price index of the goods CES aggregate. The consumption price index is then given by $P_d = c\left(P_d^G\right)^{\alpha_d}\left(P_d^S\right)^{1-\alpha_d}$, where c is a normalization constant.

Each region is endowed with L_d units of labor, supplied inelastically. I assume that labor is perfectly mobile across the two sectors, reflecting the fact that my counterfactuals are designed to study long-term effects of infrastructure changes.

1.6.2 Production

Services Services are not tradable. The production of services uses labor only, with the following production function:

$$y_d^S = A_d^S L_d^S, \tag{1.14}$$

where A_d^S is labor productivity in the production of services in region d. There is perfect competition, so the price of services in region d is w_d^S/A_d^S, and total sales are given by $Y_d^S = w_d^S L_d^S$, where w_d is the wage in region d.

Goods The production of manufacturing goods is similar to Krugman (1980). The is a continuum of firms in each region. Each firm i produces a differentiated variety corresponding to a good i. Firms compete in a monopolistically competitive fashion, and the production features a fixed cost of entry and a constant marginal cost. More precisely, a firm i in region o is required to pay a fixed cost f_o in units of labor to enter the market, and requires $1/A_o$ units of labor to produce each marginal unit of good. Trade of goods is costly. A firm located in an Indian district o needs to ship $\tilde{d}_{od}$ units of goods to have 1 unit reach an other Indian district d, where $\tilde{d}_{od}$ is fixed, common to all firms in o, and depends on the quality of the roads. To ship to a foreign country d through port ρ, the firm i faces the iceberg trade cost defined above in (1.1) and repeated here for convenience:

$$\tau_{io\rho d} = \frac{\tau_{op}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}.$$

Hence firm i's cost of exporting to region d is given by $\tilde{d}_{od}(i) = \min_{\rho} \frac{\tau_{op}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}$. A firm in a foreign region o shipping to an other foreign country d faces an iceberg trade cost $\tilde{d}_{od}$, common to all firms in o. To ship to an Indian district through Indian port ρ, it also faces an idiosyncratic cost that depends on the port, in a symmetric vein as the Indian exporters. The firms only learn their idiosyncratic port-route productivities $\varepsilon_{io\rho d}$ after paying the fixed cost.

Conditional on entry, profit maximization combined with the CES demand function implies that exports to destination d are given by:

$$X_{od}(i) = \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o}\tilde{d}_{od}(i)\right)^{1-\sigma}\frac{X_d^G}{(P_d^G)^{1-\sigma}}, \tag{1.15}$$

and variable profits are given by:

$$\frac{1}{\sigma}\sum_d \left(\frac{\sigma}{1-\sigma}\frac{w_o}{A_o^G}\tilde{d}_{od}(i)\right)^{1-\sigma}\frac{X_d^G}{(P_d^G)^{1-\sigma}}.$$

Taking expectation over the Fréchet draws that enter $\tilde{d}_{od}(i)$, expected variable profits before the realization of the Fréchet draws are given by:

$$\frac{1}{\sigma}\sum_d \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o}d_{od}\right)^{1-\sigma}\frac{X_d^G}{(P_d^G)^{1-\sigma}},$$

where $d_{od} = \tilde{d}_{od}$ when o and d are Indian districts, or when both o and d are foreign countries. When o is an Indian district and d is a foreign country, and vice-versa, so that trade passes through the ports d_{od} is given by:

$$d_{od} = \left[\sum_{\rho}(\tau_{o\rho d})^{-\theta}\right]^{-\frac{1}{\theta}}\Gamma\left(1-\frac{\sigma-1}{\theta}\right)^{\frac{1}{1-\sigma}}.$$

Integrating equation (1.15) over firms and their corresponding Fréchet draws, total aggregate exports from o to d are given by:

$$X_{od}^{G}=N_{o}^{f}\left(\frac{\sigma}{\sigma-1}\frac{w_{o}^{G}}{A_{o}}d_{od}\right)^{1-\sigma}\frac{X_{d}^{G}}{\left(P_{d}^{G}\right)^{1-\sigma}},$$

where N_o^f is the number of manufacturing firms entering production in region o.

Labor demand from firm i is given by:

$$l_{o}\left(i\right)=\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\frac{1}{w_{o}^{G}}\sum_{d}\left(\frac{w_{o}^{G}}{A_{o}}d_{od}\left(i\right)\right)^{1-\sigma}\frac{X_{d}^{G}}{\left(P_{d}^{G}\right)^{1-\sigma}}+f_{o},$$

and aggregate labor demand is given by:

$$N_{o}^{f}\left(\frac{\sigma}{\sigma-1}\right)^{-1}\frac{\sigma}{w_{o}^{G}}\underbrace{\frac{1}{\sigma}\sum_{d}\left(\frac{\sigma}{\sigma-1}\frac{w_{o}^{G}}{A_{o}}d_{od}\right)^{1-\sigma}\frac{X_{d}}{P_{d}^{1-\sigma}}}_{\text{equal to expected variable profits}}+N_{o}^{f}f_{o}.$$

Zero expected profits implies that the variable profits are equal to the fixed cost $w_o^G f_o$. Plugging that in the total labor demand from the goods sector gives the following demand for labor in the goods sector L_o^G:

$$L_{o}^{G}=\sigma N_{o}^{f}f_{o}.$$

1.6.3 Equilibrium

Goods and services market clearing Market clearing in the service sector implies that expenditure on services equals total sales in services and total labor payment in services:

$$\begin{aligned}Y_{d}^{S}&=X_{d}^{S}\\ w_{d}L_{d}^{S}&=\left(1-\alpha_{d}\right)X_{d},\end{aligned}$$

and market clearing in the goods sector implies that:

$$\sum_{d}X_{od}^{G}=Y_{o}^{G},$$

where Y_o^G are total manufacturing sales of region d. Further assuming balanced trade implies that $Y_d^S + Y_d^G = X_d^S + X_d^M$. Since services are non-tradable, $Y_d^S = X_d^S$ and $Y_d^G = X_d^G$. As a consequence:

$$\sum_d X_{od}^G = \alpha_o X_o = \alpha_d w_d X_d,$$

and

$$w_d L_d^S = (1 - \alpha_d)\, w_d X_d,$$

so that the sectoral labor allocation to services is determined by the share of services in consumption:

$$L_d^S = (1 - \alpha_d)\, X_d,$$

and aggregate labor market equilibrium implies that:

$$L_o^S = \alpha_o L_o = \sigma N_o^f f_o.$$

Equilibrium system In the end, equilibrium is a set of trade flow X_{od}^G, total consumption X_d, sectoral labor allocations L_o^G and L_o^S, number of firms N_o^f, wages w_o and goods sector price indices P_o^G that satisfy

- Labor market clearing

$$\alpha_o L_o = \sigma N_o^f f_o \tag{1.16}$$

$$(1 - \alpha_o)\, L_o = L_o^S \tag{1.17}$$

- Budget constraint and balanced trade in goods

$$X_d = w_o L_o \tag{1.18}$$

$$\sum_d X_{od}^G = w_o L_o^G \tag{1.19}$$

- Optimal consumption choices

$$\alpha_o X_o = \sum_d X_{od}^G \tag{1.20}$$

$$X_{od}^G = N_o^f \left(\frac{\sigma}{\sigma - 1} \frac{w_o}{A_o} d_{od} \right)^{1-\sigma} \frac{\alpha_d X_d}{(P_d^G)^{1-\sigma}}, \tag{1.21}$$

where

$$\left(P_d^G\right)^{1-\sigma} = \sum_o N_o^f \left(\frac{\sigma}{\sigma - 1} \frac{w_o}{A_o} d_{od} \right)^{1-\sigma} \tag{1.22}$$

and

$$d_{od} = \begin{cases} 1 & \text{if } o = d \\ \tilde{d}_{od} & \text{if } o, d \in IN \text{ or } o, d \notin IN \\ \left[\sum_\rho \left(\tau_{o\rho} \tau_\rho \tau_{\rho d} \right)^{-\theta} \right]^{-\frac{1}{\theta}} & \text{if } o \in IN \text{ and } d \notin IN, \text{ or } d \in IN \text{ and } o \notin IN \end{cases} \tag{1.23}$$

1.7 Counterfactuals

I use the model to solve for changes in district-level real wags following changes in either port costs (τ_ρ) or costs on the road to the port ($\tau_{o\rho}$).

1.7.1 Solution method and model calibration

I solve for counterfactual real wage changes by using Dekle et al. (2008)'s framework of exact-hat algebra detailed in Appendix A.5.1. For that purpose, the only data requirements are data on goods trade shares $\pi_{od} = X_{od}^G / X_d^G$ and port shares $\pi_{o\rho d}$, as well as parameter values for σ and θ. I use the common value of the trade elasticity of 5 (e.g. Costinot and Rodríguez-Clare, 2014), corresponding to $\sigma = 6$, and a value for θ of $5/0.88 \approx 5.7$, consistent with my estimates. Since my sample of firms doesn't cover all Indian districts, and data on trade at the district level is unavailable, I need to impute some port shares and trade shares.

Port shares To calibrate port shares of the missing districts, it is straightforward to compute them using the road cost estimates $\tau_{o\rho}$, port-level cost estimates τ_ρ, and sea distance estimates $\tau_{\rho d}$ using the parametrization described in section 1.4.2:

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}}{\sum_k \left(\tau_{ok}\tau_k\tau_{kd}\right)^{-\theta}},$$

where $\tau_{o\rho}$ depend on the road costs estimates, τ_ρ come from the port productivity estimates, and $\tau_{\rho d}$ depend on the sea estimate. Because I don't have data on import port shares at the origin country level, I assume that the relative port productivities are the same for export and import and impute the port shares for import in the same way. In that case $\tau_{o\rho}$ is the sea cost and $\tau_{\rho d}$ is the road cost.

Trade shares Trade shares are observable at the country-country level, but not at the district-country or district-district level. To calibrate the unobservable trade shares in a theory consistent way, I follow a similar approach to Eckert (2019) who infers unobservable service trade flows in the US from the gravity structure and other region-level data. It is useful to rewrite the equilibrium conditions in the goods sector into the following single equation where the only endogenous object is the vector of X_o. Combining equations (1.21), (1.20) and (1.22), the following equation holds:

$$\underbrace{\alpha_o X_o}_{\text{data}} = \sum_d \frac{\lambda_o \left(d_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(d_{kd}\right)^{1-\sigma}} \underbrace{\alpha_d X_d}_{\text{data}}, \tag{1.24}$$

where $\lambda_o = N_o^f \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o^G}\right)^{1-\sigma}$. In this equation, the $\alpha_o X_o$ terms can be taken directly form data on region GDP and goods consumption shares. The d_{od} terms are known from the trade cost calibration on road, sea, and ports (up to a normalization constant), and the λ_o's are the only unknown.

Equation (1.24) is useful to calibrate the model, because there is a unique vector of λ_o consistent with data on $\alpha_o X_o$ and trade frictions d_{od} (see the useful Lemma A.1 in Appendix A.4.1, taken from Eckert (2019)). Since data on trade across Indian districts and between districts and foreign countries is not readily available, I use equation (1.24) to recover the λ_o from data on district and foreign country level GDPs as well as road and sea distances to compute X_o and $\tilde{\tau}_{od}$.

The last hurdle to solve is that the port-level productivities τ_ρ are only estimated up to a constant, and that trade costs also include additional components not taken into account by the road, port, and sea components, such as tariffs or language barriers. To jointly solve for these issues, I add a set of origin- and destination-specific free parameters scaling the district-foreign trade costs that allow me to match the aggregate India-foreign trade shares exactly, while using the road and ports relative costs to calibrate the relative shares of Indian districts in the aggregate India-foreign shares. Appendix A.4.1 describes the procedure in details.

The result of the calibration procedure is a vector of λ_o from which the trade shares π_{od} can be readily computed as $\pi_{od} = \frac{\lambda_o (d_{od})^{1-\sigma}}{\sum_k \lambda_k (d_{kd})^{1-\sigma}}$. The recovered trade shares are consistent with observed district-level GDPs, goods consumption shares, and country-level trade shares.

Finally, the structure of the model gives an expression for the goods price index in each region, since $\left(P_d^G\right)^{1-\sigma} = \sum_o \gamma_o \left(d_{od}\right)^{1-\sigma}$. I combine it with district-level data on population to compute a baseline real wage at the Indian district level. The real wage is given by w_d/P_d, where $P_d = c\left(P_d^G\right)^{\alpha_d}\left(P_d^S\right)^{1-\alpha_d}$. Because the price of services $P_d^S = w_d/A_d^S$ is unobservable, I construct a baseline real wage that ignores the differences in service productivity A_d^S:

$$\frac{w_d}{P_d} = \frac{X_d/L_d}{P_d} = \frac{X_d/L_d}{\left(P_d^G\right)^{\alpha_d}\left(\frac{w_d}{A_d^S}\right)^{1-\alpha_d}}$$

$$\log\frac{X_d/L_d}{P_d} = \alpha_d \underbrace{\log\frac{X_d}{L_d}}_{data} - \alpha_d \underbrace{\log P_d^G}_{model+data} + \underbrace{\log A_d^S}_{unknown}.$$

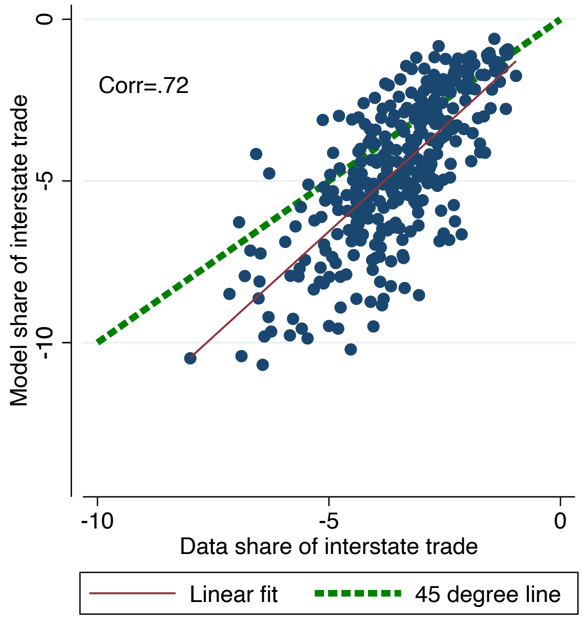
My measure of the real wage is the sum of the first two terms, which correspond to the real wage up to productivity differentials in the service sector. While I don't need it to solve for counterfactual real wage changes, I will correlate the change in real wage against this initial real wage to assess if the counterfactual changes in infrastructure have an equalizing effect between districts. The change in real wage in the counterfactuals is exactly equal to the change in my measure of initial real wage, as all my counterfactuals keep the service productivity A_d^S constant.

Data sources I use the OECD Inter-Country Input-Output (ICIO) Tables to get data on country-level trade shares (π_{od}) in the goods sector, and the share of goods in consumption (α_d).[8] I get data on district-level GDP in India from ICRISAT for 535 Indian districts, and population data for 636 districts or union territories from the 2011 Indian Census. The ICRISAT data doesn't cover all districts. To calibrate GDP in the missing districts, I use additional data on the share of literacy by district from the Census and on night lights from Asher et al. (2021) to predict GDP per capita based on these observables.[9] I first regress GDP per capita on population, literacy and maximum observed night lights using data on the 535 available districts. I then use the coefficients to predict GDP per capita in other districts, which I multiply by

[8] I define goods as Agriculture, Mining, and Manufacturing. The average share of goods in final consumption is around 0.38 across countries. I use the aggregate India value of 0.39 for all Indian districts. The country-level trade shares together with balanced trade imply a level of goods expenditure for each country.

[9] Following Henderson et al. (2012), a large literature as been using night-light as a measure for real income when official data is missing. Alder (2019) uses it in the context of India. Here, I don't use it as a measure, but rather as a predictor of GDP per capita.

Figure 1.4: Calibration fit of interstate shares



Notes: The figure displays the share of interstate imports in the model against the data. Each dot is the share of bilateral flows in the exporting state's total interstate exports. Each dot is the share of state-destination flows in the state's total international exports.

population to construct GDP for the missing districts. The correlation between the predicted and observed GDP for the districts with existing data is high at 0.9.

The resulting model consists of 56 countries, 636 districts and a composite rest of the world. Trade between the districts and the rest of the world takes place through 22 ports. Within India trade between districts takes place on the road network depicted in Figure 1.3.

Model calibration fit Figure 1.4 shows how the calibrated within-India trade shares perform against untargeted data. The panel compares the model with data on more aggregated inter-state trade shares within India. The interstate trade flows data refer to the 2015-16 flows published in the 2016-2017 Indian Economic Survey. The correlation is around 0.72.

1.7.2 Counterfactuals cost changes

Improvement counterfactuals

I perform three counterfactuals that harmonize the quality of infrastructures for all region and bring them to the best level. The first one is a world in which all ports have the level of the best port. The second one is a world in which all costs to the port are what they would be if all roads where expressways, but internal trade costs remain constant, to isolate the effect of internal trade costs on international market access. The third simulates a counterfactual where all roads are expressways, and all internal trade costs as well as costs to the port diminish.

The counterfactual changes in port quality are computed by simulating a change in port quality as:

$$\hat{\tau}_\rho = \frac{\min_p \tau_p}{\tau_\rho}, \tag{1.25}$$

where $\min_p \tau_p$ is the minimum port cost. That is, I bring all ports to the best level.

To equate road infrastructure everywhere, I change $\tau_{o\rho}$ in the following way:

$$\hat{\tau}_{o\rho}^{CF} = \exp\left(\left[\beta^{expressway} - \beta^{normal}\right] dist_{o\rho}^{normal}\right) \tag{1.26}$$

This counterfactual abstracts away from the effect of road improvement on internal trade costs. This is useful to isolate the international market access component of changes in infrastructure. I also run the road improvement counterfactual allowing for internal trade costs to change when the roads are improved, where the formula of district-to-district trade cost changes is the same as in equation (1.26).

Bottleneck ports

In a final counterfactual, I compute the gains associated with improving each port individually. I define the "bottleneck" port as the one that leads to the highest

Table 1.5: Real wage changes - counterfactuals results

	Equal ports (τ_ρ)	Equal road to ports ($\tau_{o\rho}$)	Equal roads (incl. internal)
Average	5.99	0.27	2.32
Median	4.79	0.08	2.15
Std.	5.26	0.39	1.40
P25	0.98	0.02	1.28
P75	10.3	0.41	3.13

Notes: This table shows summaries of the percentage change in real wages across Indian districts in the counterfactuals. The summary statistics are weighted by district population. "Equal ports" refers to the counterfactual where all ports costs are put to the same level as the minimum port cost. "Equal road to ports ($\tau_{o\rho}$)" refers to the scenario where costs from Indian districts to the ports are lowered to their level if all roads where expressways, but internal trade costs between Indian districts remain constant. "Equal roads (incl. internal)" changes all internal trade costs (to the port and between districts) to the level they would be at if all roads where expressways.

change in real wages. In practice, I reduce each port's iceberg cost by 10% and compute the counterfactual real wage change for all regions. This also allows me to compute which port is the bottleneck for different districts in India.

1.7.3 Counterfactual results

Table 1.5 shows the results of the counterfactuals. It shows summary statistics of the percentage change in real wages across Indian districts, weighted by district population. The first column displays the results of bringing all ports to the best level, the middle column displays the results of bringing all costs to the ports their level if all roads where expressways, and the last column shows the results when all roads are expressways and internal trade costs also change as a result.

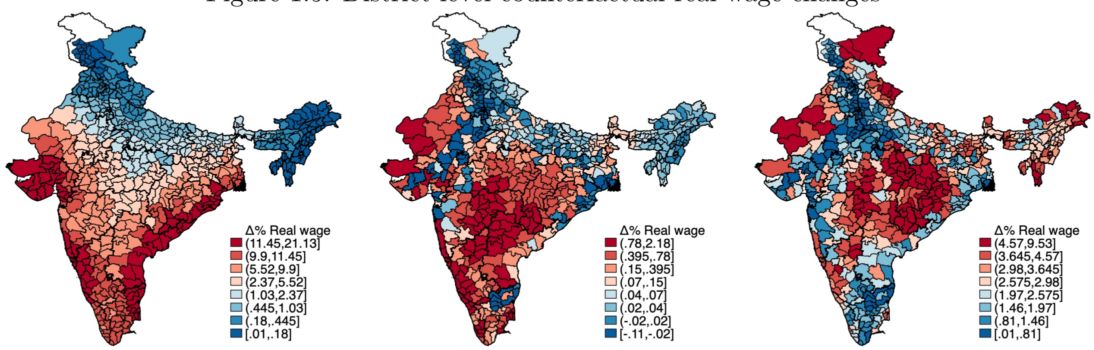
Overall, changes in average real wage are large when ports are improved, with an increase in real wage of about 6%. This is an order of magnitude higher than when access to ports is improved, as the second column shows an average real wage increase of 0.27% only. This implies that improving port infrastructure rather than connections to the port has a larger impact on international market access and in turn welfare. Even when internal costs are reduced as a result of road improvement (column 3), the average welfare change of road improvement is about half of that of port improvements.

The distributional impact of these counterfactual is also large, with the standard deviation across districts of the same order of magnitude as the average effect. Figure 1.5 displays the real wage changes across Indian districts in the infrastructure improvement counterfactuals. Dark red implies a larger increase in real wage, while blue implies a lower increase.

The left panel shows the real wage change when all ports are brought to the best level. Regions near the coast benefit more from the lower port costs. Within coastal regions, there is also heterogeneity in how much districts gain, with a direct link to the map of estimated port quality in Figure 1.3. Districts on the central West coast, close to the most productive port of Nava Sheva (Mumbai), as well as in the south close to the (relatively) more productive port of Tuticorin, are lighter than districts near low quality ports such as in the North-East. On the other hand, districts along the the North-East coast are relatively better off because the high-cost ports of Vishakhapatnam and Paradip are improved in the counterfactual.

Improving access to port benefits regions whose current connectivity to ports is low, such as the center of India. The Golden Quadilateral highway connecting Delhi (to the North), Mumbai (to the West), Chennai (to the South-East) and Kolkata (to the North-East) is clearly visible on the map of road improvements (middle and right panel of Figure 1.5, to compare with the road network displayed in Figure 1.3). Regions located close to the existing expressways that connect to the ports don't benefit as much from the road improvements. In the middle panel, the North-South corridor expressway cannot be discerned because it is not used to reach the port, so that regions in the center benefit from road improvement to the port even though they already have an important expressway passing through. The right panel does show that the central regions benefit slightly less when internal trade costs also decrease, since they are already connected to important economic centers such as Delhi through an expressway.

Figure 1.5: District-level counterfactual real wage changes

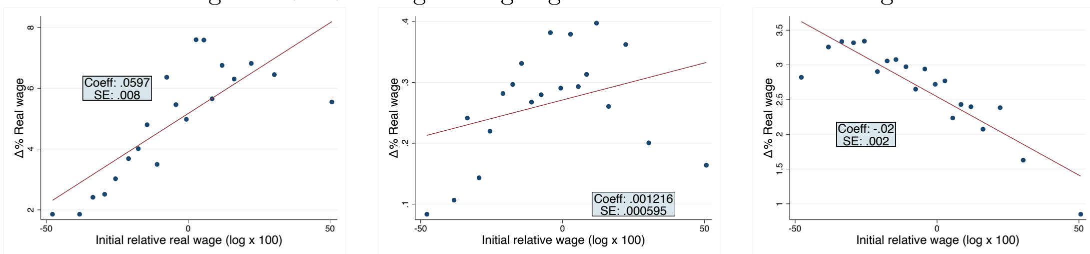


Equal ports | Equal Road to Port | Equal roads

Notes: The left panel displays the district-level change in real wage when all ports are brought to the level of the best port. The middle panel displays the district-level change in real wage when all cost to the ports are brought to the level achieved if all roads where expressways, but internal trade costs are kept constant. The right panel shows the changes when internal trade costs also decrease after road improvements. Red districts benefit more while blue districts benefit less.

The regional heterogeneity might have either positive or negative impact on regional inequality, depending on wether regions that benefit more had originally higher or lower welfare. Figure 1.6 displays the binscatter plot of the change in district real wage against the initial relative real wage. In the ports improvement scenario, districts with higher initial wages tend to benefit relatively more from the port improvements, thereby increasing regional inequality. Accordingly, the standard deviation in log real wages increases by 8% from 24% to 26%. This is explained by the fact that coastal regions have a higher initial wage, and benefit disproportionately more from the reduction in port costs. In the road to port improvement scenario, there is no significant change in regional variation. The right panel shows that improving the roads has a modest equalizing effect, as regions with higher lower wage benefit

Figure 1.6: Real wage change against initial relative real wage



Ports — Roads (to port) — Roads (incl. internal)

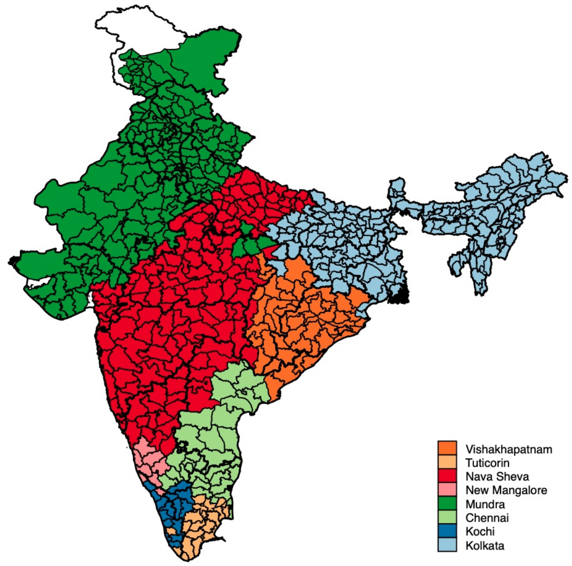
Notes: The figure displays the bin-scatter plot of real wage changes against initial real wage in the infrastructure improvement scenarios.

less. The standard deviation in log real wages drops by 2%.

Overall, the counterfactual results show that on aggregate, port improvements might have more potential in terms of average welfare improvement than road improvements. However, port improvement has relative distributional consequences in favor of coastal regions. While road improvements have lower aggregate effect, their distributional impacts are different from port improvements and policymakers might find a combination useful to balance the effects of infrastructure improvement across all regions.

Bottleneck ports An other way to balance distributional consequences of port improvement is to improve specific ports depending on which regions are targeted. Figure 1.7 makes this point clear by plotting the bottleneck port for each district. The bottleneck port is defined as the port for which the real wage change is the largest when each port is individually improved by 10%. It is clear that targeting different ports has distributional consequences: improving the two west coast ports of Mundra and Nava Sheva (Mumbai) would result in larger gains for most districts, but less so for regions in the south and east.

Figure 1.7: District-level bottleneck port



District-level bottleneck port

Notes: The figure displays the port that has the largest effect on the district's real wage when improved.

1.7.4 Robustness

I check the sensitivity of my results to changes in the estimate of the port elasticity θ and to the fact that the port cost estimates are estimated as fixed effects while the road cost parameters are based on observables.

Port elasticity sensitivity I run the counterfactuals based on higher and lower values of the ratio between the trade elasticity and the port elasticity. My estimates from section 1.5 imply a value of $\frac{\sigma-1}{\theta}$ around 0.88, but estimates in the robustness appendix A.3.1 range between 0.7 and 1. I run the counterfactuals using these values, resulting in values of θ of 7.1 and 5.

In all cases, the relative ranking of port improvement, access to port improvement, and overall road improvement stays the same as in the baseline estimate. As θ decreases, the differential in port costs implied by the differences in shares increases.

Hence for lower θ, the variation across ports is higher and bringing all ports to the best level results in larger reduction in overall trade costs.

Port cost estimates The results in the previous section imply that bringing ports to the best level results in higher welfare gains than transforming all roads to expressways. A potential explanation for this result is that the port costs are estimated by fixed effects while the road costs are based on regression on observables. The variation in the fixed effect might be higher because it picks up variation not contained in observables, while the variation in road costs in constrained to variation in observables.

As a robustness check, I rerun the port counterfactual by first projecting the port fixed effects on the port-level turnaround time, and then use the estimated coefficient to predict changes in port cost by bringing all turnaround times to the shortest observed turnaround time.[10] The resulting counterfactual wage changes, summarized in the last column of Table 1.6 are of similar magnitudes as the baseline, implying that the variation in observable measures of productivity also leads to large reductions in trade costs.

1.7.5 Infrastructure improvement costs

The previous section shows that the welfare gains from port improvements are larger than the gains from road improvements. This sections provides an estimate of the costs associated with both improvement scenarios.

Port improvement costs To estimate the costs of improving ports, I use data on investments made as part of India's Sagarmala program. That program established

[10] Precisely, I regress the estimated port cost on the turnaround time as in the left panel of Figure 1.2. I then feed in changes in τ_ρ such that $d\ln\tau_\rho = \hat{\beta}^{turnaround}\left(\min_{\rho'} turnaround_{\rho'} - turnaround_\rho\right)$.

Table 1.6: Real wage changes - robustness

	$\theta = 7.1$			$\theta = 5$			Equal turn-around time
	Port	Road ($\tau_{o\rho}$)	Road (all)	Port	Road ($\tau_{o\rho}$)	Road (all)	
Average	4.37	0.23	2.06	7.15	0.29	2.48	5.51
Median	3.77	0.10	1.91	5.40	0.07	2.27	4.41
Std.	3.54	0.31	1.21	6.51	0.44	1.50	4.74

Notes: This table shows summaries of the percentage change in real wages across Indian districts in the robustness checks. "Port" refers to the counterfactual where all ports costs are put to the same level as the minimum port cost. "Road ($\tau_{o\rho}$)" refers to the scenario where costs from Indian districts to the ports are lowered to their level if all roads where expressways, but internal trade costs between Indian districts remain constant. "Road (all)" changes all internal trade costs (to the port and between districts) to the level they would be at if all roads where expressways.

a list of planned improvements of ports and port connectivity projects in 2016. I retrieve the list of project that contains the details of the targeted port, the amount budgeted for the project, and whether the project has already been completed, is under completion, or hasn't been implemented yet as of end of 2019.[11]

Taking log-differences of the port share equation (1.2) between 2015 and 2019 gives:

$$\ln \pi_{o\rho d,2019} - \ln \pi_{o\rho d,2015} = \theta \Delta \ln \tau_{\rho} + \theta \Delta \ln \tau_{o\rho} + \theta \Delta \ln \tau_{\rho d} + \alpha_{od}. \tag{1.27}$$

I parametrize the change in port-level cost $\Delta \ln \tau_{\rho} = \beta^{invest} invest_{\rho}^{portimp.}$, where $invest_{\rho}^{portimp.}$ is the amount of dollars spent in investments on port improvements (in dollars), and estimate the following equation:

$$\ln \pi_{o\rho d,2019} - \ln \pi_{o\rho d,2015} = \theta \beta^{invest} invest_{\rho}^{portimp.} + \alpha_{od} + u_{o\rho d}. \tag{1.28}$$

The error term $u_{o\rho d}$ contains the changes in other unobservable port-destination costs and origin-port costs. Investments are potentially correlated with that error term if policymakers target ports where they are able to anticipate changes in origin-port and port-destination costs. To assess the relevance of the identification threat, I run

[11] Examples of port improvements include additional berth or jetties construction, container x-ray scanner installations, or additional truck parking spaces. See additional details about the program at `http://sagarmala.gov.in`.

a placebo test using the timing of different investments. The full list of projects under the Sagarmala umbrella was crafted prior to April 2016, when the list was published together with costs estimates. Some projects were completed, some were under completion, and some were still under preparation at the end of my sample in 2019. My placebo test estimates equation (1.27), using *completed* investments, *partially completed* investments, and *planned but not started* investments. If projects targeted ports with anticipated growth in the $u_{o\rho d}$ residual, the planned investments would be correlated with port share growth. Table 1.7 shows the results of the estimation. Reassuringly, planned investments are not significantly correlated with port share growth.

Table 1.7: Effects of improvement investments

	Change in port share		
Completed	.374***		
	(.125)		
Under completion		-.151	
		(.208)	
Planned			-.140
			(.110)
origin-dest FE	yes	yes	yes
N	30,260	30,260	30,260
Port cluster	yes	yes	yes

The estimate in the first column of Table 1.7 has the structural interpretation of $\theta\beta^{invest}$, and implies that an additional billion USD spending on port improvement reduces the port's (log) iceberg trade cost by around 0.065 (0.37/5.7), using my estimate of $\theta = 5.7$. Using this estimate and the fact that improving all ports to the best level implies a cumulated change in port (log) iceberg trade cost of 15.31, the total cost of the port improvement counterfactual is around 235 billion USD.[12]

[12]Note that the final result of this computation is actually independent of θ, because the port iceberg trade costs are taken from the port fixed effect divided by θ, and the coefficient in Table 1.7 is also divided by θ.

Road improvement costs To estimate the costs of improving the road network to expressways, I take all projects under the Sagarmala program that improve road segments from 2 lanes to 4 lanes, and compute the average cost per kilometer. The cost is around 1.52 million dollars, and multiplying this average cost by the total distance improved under the road improvement counterfactual yields a total cost of around 250 billion dollars, of the same order of magnitude as the port improvement cost estimate.

As a result, while the potential gains from port improvement are higher than those of road improvement, their cost is of similar magnitude. This implies that port improvements might be a more interesting avenue for infrastructure improvement.[13]

1.8 Conclusion

Port and road infrastructure connect regions to the world market. In this paper, I build a framework to estimate the cost of using the two types of infrastructure, and to compare their relative importance in shaping international market access. I find that port infrastructure improvements might improve aggregate welfare relatively more than road improvement for comparable costs. I also show that their regional distributional implication are different: port improvements benefit coastal regions relatively more, while road improvements tend to benefit inland regions. Policy-makers interested interested in targeting specific regions might thus favor one or the other type of infrastructure improvement depending on whether they want to target inland or coastal regions.

[13]This back of the envelope computation makes numerous simplifying assumptions. It doesn't take into account maintenance costs and assume that the costs of port improvement are constant. As a results, I don't interpret the exact difference in cost magnitudes not compare it to the potential gains, but limit myself to the conclusion that the port and road improvement counterfactuals have a cost of similar magnitude.

CHAPTER II

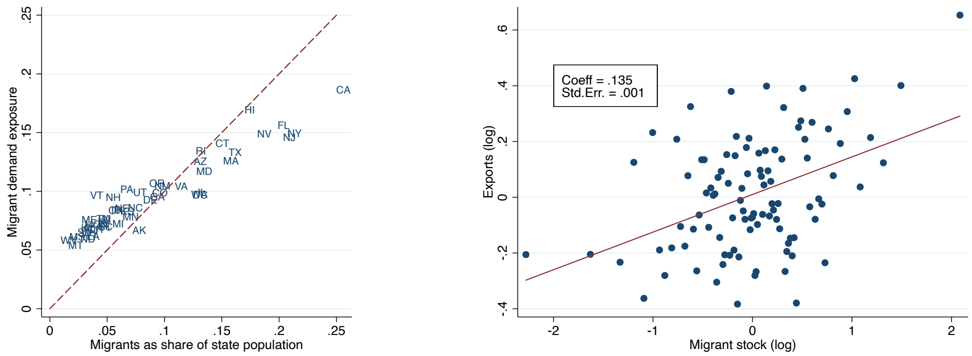
Migrants, Trade, and Market Access

2.1 Introduction

Immigrants affect both the local supply of labor, and the demand for output produced by a geographic unit. The majority of research on the impact of immigration on natives has focused on understanding the wage impact of the migrant labor supply (e.g. Card, 1990; Abramitzky and Boustan, 2017). This paper instead explores the impact of migration on market access – the demand for output produced by a geographic unit. I use data on US states' intra- and inter-national trade and migration to calibrate a multi-region model to estimate and quantify the impact of immigration into the United States on market access faced by US states.

I emphasize two economic mechanisms. First, immigrants increase the intra-national market access. Immigrants demand goods and services from both the state they reside, and other US states. A fall in the US migrant population is a reduction in US states' market access, as overall demand shifts towards higher export trade cost destinations. The effect is heterogeneous: states that rely more on immigrant demand for their output, both from within-state migrants and from immigrants living in other US states, experience greater reductions in market access. In an environment with inter-state trade linkages, this change in market access is distinct from the change

Figure 2.1: The two mechanisms in the data



a) Migrant demand exposure against migrant share of population

b) Residuals of exports against residuals of the migrant stock, after controlling for multilateral resistance and distance

in the in-state immigrant population. The left panel of Figure 2.1 illustrates this point by plotting the share of a state's output sold to migrants residing in the US against the share of migrant population in the state.[1] 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.

The second mechanism is that immigrants expand international market access, by reducing the costs of foreign trade (see e.g. Gould, 1994; Ottaviano et al., 2018; Cardoso and Ramanarayanan, 2019). The right panel of Figure 2.1 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

[1] 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 distance.[2] In this paper, I estimate the causal impact of migrants on exports in the US using an instrumental variable approach based on push-pull factors similar to Burchardi et al. (2019). I show that migrants have a positive causal impact on exports from US states to their country or origin, and that the positive effect of migrants on trade comes mainly through high-skill rather than low-skill migrants.

I build a model combining Ricardian trade, labor mobility, and an endogenous response of trade costs to migration. I calibrate it to an economy composed of the 50 US states, the District of Columbia, and 56 countries, to provide the first quantitative assessment of the effect of migration on natives' welfare through shaping both intra- and inter-national market access of US states. I estimate an elasticity of exports to migrant population of around 0.2 which I use to calibrate the model. I simulate a counterfactual scenario where migrant population in the US is reduced by half, about the same as bringing migrant population share to 1980 levels. This would increase export weighted trade costs by 3.5% on average across US states, which is of similar magnitude as the 4.9% current ad valorem export tariffs faced by US exporters (WEF, 2016). The reduction in migrant population would lead to a decrease in aggregate US-born welfare by 0.13%. The average real wage change in US states drops by 0.16%, decomposed into −0.11% due to reduced international market access, −0.31% due to reduced market access from other states, and +0.26% due to own-state migrant reduction. The effect of own-state migrant reduction captures the reduction of labor competition net of the loss of market access from own-state migrants. There is substantial heterogeneity across US states, with changes in real wages ranging from −0.44% in Vermont to 0.20% in New Jersey. Differences in intra-national migrant demand exposure, export exposure, and local migrant population

[2] 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.

share explain the regional dispersion of wage changes.

To supplement these results, I also investigate different effects of migration on trade costs by skill. I find that high-skill migrants have a positive effect on exports, while low-skill migrants' effect is muted. The elasticity of exports to high-skill migrant population is around 0.3. Adding a skill dimension to the model induces differential effects on high and low skill workers' wages, and imperfect substitutability between native and migrant workers induces an additional negative effect of the removal of migrants. The two main mechanisms affecting market access, however, are largely unaffected. The reduction of overall migrant share by half would result in a decrease in US native workers' welfare of 0.34% for low-skill and 0.37% for high-skill workers on average. Again, regional heterogeneity would occur because of differential migrant demand exposure across states. The larger overall drop in welfare (0.13 against $0.34 - 0.37$) is explained by the complementarity between natives and migrants' labor, and a larger increase in export trade costs in the skill model because high-skill migrants have a higher impact on export costs than in the pooled regression.

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

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

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

The rest of the paper is structured as follows. Section 2.2 describes the quantitative framework used for the counterfactual analysis, Section 2.3 estimates the sensitivity of exports to migrant population, and Section 2.4 presents the main counterfactual results. Section 2.5 investigates the skill heterogeneity and imperfect substitutability between migrants and natives. Section 2.6 concludes.

2.2 Quantitative framework

2.2.1 Model set up

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

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

where W_n is a CES aggregator of a continuum of goods and κ_{in} is a migration cost in term of utility. The CES aggregator over goods j is given by:

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

where j is a variety, σ is the elasticity of substitution of consumption goods. For a given location, the price index is given by:

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

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

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

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

Production and trade costs Labor is the only factor of production. Each location draws an idiosyncratic productivity $z(j)$ for each good j. The productivity draw are iid and followsa Fréchet distribution:

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

where θ is the shape parameter governing the dispersion of productivity and A_n is a scale parameter governing average productivity. Assuming perfect competition and an iceberg trade cost d_{ni}, the price at which location n can supply location i with good j is given by:

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

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

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

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

2.2.2 Trade and migration shares

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

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

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

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

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

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

$$V_n(\omega) = b_{in}(\omega) \frac{w_n}{P_n} \frac{1}{\kappa_{in}},$$

where w_n is the wage in region n received by the worker, their only source of income. The worker chooses the location with the highest indirect utility, so usual steps using the Fréchet distribution properties give rise to the following residential choice shares:

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

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

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

where N_i is the total population born in region i, and $\tilde{\gamma} = \Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)$.[3]

2.2.3 Equilibrium

The equilibrium is a set of trade shares π_{ni}^{trade}, wages w_n, efficiency labor units L_{in}, migration shares π_{in}^{mig}, price indices P_n and trade costs d_{in}, which satisfy the following set of equations given primitives A_i, N_i, B_{in}, κ_{in} and τ_{in}.

On the goods market, the trade shares satisfy

$$\pi_{ni}^{trade} = \frac{A_n(d_{ni}w_n)^{-\theta}}{\sum_s A_s(d_{si}w_s)^{-\theta}}, \tag{2.1}$$

and in the labor market, total labor factor revenue is equal to total output because of a balanced trade assumption:[4]

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

where:

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

The migration shares satisfy

$$\pi_{in}^{mig} = \frac{B_{in}\left(\frac{w_n}{P_n\kappa_{in}}\right)^{\varepsilon}}{\sum_k B_{ik}\left(\frac{w_k}{P_k\kappa_{ik}}\right)^{\varepsilon}},$$

where

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

Finally, the trade costs are given by

$$d_{ni} = \tau_{ni} \times \begin{cases} \left(\frac{N_{in}}{\sum_j N_{jn}}\right)^{-\eta} & \text{if } N_{in} \neq 0, \text{ and } n \in US, i \notin US \text{ or } i \in US, n \notin US \\ 1 & \text{otherwise} \end{cases} \tag{2.2}$$

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

[4] Appendix B.6.1 shows how to solve the model with trade deficits with little impact on the results.

where

$$N_{in} = \pi_{in}^{mig} N_i.$$

2.2.4 Equilibrium in changes

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

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

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

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

$$\hat{P}_n = \left(\frac{\hat{A}_n (\hat{w}_n)^{-\theta}}{\hat{\pi}_{nn}^{trade}}\right)^{-\frac{1}{\theta}},$$

$$\hat{d}_{ni} = \hat{\tau}_{ni} \left[1\left(i \mid n \notin US\right) \hat{\pi}_{in}^{mig} \left(\frac{\sum_j \hat{\pi}_{jn}^{mig} N_{jn}}{\sum_j N_{jn}} \right) + 1\left(i, n \in US\right) \right]^{-\eta}.$$

Solving the model in proportional changes enables me to solve for counterfactual quantities by using only data on baseline trade, migration, and wage bill shares (π_{is}^{trade}, π_{is}^{mig}, X_i, and $\Theta_{in} = \frac{w_n L_{in}}{X_n} = \frac{w_n L_{in}}{w_n \sum_k L_{kn}}$), as well as parameter values for ε, θ and η.

Change in the welfare of natives The expected utility of a person born in location i is given by:

$$U_i = \delta \left[\sum_n B_{in} \left(\frac{w_n}{P_n \kappa_{in}}\right)^{\varepsilon} \right]^{\frac{1}{\varepsilon}},$$

where δ is a constant involving the Gamma function. Using the expression for π_{in}^{mig} and solving for the change in welfare, one can show that the change in welfare for a person born in location i is given by:

$$\hat{U}_i = \left[\sum_n \hat{B}_{in} \left(\frac{\hat{w}_n}{\hat{P}_n \hat{\kappa}_{in}} \right)^{\varepsilon} \pi_{in}^{mig} \right]^{\frac{1}{\varepsilon}}. \tag{2.3}$$

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

2.2.5 A simpler version to illustrate the mechanisms

To illustrate the mechanisms in play, consider a simpler version of the model where migration is exogenous and workers have the same efficiency everywhere. Suppose there are N states and a rest of the world region. Initially, every state is symmetric except for the fraction of migrant in the state's total population. To fix ideas, assume that there is a total number of native US workers equal to L, each attributed to a state in a fixed and exogenous proportion β_i. The overall fraction of migrant in the US is α, and the total migrant population is in the US is equal to $\frac{\alpha}{1-\alpha}L$ and is attributed to a state in a fixed and exogenous proportion γ_i.

It is straightforward to show that a state population is equal to $\frac{\alpha\gamma_i+(1-\alpha)\beta_i}{1-\alpha}L$. The rest of the world native population is given by R, of which $\frac{\alpha}{1-\alpha}L$ live in the US. For simplicity, assume there is no migrants from the US into the rest of the world (RW). This is similar to the full model above, with an exogenous π_{RWi}^{mig} equal to $\frac{\gamma_i\alpha}{R}$ for every state i. This would be achieved by letting the migration elasticity ε going to 0, and setting $B_{RWi} = \frac{\gamma_i\alpha}{R}$ for $i \in US$ and $B_{RWRW} = \frac{R}{\alpha} - 1$.

We are interested in the reaction of wages in different states as the national fraction of migrant α varies.[5]

[5] Because in the full model, the change in B_{in} is equivalent to a change in $\kappa_{in}^{\varepsilon}$, one can think of this comparative static exercise as an approximation of what would happen in the full model if the migration costs to US states were to increase uniformly for all foreign countries.

The labor market clearing implies that:

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

Appendix B.1 shows that differentiating the previous equation with respect to α, keeping β_i and γ_i constant, the elasticity of state n's wage with respect to α, denoted ξ_n, satisfies:

$$\begin{aligned}
&\left(\xi_n - \sum_i \frac{X_{ni}}{X_n} \xi_i \right) + \theta \left(\xi_n - \sum_{k,i} \frac{X_{nk}}{X_n} \pi_{ik} \xi_i \right) = \\
&\frac{1}{1-\alpha} \left(\underbrace{\sum_{i\in US, i\neq n} \frac{X_{ni} shmig_i}{X_n}}_{\text{other states mig. expos.}} - \underbrace{\left(1 - \frac{X_{nn}}{X_n} \right) shmig_n}_{\text{own mig. share - own mig. expos.}} \right) \\
&+ \underbrace{\frac{X_{nRW}}{X_n}}_{\text{export expos.}} \frac{1}{1-\alpha} \left\{ \theta\eta \left[\underbrace{1 - shmig_n}_{\text{cost decrease}} - \underbrace{\sum_{k\in US} \pi_{kRW}^{trade} (1 - shmig_k)}_{\text{price index}} \right] - \frac{MIGPOP}{RWPOP} \right\},
\end{aligned} \tag{2.4}$$

where RW denotes rest of the world. 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 ($\sum_{i\in US, i\neq n} \frac{X_{ni} shmig_i}{X_n}$), and the difference between own migrant share and own-migrant demand exposure ($\left(1 - \frac{X_{nn}}{X_n}\right) shmig_n$), and the term on the last row that depends on export exposure.

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 compensated by a high enough increase in own expenditure. However, a low absorption share also implies that the state is selling its output to other states as well, so that the two terms in the middle row are correlated. The sum of the two terms is equal to the total migrant demand exposure ($\sum_{i \in US} \frac{X_{ni} shmig_i}{X_n}$) minus the share of migrant in the state's labor force. These are the two quantities depicted in the introduction in the left panel of Figure 2.1 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 θ, and the migration trade cost elasticity η, which is intuitive: a change in migrant population affects trade costs which in turns affects exports. State n's export trade cost elasticity with respect to the aggregate migrant share α is equal to η multiplied by 1 minus the share of migrant $shmig_n$.[6] 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 all the US states' decrease in trade cost, 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 others, and the middle row in equation (2.4) governs the relative gains and losses.

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

Of course, these analytical results only hold for the simplified case where migration shares are exogenous, and don't say anything about the evolution of the price index, which is likely to fall as the labor supply moves toward closer locations in the US. However, even in nominal terms, wages might increase following an increase in migrant share if η is big enough to compensate for the loss in international demand. To estimate the full effect of migration changes, I now turn to the calibration of the quantitative model required to conduct counterfactuals.

2.3 Parameter estimation and calibration

To solve for counterfactual changes in the model, all that is left to do is specify values for the trade elasticity θ, the migration cost elasticity ε and the trade cost migration elasticity η. The first two elasticities have been estimated in the literature, while the third one is still relatively understudied. For this reason, I estimate it in this section.

2.3.1 Trade cost elasticity of migration

To estimate η, I use the gravity equation coming from the model and estimate it using exports from the 50 US state and DC to the rest of the countries. Combining equations (2.1) and (2.2) and taking logs gives the following estimation equation, for exports from state s to country i:

$$\log X_{si} = \gamma_s + \delta_i - \theta \log \tau_{si} + \theta\eta \log (N_{is}) + \varepsilon_{si}.$$

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

$$\log X_{si} = \gamma_s + \delta_i + \theta\eta \log (N_{is}) - \beta_1 \log dist_{si} + \beta_2 COMMON_{si} + \varepsilon_{si}. \tag{2.5}$$

Note that all country level determinants of trade costs common to all US states, such as tariffs, are included in the destination fixed effect.

Instrument Migrants might choose to settle in a state because unobservable trade frictions between their home country and the host 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 home country, because that is where their country-specific skill would be especially beneficial in lowering export costs. In that case, the OLS regression would have a downward bias.

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 and who reside in state i, 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' residing in state i, who migrated at time t. 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 with an instrument for the number of migrants from country i who entered the US at time t and reside in state j that does not rely on any bilateral migration information. Finally, summing over all years of migration provides with an instrument of 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 L_{ij}.

Other studies have dealt with endogeneity concerns by using natural experiments distributing the migrants of a single country across US states (e.g. Parsons and Vézina, 2018). An advantage of my estimation strategy is that it uses many countries which allows me to 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, as well as trade flows, for the 50 US states (and the District of Columbia) and 56 countries, with the reference year 2013.[7] The data source for migrant stocks in US states is the American Community Survey (ACS). The ACS also contains the year of migration to the US, the state of residence, and the country of origin which I use to construct the instrument. For trade flows at the state-destination level, I use US Census Bureau data on state-level exports.

Results Table 2.1 shows the results of the estimation. The structural interpretation of the coefficients on $\log(migrants)$ is $\theta \times \eta$. The results show a positive effect of overall migrant population on exports, consistent with a reduction of export trade costs. The elasticity of 0.2 is in line with existing estimates ranging from 0.1 to 0.4

[7] I use 56 countries because they are those for which I have data required to solve the quantitative model in the next section. Appendix B.2 shows consistent regression results using a larger sample of countries.

Table 2.1: Estimation of the effect of migrants on exports

	OLS regression	IV regression
	$\log(exports)$	$\log(exports)$
$\log(migrants)$	0.152***	0.208***
	(0.059)	(0.065)
Adjacency	✓	✓
Distance	✓	✓
Imp. and exp. FE	✓	✓
Country clust. SE	✓	✓
First stage KPF-stat		791
N	2511	2511

Notes: Results from estimating equation 2.5, using the instrument described in the text. Standard errors in parenthesis, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

(Peri and Requena-Silvente, 2010). The OLS coefficient is slightly lower, at 0.15. This is consistent with migrants selecting their state of destination based on low exports, or could be due to an attenuation bias due to measurement error.

Full results, first stage results and robustness checks are relegated to Appendix B.2. The positive effects of migrants on exports is robust to PPMLE estimation, preserving observations with 0 migrants, and using a larger set of countries.

2.3.2 Calibration

I calibrate the model to the 50 US states, the District of Columbia, and 56 countries, and a composite "Rest of the World" (ROW), for a total of 108 regions.[8] Table 2.2 summarizes the parameters and their calibrated value, as well data for the data shares needed to solve the model (trade, migration and wage shares).

Data sources I use migration data from the World Bank's Bilateral Migration Matrix for 2013, and combine it with the American Community Survey (ACS) to construct measures of migrant stock in every regions. International trade data comes

[8]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.

from the OECD Inter-Country Input-Output table for 2013, and within-US trade data comes from the Commodity Flow Survey (CFS).[9] Wage bill shares are calibrated using survey data from the ACS for US states, and from other national surveys for other countries, obtained through IPUMS-International (MPC, 2019). Section B.4 in the Appendix provides additional details on the sources and the exact mapping between the data and the model objects.

Parameter values For the trade elasticity and the migration elasticity, I take values from the literature. I set the trade elasticity θ to 4, following Simonovska and Waugh (2014), and the migration elasticity ε to 2.3 as in Caliendo et al. (2017). For the elasticity of trade costs to migration, I use my estimate of 0.2 from above, whose structural interpretation is $\eta \times \theta$, and thus set $\eta = 0.2/\theta = 0.05$. In Appendix B.5, I explore different values of elasticities, with no significant differences in the results interpretation.

2.4 Counterfactual simulations

To quantify the effect of migration, I conduct the following counterfactual: I increase migration costs to the US uniformly for all foreign countries (κ_{iUS}) such that the migrant share of US population is reduced by 50%. This is similar to reducing the migrant population shares to that of 1980.[10] It is also consistent with proposed legislation that aim to reduce legal annual immigration flows by half.[11] The resulting changes in variables can be interpreted as if the economy moved to a

[9] See Appendix B.4.2 for a discussion of the data coverage in the CFS, and a robustness check for its limitations.

[10] In 1980, the share of migrant population in the US was 6.2%. Reducing the migrant population in 2013 (base year for my analysis) by half would bring the migrant share to around 6.8%.

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

Table 2.2: Link between the model and the data

	Description	Value	Source
Parameter			
ε	migration elasticity	2.3	Caliendo et al. (2017)
θ	trade elasticity	4	Simonovska and Waugh (2014)
η	migration-elasticity of trade costs	$\eta = 0.2/\theta$	own estimate
Exogenous object			
$\hat{A}_n$, $\hat{B}_{in}$,$\hat{\tau}_{in}$		1	keep constant
$\hat{\kappa}_{in}$	migration costs		uniformly increased for $i \notin US$, $n \in US$, to target a reduction of 50% in total migrant stock living in the US
Data			
π_{in}^{mig}, N_{in}	population data		ACS, World Bank
π_{in}^{trade}, X_n	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 B.4 in the appendix for details on the sources and exact mapping between the data and the model objects.

different steady state.

To further understand the role of migration in shaping market access of each state, I also run three additional counterfactuals for each state: the first increases migration costs in the particular state only, the second increases migration costs in all other states except the state of interest, and the third leaves migration costs unchanged but increases the export trade costs to the level they reach in the main counterfactual.[12] These counterfactuals provide an approximate decomposition of the full effect of the nation-wide increase in migration costs into:

1. A shock to the labor supply and migrant-induced within-state market access in state s, leaving demand from international migrants in other states unaffected (outside of general equilibrium forces) and export trade costs unchanged. I define the wage changes from this counterfactual as the "own-state effect".

2. A shock to internal market access due to a decrease in demand from international migrants living in other states, leaving the labor supply and export trade costs in state s unaffected. I define wage changes from this counterfactual as the "intra-national market access effect".

3. A shock to international market access due to the increase in export trade costs. I define wage changes from this counterfactual as the "international market access effect".

2.4.1 Results

I present first the aggregate US-wide results, before turning to the regional impacts and their decomposition.

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

Table 2.3: Average changes

	Constant trade costs	Endogenous trade costs
% Change in state export costs, exports weighted	0	3.7
	(0)	(0.16)
% Change in exports as share of output	1.56	-4.47
	(0.56)	(1.07)
% Change in natives' welfare	-0.01	-0.13
	(0.10)	(0.09)

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

Aggregate results Table 2.3 shows the average change in export trade costs across US states and the average change in exports as share of state output, as well as the average change in welfare in the US. Standard deviations across states are also shown in parentheses.

On average, export trade costs faced by US states increase by 3.7%, which is of similar magnitude as the 4.9% current ad valorem export tariffs faced by US exporters (WEF, 2016). The average change in welfare is close to 0 when trade costs are not allowed to react to migrant population, but becomes negative at -0.13% when export costs increase because of the reduction in migrant population. This underpins the importance of the trade cost reduction channel of migrants. In fact, exports as a share of output increase in the first case, as demand moves out of the US, but decreases in the second case, as the increase in export trade costs is high enough to offset the geographical shift in demand.

The standard deviation of trade costs changes is low compared to the average effect. This is because the uniform increase in migration costs leads, to a first order approximation, to a proportional reduction of migrant population of every country in every state, hence affecting trade costs similarly.[13] The dispersion of welfare changes across US states is however of the same order of magnitude as the average effect and I therefore analyze the geographical dispersion in the next subsection.

Regional heterogeneity This section investigates what drives the heterogenous response to the drop in migrant population across states, focusing on explaining the variation in real wage change across US states.[14]

Figure 2.2 plots the percentage change in a state's real wage for the main counterfactual as well as the three additional counterfactuals. The first bar (in blue) displays the change in real wage for the main counterfactual, the second bar (in grey) displays the own-state effect (defined as the change in real wage when only own-state migrant population is reduced), the third bar (in white) displays the intra-national market access effect (defined as the change in real wage when other-state migrant population is reduced), and the last bar shows the international market access effect (defined as the change when only export trade costs are changed). While the sum of the additional counterfactuals is not 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.[15]

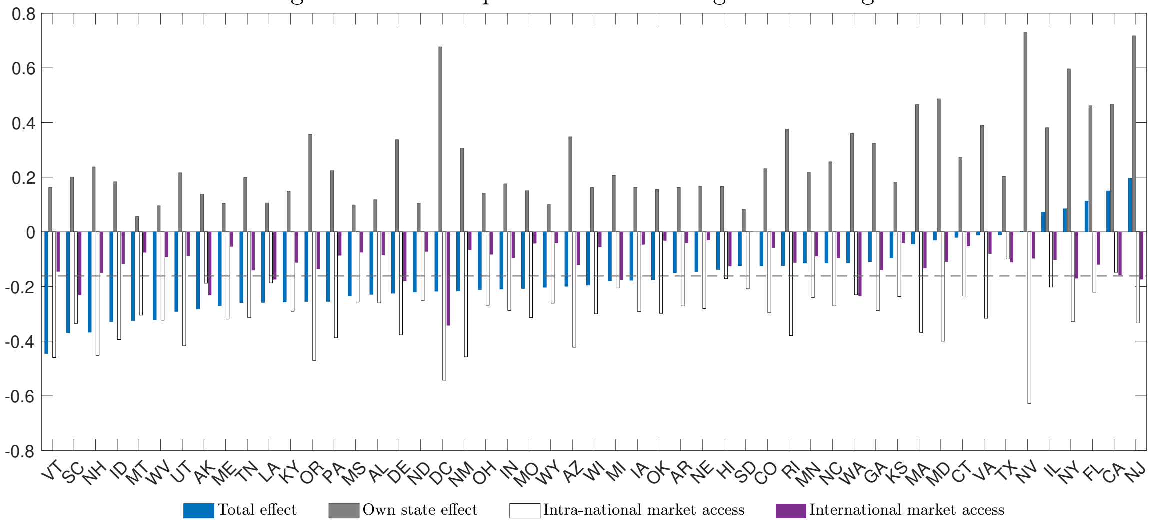
The average real wage change of -0.16% can thus be decomposed into an own-state effect of $+0.26\%$, an intra-national market access effect of -0.31 and and in-

[13] Some states are affected differentially depending on the composition of their migrant population. For example, almost 10% of Mexican-born population resides in the USA. About half of these move to Mexico in the counterfactual, thereby increasing labor supply in Mexico and leading to a drop in real wage, which compensates the drop in attractivity of the US due to the increased migration cost. Hence states with a high share of Mexican migrants will experience a slightly lower drop in migrant population, leading to a lower increase in trade costs. These effects, however, are all second-order, which is why the increase in trade costs are fairly homogenous.

[14] Note that because of migration, the change in state-level real wage is somewhat different from the change in welfare of the state's natives. I focus on change in real wages in this section as it is easier to interpret its reaction to migrant demand and export exposure through the 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 2.3).

[15] The correlation between the sum of the decompositions and the main counterfactual is 0.99, and the average absolute difference is around 0.002 percentage points.

Figure 2.2: Decomposition of the change in real wage



Notes: The figure plots the counterfactual real wage change in each state in the main counterfactual and the three decompositions.

ternational market access effect of -0.11%. The state-level results reveal several interesting patterns.

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

Second, even small state-level wage changes can mask large underlying changes caused by labor supply reduction or market access. For example, Nevada (NV)'s real wage barely reacts to the nationwide migrant share reduction. However, if its migrant population were to decrease leaving the rest of the US's migrant population constant, real wage would increase because the drop in labor supply would be larger than the drop in market access, as illustrated in the positive grey bar. However, because of its exposure to migrant demand from other states due to trade linkages with large migrant states such as California, its wage falls when migrants in other states disappear, as indicated by the negative white bar. Furthermore, the drop in international market access due to the increase in export costs depresses the wage even further, as evidenced by the negative purple bar.

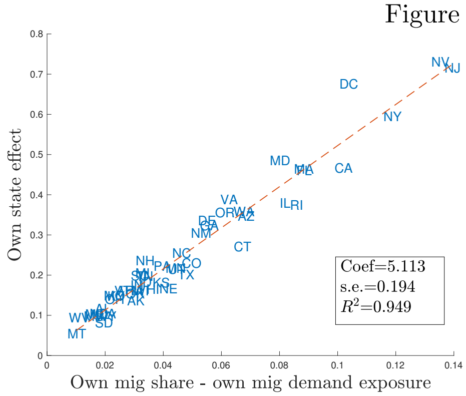
Finally, the size of the intra-national market access effect is larger and more disperse than the international market access effect, implying that the heterogeneity across states is mostly driven by internal rather than international market access. The international component still remains sizable at negative 0.11% on average.

To clearly illustrate the mechanisms at play, Figure 2.3 plots the value of each decomposition bar against the relevant heuristic measures mentioned in Section 2.2.5. The left panel plots the own-state effect against the difference between own migrant share and own migrant demand exposure. As expected, the relationship is positive. States with a higher migrant share than own-migrant absorption benefit from the removal of migrants in their state, because their labor supply drops by more than the demand for their output. The middle panel plots the intra-national market access effect on exposure to migrants from other states. The relationship is negative, as states who sell a larger share of their output to migrants in other states experience a larger decline in market access. Finally the right panel of Figure 2.3 plots the international market access effect against the export exposure. The relationship is negative as states with a higher export exposure suffer more from the increase in trade costs.

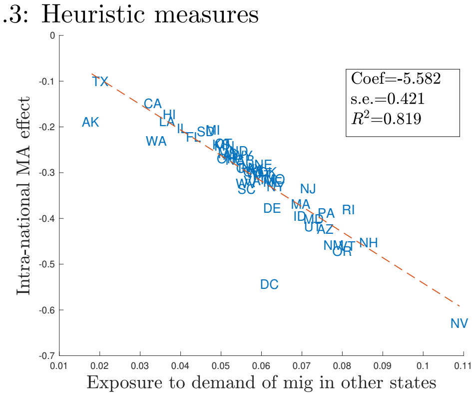
2.5 Skill heterogeneity and migrant-native work substitutability

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

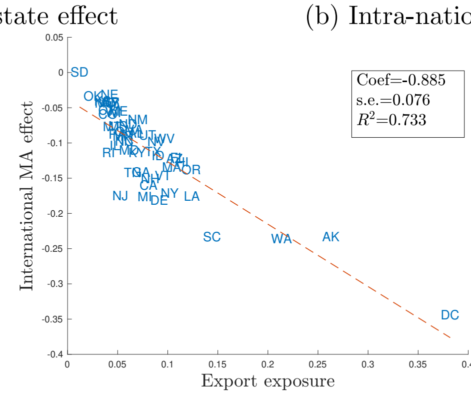
Figure 2.3: Heuristic measures



(a) Own-state effect



(b) Intra-national market access



(c) International market access

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.

demand unchanged.

2.5.1 Empirical evidence on skill heterogeneity

To investigate the differential impact of skilled and unskilled migration on trade costs, I run the same regression as in section 2.3.1, separating high-skill migrants (defined as migrants with some college level education) and low-skill migrants. The instrumental variable approach is the same, except for the instrument being computed at the skill level.

Formally, I run the following regression:

(2.6)

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

where N_{is}^H and N_{is}^L are the number of high- and low-skill migrants from country i residing in state s. Table 2.4 reports the results of the regression, together with the pooled results from above for convenience.

The results reveal that high-skill migration is responsible for the positive impact of migration on exports, with an elasticity of around 0.3, while low-skill migration has no significant effect. High-skill migrants are probably more likely to perform managerial tasks or occupy jobs with higher responsibility, where finding new customers is more common.

The OLS results are upward biased for low-skill migrant and downward biased for high-skill migrants. This is consistent with low-skill migration taking place towards states that have lower unobservable migration cost correlated with lower unobservable trade costs, while high-skill migrants target states for which their knowledge allow them to lower an otherwise higher trade cost.

Table 2.4: Estimation of the effect of migrants on exports by skill

	OLS regression		IV regression	
	$\log(exports)$	$\log(exports)$	$\log(exports)$	$\log(exports)$
$\log(migrants)$	0.152**		0.208***	
	(0.059)		(0.065)	
$\log(HSmig)$		0.091*		0.308***
		(0.052)		(0.105)
$\log(LSmig)$		0.057		-0.056
		(0.038)		(0.077)
Adjacency	✓	✓	✓	✓
Distance	✓	✓	✓	✓
Imp. and exp. FE	✓	✓	✓	✓
Country clust. SE	✓	✓	✓	✓
First stage KPF-stat			791	141
N	2511	2511	2511	2511

Notes: Results from estimating equation 2.5, using the instrument described in the text. Standard errors in parenthesis, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$

2.5.2 Model

I modify the model in Section 2.2 to include different skilled and unskilled labor, as well as imperfect substitutability between migrant and native workers. Details of the model are relegated to Appendix B.3 and are mostly the same as the model in Section 2.2. I present the main differences below.

Production There are now four types of labor used for production: migrant and native, high- and low-skill labor. Low-skill and high-skill labor (L^L and L^H) are measured in efficiency units of labor, with migrant and domestic labor being imperfectly substitutable. More precisely, the production function for good j is given by:

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

where $z(j)$ is a location-specific idiosyncratic productivity for each good j and ρ is the elasticity of substitution across skills. The amount of s-skill labor, L^s, is itself a CES aggregate of native and migrant workers:

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

where λ is the elasticity of substitution across native and migrant labor, L^{sd} is the amount of domestic (native) units of labor of skill s and L^{sm} is the amount of migrant units of labor of skill s.

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

$$U^s_{in} = \frac{W_n}{\kappa^s_{in}},$$

where W_n is the same CES aggregator of the continuum of goods as in the baseline model and κ^s_{in} is a migration cost in term of utils.

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

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

$$F^s_{in}(b) = e^{-B^s_{in} b^{-\varepsilon}},$$

where ε is the shape parameter governing the dispersion of efficiencies and B^s_{in} is a location parameter: workers of skill s from region i are in general more efficient in regions n with higher B^s_{in}.

Trade costs Consistent with the evidence in section 2.5.1, trade costs depend on the high and low-skill migration as follows:

$$d_{ni} = \tau_{ni} \times \begin{cases} \left(\frac{N^L_{in}}{\sum_{j,s} N^s_{jn}}\right)^{-\eta^L} \left(\frac{N^H_{in}}{\sum_{j,s} N^s_{jn}}\right)^{-\eta^H} & \text{if } N^s_{in} \neq 0, n \in US, i \notin US \text{ or opposite} \\ 1 & \text{otherwise} \end{cases}.$$

Trade costs are negatively affected by the share of migrants of skill s in the exporter's population, but the effect of different skill level is heterogeneous, governed by the two elasticities η^H and η^L.

The rest of the model follow the quantitative framework in section 2.2, and additional description of the equilibrium with skill as well as calibration of the parameters is relegated to Appendix B.3. For the trade elasticity and migration elasticity, the parameter values are similar to the ones in the main model. Regarding trade cost elasticities, I set $\eta^H = 0.3/\theta$ and $\eta^L = 0$ consistent with the estimates in 2.5.1. Finally, the elasticity of substitution between skills ρ is set to 1.6 following Katz and Murphy (1992), and the elasticity of substitution between native and migrant work λ is set to 20 following Ottaviano and Peri (2012). Alternative calibration is explored in Appendix B.5.

2.5.3 Counterfactual results

Table 2.5 shows the average change in export trade costs across US states and the average change in exports as share of state output, as well as the average change in wages in the US for different skill levels, defined as the native-population weighted average of wage changes in each state. Standard deviations across states are also shown in parentheses.

The average change in welfare is negative, at -0.17% and -0.22% for low and high skill respectively, when trade costs are left constant. Exports as a share of

Table 2.5: Imperfect substitutability scenario: average changes across US states

	Constant trade costs	Endogenous trade costs
% change in state export costs, exports weighted	0 (0)	5.49 (0.23)
% change in exports as share of output	1.46 (0.60)	-7.14 (1.34)
% change in US low-skill welfare	-0.16 (0.16)	-0.34 (0.18)
% change in US college welfare	-0.20 (0.07)	-0.37 (0.07)

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

output increase, as demand moves out of the US when the migrants leave the US. When trade costs are endogenous, export trade costs faced by US states increase by 5.49% on average, a larger increase than in the results that don't account for skill differential, because the elasticity of trade costs on high-skill migrants is higher. The resulting drop in welfare of low- and high-skill US natives are around 0.34 and 0.37% respectively. The larger drop in average welfare than in the baseline model is explained by the larger increase in export costs and by the complementarity between native and foreign labor. Appendix B.5 shows that the changes in welfare are dampened when the elasticity of substitution between migrants and natives' labor is increased.

Regional heterogeneity As for the main counterfactual, I decompose the effect into an "own-state" reduction of migration an intra-national market access effect, and an international market access effect. Figure 2.4 displays the total change in real wage (first bar in blue), the own-state effect (second bar in gray), the intra-national market access effect (third bar in white), and international market access effect (fourth bar in purple). Subfigure 2.4 shows the response of native low-skill wages, while subfigure 2.4 depicts the reaction of native high-skill wages.

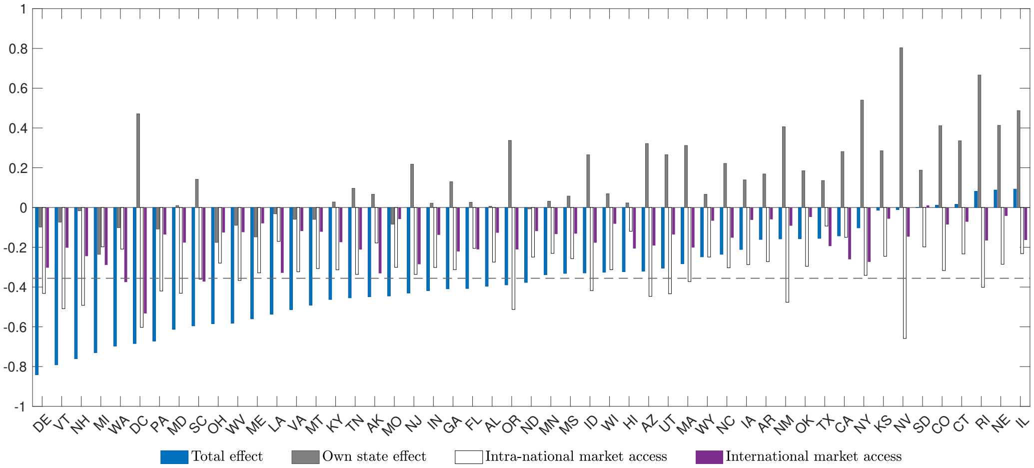
The shock to own-state migrant population, while having a positive impact on average, is negative in some states, as complementarities induce a lower wage for native workers after the reduction of migrant labor supply. Both intra- and international market access effects are negative, as the negative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

Overall, the skill and native-migrant imperfect substitutability dimensions affect how the labor supply shock feeds in the economy: it affects the magnitude, and even sometimes the sign of the own-state effect. The market access effect of reducing migrant population, however, remains unaffected by these production elasticities. Table 2.6 makes this point clear by displaying the correlation between the baseline model and imperfect substitutability model decompositions. The correlation is high at 0.99 for the internal and international market access effects: these mechanisms operate through the demand channel and their regional impact are similar regardless of the production elasticities. The own-migrant effect correlation is lower between the baseline and imperfect substitutability model, because the production elasticities λ and ρ affect the reaction of the wage to the increased labor supply.

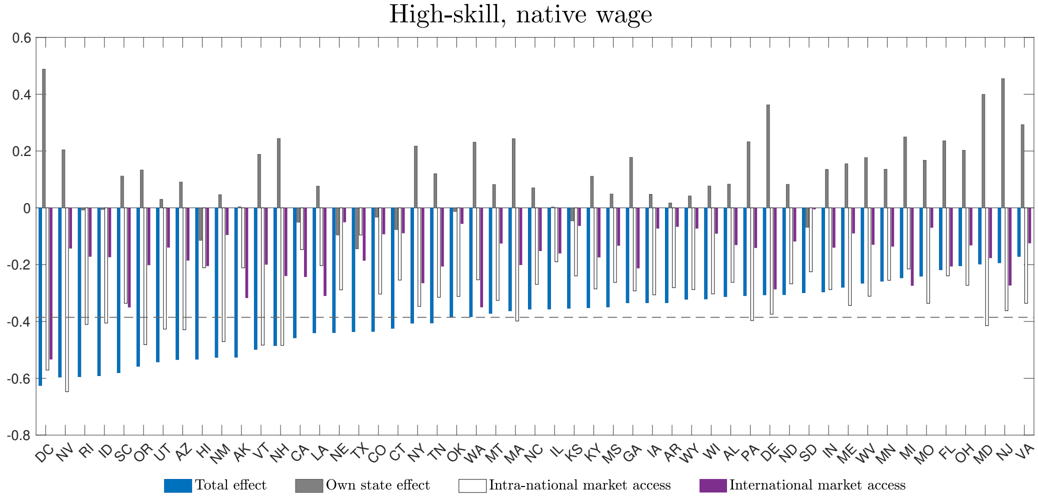
2.6 Conclusion

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

Figure 2.4: Imperfect substitutability scenario: decomposing regional effects
Low-skill, native wage changes



High-skill, native wage



Notes: The figure plots the counterfactual real wage change in each state in the main counterfactual and the three decompositions, for the model with skills and imperfect substitutability between native and foreign workers.

Table 2.6: Comparison between baseline and imperfect substitutability model

	$corr\left(w_i^{base}, w_i^{low}\right)$	$corr\left(w_i^{base}, w_i^{high}\right)$	$corr\left(w_i^{high}, w_i^{low}\right)$
Own effect	0.556	0.552	-0.233
Internal MA	0.991	0.994	0.975
International MA	0.992	0.993	0.998

Notes: The table shows the correlation between the real wage changes resulting from own-migrant removal (first row), other-states migrant removal (middle row), and increased trade costs (third row). The first column shows the correlation across states between the wage change in the baseline model and the low-skill wage in the imperfect substitutability model. The middle column displays the correlation between baseline and high-skill wages, and the right column displays the correlation between the high- and low-skill wage changes.

country's market.

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

CHAPTER III

The Economics and Politics of Revoking NAFTA

with Raphael A. Auer and Andrei A. Levchenko[1]

3.1 Introduction

With the onset of the global financial crisis, the longstanding downward trend in tariffs and other barriers to trade has come to a halt. Recent political events such as the election of the Trump administration in the US and the British vote to leave the European Union indicate an acute danger of rising protectionism and renationalisation of production and consumption. International trade has become salient in voters' minds and some parties and politicians profess strong views on the benefits and costs of particular trade policies. However, in a highly interconnected world economy with supply chains that cross country borders, who gains and who loses from trade policies is far from transparent.

Against this backdrop, this paper studies the distributional impacts of one prominent proposed protectionist measure – revoking NAFTA – in the global network of

[1]Preliminary version of a paper prepared for the 2018 IMF Jacques Polak Annual Research Conference and the *IMF Economic Review.*

input-output trade. To examine the general equilibrium effects of this policy, we combine the multi-sector, multi-country, multi-factor general equilibrium Ricardian trade model (e.g. Eaton and Kortum, 2002; Caliendo and Parro, 2015; Levchenko and Zhang, 2016) with a specific-factors model that generates distributional effects of trade across sectors (Jones, 1971; Mussa, 1974; Levchenko and Zhang, 2013; Galle et al., 2017). We calibrate the model to the global matrix of intermediate and final goods trade from the 2016 edition of the World Input-Output Database (WIOD) and WIOD's Socioeconomic Accounts (Timmer et al., 2015). We then simulate a scenario in which NAFTA is dismantled. In particular, this counterfactual entails a rise in tariffs from the current NAFTA-negotiated ones to the Most-Favored Nation (MFN) level, as well as an increase in non-tariff barriers in both goods and service sectors estimated by Felbermayr et al. (2017).

We first assess the economic impact of this policy at the level of US congressional districts, Canadian provinces, and Mexican states. To do so, we combine the sector-country-specific real wage changes resulting from our general equilibrium model with information on employment shares in those geographical units. We then analyze the political dimension of this policy by correlating the economic outcomes with recent voting patterns. Since the threat to revoke NAFTA comes from the United States, we focus on this country and examine in particular the Trump vote shares in the 2016 election. This exercise sheds light on whether districts that voted for the arguably most protectionist candidate stand to benefit or lose disproportionately from this particular potential trade policy.

Our results can be summarized as follows. The total welfare change from revoking NAFTA would be -0.22% for the United States, -1.8% for Mexico, and -2.2% for Canada. These aggregate numbers are an order of magnitude smaller than the distributional effects across sectors. Sectoral real wage changes range from −2.72% to 2.25% for the US, from −16.85% to 9.45% for Mexico, and from −14.06% to 1.71% for Canada. Because sectoral employment is unevenly distributed across geographic locations, there are considerable distributional consequences across space as well. In the United States, average wage changes range from −0.41% in Ohio's 4th district to 0.08% in Texas' 11th district, with a cross-district standard deviation of 0.05%. Average wage changes range from −3.35% to −1.35% across Canadian provinces and from −4.11% to −0.85% across Mexican states. Thus, both the aggregate welfare changes, and the extent of distributional impacts are significantly greater in Canada and Mexico in percentage terms.

Turning to the relationship with political outcomes, we find that if anything there is a negative correlation between the real wage change in a congressional district and the Trump vote share. Though dismantling or renegotiating NAFTA was a prominent pillar of the Trump presidential campaign, Trump-voting districts would experience systematically greater wage decreases if NAFTA disappeared.[2]

To better understand this somewhat surprising pattern, we construct three simple, heuristic measures of trade exposure to NAFTA at the US congressional district level. The first is a measure of *import exposure* to the NAFTA partner countries, defined as the employment share-weighted average of sectoral imports from NAFTA partners in total US absorption. Intuitively, import exposure to NAFTA partners is high in a congressional district if it has high employment shares in sectors with greater import competition from those countries. All else equal, we should expect wages to rise the most in locations that in the current regime compete most closely with Canada and Mexico. The second is an *export orientation* measure, which is

[2]The exception to this empirical regularity are congressional districts with a large share of Mining and quarrying in employment, such as the Texas 11th congressional district, or the state of Wyoming.

the employment share-weighted average of sectoral exports to NAFTA partners in total US output. Intuitively, we should expect locations with higher employment shares in NAFTA-export-oriented industries to lose disproportionately from NAFTA revocation. Finally, the third measure is NAFTA *imported input intensity*, defined as the employment-weighted share of spending on NAFTA inputs in total input spending. We should expect congressional districts that rely on NAFTA inputs to experience relatively larger wage decreases when NAFTA is revoked, although this prediction is contingent on the relevant substitution elasticities.

Taken individually, the bilateral relationships between all three heuristics and model-implied wage changes are negative and statistically significant. This is intuitive for two measures – export orientation and imported input intensity – but counterintuitive for import exposure, as it implies that congressional districts most exposed to direct import competition actually see larger real wage reductions when protection increases following a dismantling of NAFTA.

At the same time, the statistical association between all three of these heuristics and the Trump vote share is positive and significant. This is intuitive for the import exposure measure – locations suffering the most from import competition voted more for Trump – but less so for the other two measures, as locations exporting to NAFTA or sourcing inputs from NAFTA should foresee wage decreases if NAFTA is done away with.

The apparent mystery is resolved by the fact that the correlation between the three heuristics is extremely high: the export orientation has a 0.92 correlation with import exposure, and a 0.86 correlation with imported input intensity. Less surprisingly, imported input intensity has a 0.95 correlation with import exposure. Thus, the picture that emerges from this exercise is first and foremost one of differences across locations in the overall level of integration with NAFTA countries. Places that suffer the most from NAFTA import competition are also overwhelmingly those that export to NAFTA and use NAFTA intermediates.

It is thus not surprising that the locations overall more open to NAFTA trade experience larger net welfare losses: effectively, a revocation of NAFTA represents a relatively greater reduction in trade openness for those locations. We do show, however, that these locations are also the ones that voted systematically more for Trump. This exercise underscores the need for a model-based quantitative assessment that takes into account multiple import and export linkages and general equilibrium adjustments. Heuristic measures of import competition that have been used in other contexts (e.g. Autor et al., 2013, and the large literature that followed) would be misleading as to which locations would stand to lose the most from NAFTA revocation, and how the distributional effects of NAFTA correlate with Trump vote. Indeed, while the bivariate relationships between all three of the heuristic measures and real wage changes or Trump vote all have the same sign, the conditional relationships all have the expected signs: when controlling for export orientation and imported input intensity, the locations with greater NAFTA import exposure experience relative wage gains from NAFTA rollback. Similarly, controlling for import exposure, districts with greater export orientation actually tended to vote less for Trump.

Our work follows the tradition of quantitative assessments of trade policy, going back to the first-generation CGE literature (see, among many others, Deardorff and Stern, 1990; Harrison et al., 1997; Hertel, 1997). More recent contributions extend the Eaton and Kortum (2002) framework to study the welfare effects of NAFTA (e.g. Caliendo and Parro, 2015), the effect of the UK leaving the European Union (Dhingra et al., 2017), or greater potential US protectionism (Felbermayr et al., 2017). Our two main contributions are (i) to bring to the fore the distributional aspects of trade policies, and (ii) to systematically relate those distributional aspects to the variation in political support for the presidential candidate that proposed implementing these policies.

The rest of the paper is organized as follows. Section 3.2 lays out the quantitative framework used in the analysis, and Section 3.3 describes the data. Section 3.4 presents the real wage and income changes following the revocation of NAFTA, and Section 3.5 relates those to voting patterns in the US. Section 3.6 presents some extensions and robustness checks, and Section 3.7 concludes. Details of data, calibration, and model solution are collected in the Appendix.

3.2 Quantitative framework

The world is composed of N countries denoted by m, n, and k, and J sectors denoted by i and j. Each sector produces a continuum of goods. The factors of production are capital (K) and three types of labor: high- (L_H), medium- (L_M), and low-skill (L_L). Capital and labor are perfectly mobile across goods within a sector, but immobile across sectors (Jones, 1971; Mussa, 1974). This assumption means that the results should be interpreted as the short-run effects of the policy experiments we simulate.[3] Micro evidence shows that following trade shocks, worker mobility across sectors is quite limited (e.g. Artuç et al., 2010; Dix-Carneiro, 2014), and thus our model provides a good approximation to the factor adjustment in the short run. Country n, sector j are endowed with $L_{H,jn}$ units of high-skilled labor, $L_{M,jn}$ units of medium-skilled labor, $L_{L,jn}$ units of low-skilled labor, and K_{jn} units of capital.

[3]Section 3.6.1 presents the results when factors are mobile across sectors, a scenario intended to capture the long-run outcomes.

Preferences and final demand Utility is identical and homothetic across agents in the economy. Individual ι maximizes utility

$$U_n(\iota) = \prod_{j=1}^{J} Y_{jn}(\iota)^{\xi_{jn}},$$

where the $Y_{jn}(\iota)$ is ι's consumption of the composite good in sector j, subject to the budget constraint:

$$\sum_{j=1}^{J} p_{jn} Y_{jn}(\iota) = I(\iota),$$

where p_{jn} is the price of sector j composite good, and $I(\iota)$ is ι's income. Income in this economy comes from labor and capital earnings, tariff revenue, and a trade deficit in the form of a transfer to n from the rest of the world (which will be negative in countries with a trade surplus):

$$I_n \equiv \sum_{\iota} I_n(\iota) = \sum_{j=1}^{J} w_{H,jn} L_{H,jn} + \sum_{j=1}^{J} w_{M,jn} L_{M,jn} + \sum_{j=1}^{J} w_{L,jn} L_{L,jn} + \sum_{j=1}^{J} r_{jn} K_{jn} + T_n + D_n,$$

where $w_{s,jn}$ and r_{jn} are the wage rate for s-skilled labor and the return to capital in sector j in country n, T_n total tariff revenue in country n, and D_n is the trade deficit. Since utility is Cobb-Douglas, this demand system admits a representative consumer, and thus final consumption spending in each sector is a constant fraction of aggregate income. Denote the economywide final consumption on sector j goods in country n by Y_{jn}. Then:

$$p_{jn} Y_{jn} = \xi_{jn} I_n.$$

The corresponding consumption price index in country n is:

$$P_n = \prod_{j=1}^{J} \left(\frac{p_{jn}}{\xi_{jn}} \right)^{\xi_{jn}}. \tag{3.1}$$

In the quantitative implementation below, agents ι will be differentiated by which sectoral factor endowments they own, and thus we will be computing income changes for medium-skilled workers in the apparel sector, for example.

Technology and market structure Output in each sector j is produced competitively using a CES production function that aggregates a continuum of varieties $q \in [0, 1]$ unique to each sector:

$$Q_{jn} = \left[\int_0^1 Q_{jn}(q)^{\frac{\epsilon-1}{\epsilon}} dq \right]^{\frac{\epsilon}{\epsilon-1}},$$

where ϵ denotes the elasticity of substitution across varieties q, Q_{jn} is the total output of sector j in country n, and $Q_{jn}(q)$ is the amount of variety q that is used in production in sector j and country n. The composite Q_{jn} is non-tradeable, and is split between final consumption and intermediate usage. Individual varieties $Q_{jn}(q)$ are tradeable subject to physical trade costs and policy trade restrictions, and can in principle come from any country. The price of sector j's output is given by:

$$p_{jn} = \left[\int_0^1 p_{jn}(q)^{1-\epsilon} dq \right]^{\frac{1}{1-\epsilon}}.$$

The production function of a particular sectoral variety q is:

$$\begin{aligned} y_{jn}(q) = \quad & z_{jn}(q) \left(l_{H,jn}(q)^{\alpha_{H,jn}} l_{M,jn}(q)^{\alpha_{M,jn}} l_{L,jn}(q)^{\alpha_{L,jn}} k_{jn}(q)^{1-\alpha_{H,jn}-\alpha_{M,jn}-\alpha_{L,jn}} \right)^{\beta_{jn}} \\ & * \left(\prod_{i=1}^{J} m_{ijn}(q)^{\gamma_{ijn}} \right)^{1-\beta_{jn}}, \end{aligned}$$

where $z_{jn}(q)$ denotes variety-specific productivity, $k_{jn}(q)$ and $l_{s,jn}(q)$ denote inputs of capital and s-skilled labor, and m_{ijn} denotes the intermediate input from sector i used in production sector-j goods in country n. The value-added-based labor intensity is given by $\alpha_{s,jn}$ for skill type s, while the share of value added in total output is given by β_{jn}. Both of these vary by sector and country. The weights on inputs from other sectors, γ_{ijn}, vary by output industry j as well as input industry i and by country n.

Productivity $z_{jn}(q)$ for each $q \in [0,1]$ in each sector j is equally available to all agents in country n, and product and factor markets are perfectly competitive. Following Eaton and Kortum (2002, henceforth EK), the productivity draw $z_{jn}(q)$ is random and comes from the Fréchet distribution with the cumulative distribution function

$$F_{jn}(z) = e^{-A_{jn}z^{-\theta}}.$$

Define the cost of an "input bundle" faced by sector j producers in country n:

$$\begin{aligned} b_{jn} = & \left[(w_{H,jn})^{\alpha_{H,jn}} (w_{M,jn})^{\alpha_{M,jn}} (w_{L,jn})^{\alpha_{L,jn}} (r_{jn})^{1-\alpha_{H,jn}-\alpha_{M,jn}-\alpha_{L,jn}} \right]^{\beta_{jn}} \\ & * \left[\prod_{i=1}^{J} (p_{in})^{\gamma_{ijn}} \right]^{1-\beta_{jn}}. \end{aligned} \tag{3.2}$$

The production of a unit of good q in sector j in country n requires $z_{jn}^{-1}(q)$ input bundles, and thus the cost of producing one unit of good q is $b_{jn}/z_{jn}(q)$. International trade is subject to iceberg costs: in order for one unit of good q produced in sector j to arrive at country n from country m, $d_{j,mn} > 1$ units of the good must be shipped (in describing bilateral flows, we follow the convention that the first subscript denotes source, the second destination). We normalize $d_{j,nn} = 1$ for each country n in each sector j. Note that the trade costs will vary by destination pair and by sector, and in general will not be symmetric: $d_{j,nm}$ need not equal $d_{j,mn}$.

In addition to non-policy trade frictions $d_{j,mn}$, there are two policy barriers to trade: an ad valorem tariff $\tau_{j,mn}$ that is paid at the border, and an ad valorem non-tariff barrier $\eta_{j,mn} > 1$, that distorts trade but does not result in any government revenue. The total trade cost is thus given by $\kappa_{j,mn} = d_{j,mn}\eta_{j,mn}(1 + \tau_{j,mn})$.

Goods markets are competitive, and thus prices equal marginal costs. The price at which country m can supply tradable good q in sector j to country n is equal to:

$$p_{j,mn}(q) = \frac{b_{jm}}{z_{jm}(q)}\kappa_{j,mn}.$$

Buyers of each good q in sector j in country n will select to buy from the cheapest source country. Thus, the price actually paid for this good in country n will be:

$$p_{jn}(q) = \min_{m=1,\dots,N} \{p_{j,mn}(q)\}.$$

Following the standard EK approach, define the "multilateral resistance" term

$$\Phi_{jn} = \sum_{m=1}^{N} A_{jm}\big(b_{jm}\kappa_{j,mn}\big)^{-\theta}.$$

This value summarizes, for country n, the access to production technologies in sector j. Its value will be higher if in sector j, country n's trading partners have high productivity (A_{jm}) or low cost (b_{jm}). It will also be higher if the trade costs that country n faces in this sector are low. Standard steps lead to the familiar result that the probability of importing good q from country m, $\pi_{j,mn}$ is equal to the share of total spending on goods coming from country m, $X_{j,mn}/X_{jn}$, and is given by:

$$\frac{X_{j,mn}}{X_{jn}} = \pi_{j,mn} = \frac{A_{jm}\big(b_{jm}\kappa_{j,mn}\big)^{-\theta}}{\Phi_{jn}}. \tag{3.3}$$

In addition, the price of good j aggregate in country n is simply

$$p_{jn} = \Gamma\big(\Phi_{jn}\big)^{-\frac{1}{\theta}}, \tag{3.4}$$

where $\Gamma = \big[\mathbf{\Gamma}(\frac{\theta+1-\epsilon}{\theta})\big]^{\frac{1}{1-\epsilon}}$, with $\mathbf{\Gamma}$ denoting the Gamma function.

Equilibrium and market clearing A competitive equilibrium in this economy is a set of goods prices $\{p_{jn}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, factor prices $\{w_{s,jn}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$ for $s = H, M, L$ and $\{r_{jn}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, and resource allocations $\{Y_{jn}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, $\{Q_{jn}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, $\{\pi_{j,mn}\}_{n,m=1,\ldots,N}^{j=1,\ldots,J}$, such that (i) consumers maximize utility; (ii) firms maximize profits; and (iii) all markets clear.

The market clearing condition for sector j aggregate in country n is given by

$$p_{jn}Q_{jn} = p_{jn}Y_{jn} + \sum_{i=1}^{J}(1-\beta_{in})\gamma_{jin}\Bigg(\sum_{k=1}^{N}\frac{\pi_{i,nk}p_{ik}Q_{ik}}{1+\tau_{i,nk}}\Bigg). \tag{3.5}$$

Total expenditure in sector j, country n, $p_{jn}Q_{jn}$, is the sum of domestic final expenditure $p_{jn}Y_{jn}$ and expenditure on sector j goods as intermediate input in all domestic sectors i: $\sum_{i=1}^{J}(1-\beta_{in})\gamma_{jin}\Bigg(\sum_{k=1}^{N}\frac{\pi_{i,nk}p_{ik}Q_{ik}}{1+\tau_{i,nk}}\Bigg)$. In turn, final consumption is given by:

$$\begin{aligned} p_{jn}Y_{jn} = \xi_{jn}\Bigg(&\sum_{s=\{H,M,L\}}\Bigg(\sum_{i=1}^{J}w_{s,in}L_{s,in}\Bigg) + \sum_{i=1}^{J}r_{in}K_{in} \\ &+ \sum_{m\neq n}\sum_{i=1}^{J}\frac{\tau_{i,mn}\pi_{i,mn}p_{in}Q_{in}}{1+\tau_{i,mn}} + D_n\Bigg). \end{aligned} \tag{3.6}$$

Finally, since all factors of production are immobile across sectors, sectoral skill-specific $w_{s,jn}$ and sectoral r_{jn} adjust to clear the factor markets:

$$\sum_{m=1}^{N}\frac{\pi_{j,nm}p_{jm}Q_{jm}}{1+\tau_{j,nm}} = \frac{w_{s,jn}L_{s,jn}}{\alpha_{s,jn}\beta_{jn}} = \frac{r_{jn}K_{jn}}{(1-\sum_s \alpha_{s,jn})\beta_{jn}}. \tag{3.7}$$

Formulation in changes Following Dekle et al. (2008), we express the model in terms of gross proportional changes relative to the baseline equilibrium and the baseline equilibrium observables. For any baseline value of a variable x, denote by a prime its counterfactual value following some change in parameters, and by a "hat" the gross change in a variable between a baseline level and a counterfactual: $\widehat{x} \equiv x'/x$. The shock we will consider is an increase in tariffs $\tau_{j,mn}$ and non-tariff barriers $\eta_{j,mn}$ between US, Canada, and Mexico following the revocation of NAFTA. In changes, (3.6) becomes:

$$\begin{aligned}\widehat{p}_{jn}\widehat{Y}_{jn} = & \sum_{s}\left(\sum_{i=1}^{J}\widehat{w}_{s,in}SL_{s,in}\right)+\sum_{i=1}^{J}\widehat{r}_{in}SK_{in} \\ & +\sum_{m\neq n}\sum_{i=1}^{J}\frac{\tau'_{i,mn}\widehat{\pi}_{i,mn}\widehat{p}_{in}\widehat{Q}_{in}}{1+\tau'_{i,mn}}\frac{\pi_{i,mn}p_{in}Q_{in}}{I_n}+\widehat{D}_nSD_n,\end{aligned} \tag{3.8}$$

where $SL_{s,in}$, SK_{in}, and SD_n are the initial shares of s-skill labor income in sector i, capital income in sector i, and the trade deficit, respectively. The market clearing condition (3.5) becomes:

$$\widehat{p}_{jn}\widehat{Q}_{jn}p_{jn}Q_{jn} = \widehat{p}_{jn}\widehat{Y}_{jn}p_{jn}Y_{jn} + \sum_{i=1}^{J}(1-\beta_{in})\gamma_{jin}\left(\sum_{k=1}^{N}\frac{\widehat{\pi}_{i,nk}\widehat{p}_{ik}\widehat{Q}_{ik}\pi_{i,nk}p_{ik}Q_{ik}}{1+\tau'_{i,nk}}\right). \tag{3.9}$$

The factor market clearing conditions become:

$$\widehat{w}_{s,jn} = \widehat{r}_{jn} = \frac{\sum_{m=1}^{N}\frac{\widehat{\pi}_{j,nm}\widehat{p}_{jm}\widehat{Q}_{jm}\pi_{j,nm}p_{jm}Q_{jm}}{1+\tau'_{j,nm}}}{\sum_{m=1}^{N}\frac{\pi_{j,nm}p_{jm}Q_{jm}}{1+\tau_{j,nm}}}. \tag{3.10}$$

The trade shares in changes are

$$\widehat{\pi}_{j,mn} = \frac{\left(\widehat{b}_{jm}\widehat{\kappa}_{j,mn}\right)^{-\theta}}{\sum_{k=1}^{N}\pi_{j,kn}\left(\widehat{b}_{jk}\widehat{\kappa}_{j,kn}\right)^{-\theta}}, \tag{3.11}$$

where

$$\widehat{b}_{jm} = \left[\left(\widehat{w}_{H,jm}\right)^{\alpha_{H,jm}}\left(\widehat{w}_{M,jm}\right)^{\alpha_{M,jm}}\left(\widehat{w}_{L,jm}\right)^{\alpha_{L,jm}}\left(\widehat{r}_{jm}\right)^{1-\sum_s\alpha_{s,jm}}\right]^{\beta_{jm}}\left[\prod_{i=1}^{J}\left(\widehat{p}_{im}\right)^{\gamma_{ijm}}\right]^{1-\beta_{jm}} \tag{3.12}$$

and

$$\widehat{\kappa}_{j,mn} = d_{j,mn}\widehat{\eta}_{j,mn}\frac{(1+\tau'_{j,mn})}{(1+\tau_{j,mn})}. \tag{3.13}$$

Finally, standard steps lead to the counterfactual price indices:

$$\widehat{p}_{jn} = \left(\sum_{m=1}^{N} \pi_{j,mn} (\widehat{b}_{jm} \widehat{\kappa}_{j,mn})^{-\theta} \right)^{-\frac{1}{\theta}} \tag{3.14}$$

and

$$\widehat{P}_n = \prod_{j=1}^{J} \widehat{p}_{jn}^{\xi_{jn}}. \tag{3.15}$$

Equations (3.8)-(3.15) are solved for all the price, wage, and quantity changes between the baseline equilibrium and the counterfactual. The model is solved using the algorithm described in Appendix C.1.

3.3 Data

This section describes the sources of our trade, input-output, trade policy, and voting data.

The 2016 release of the World Input-Output Database (WIOD) is our main data source. It contains data on trade flows, intermediate input usage, and final consumption at the sectoral level. The socio-economic accounts compiled by the WIOD also contain data on labor and capital share in value added. Labor is broken down into three skill levels. A low-skilled worker is defined by the WIOD as one with at most some secondary education. A medium-skilled worker has a complete secondary education. A high-skilled worker has some tertiary education or more. We use the latest year available, which is 2014.[4] The WIOD and its construction are described in detail in Timmer et al. (2015). We combine some sectors with too many zeros, and add Turkey, Russia, Luxembourg, and Malta to the composite "Rest of the World"

[4]The latest WIOD release does not include worker breakdowns by skill. For that information, we use the previous (2011) WIOD release, with skill-specific sectoral labor data pertaining to 2009.

region. The resulting dataset consists of 40 countries and 38 sectors. Tables C.1 and C.2 in the Appendix provide a list of countries and sectors.

To get a sense of the importance of input and final goods trade among the NAFTA countries, Table 3.1 reports aggregate intermediate and final spending shares according to WIOD. The left panel reports the share of spending on intermediates from the country in the row of the table in the total intermediate spending in the country in the column. Thus, the US sources 89.7% of all intermediates it uses from itself, 1.8% from Canada, and 1% from Mexico. The importance of the US for Canada and Mexico is predictably larger. The US supplies 12.1% of all intermediates used in Canada, and 15.1% of intermediates used in Mexico. The right panel presents the corresponding shares in final consumption spending. The importance of NAFTA countries in each other's final goods spending is lower, with Canada and Mexico supplying 0.6% and 0.8% of US final consumption spending, and the US supplying 6.2% and 3.5% of final consumption of Canada and Mexico, respectively.[5]

Table 3.1: NAFTA market shares

	Intermediate spending			Final consumption spending		
	Canada	Mexico	United States	Canada	Mexico	United States
Canada	.783	.007	.018	.876	.002	.006
Mexico	.006	.716	.010	.006	.914	.008
United States	.121	.151	.897	.062	.035	.943

Notes: This table reports the share of input spending (left panel) and final spending (right panel) in the column country coming from the row country. The columns do not add up to 1 because of imports from non-NAFTA countries.

Location-specific employment data come from the U.S. Census Bureau (year 2015), Statistics Canada (year 2015) and the Instituto Nacional de Estadistica y Geografia (year 2014). These are provided at the sectoral level following the NAICS

[5]de Gortari (2019) shows that according to the Mexican firm-level customs data, the input linkages between Mexico and the US are in fact greater than what is implied by the WIOD, and that a NAFTA trade war would have even larger negative consequences. By using WIOD, our approach is thus conservative and if anything understates the overall impact of NAFTA revocation.

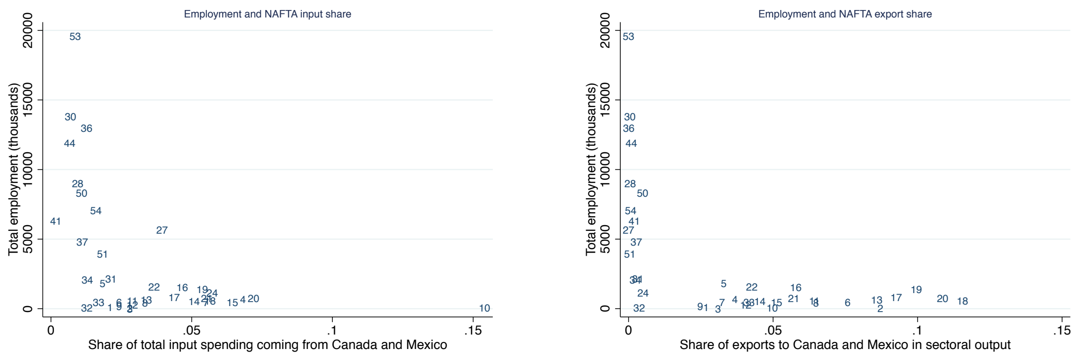
classification. We convert these to ISIC Rev. 4 using the correspondence table from the Census Bureau. Employment shares by skill for the US at the county level come from the U.S. Census Bureau (2016). For the US, we convert county-level data to congressional district by using the Census Bureau's mapping. We do not have breakdowns of location-specific employment by both skill level and industry. Finally, data on election results at the congressional district level have been compiled by Daily Kos Elections.

At the national level, the sectors in which the bulk of US employment is currently found have at best weak direct connections to NAFTA countries. The left panel of Figure 3.1 plots US employment at the sector level against the share of intermediate spending sourced from the NAFTA countries. There is a broad negative relationship: the sectors with the greatest NAFTA input spending shares tend to not have much US employment. The right panel plots employment against the share of output exported to NAFTA countries. Here, there are essentially two groups of sectors: the group with a relatively high export intensity to NAFTA and low overall US employment, and sectors that export virtually nothing to NAFTA but have higher employment. The figure conveys that the largest US sectors by employment are (relatively) non-tradeable services. The top 3 sectors in terms of US employment are "Human health and social work activities," "Retail trade, except of motor vehicles and motorcycles," and "Accommodation and food service activities."

We use the 2014 tariff data for Canada, Mexico and the US from the World Bank's WITS database.[6] We set the Canadian, Mexican, and US tariffs $\tau_{j,mn}$ on imports from all the countries in the sample to the current effectively applied tariff rates. The NAFTA revocation counterfactual tariffs $\tau'_{j,mn}$ are then set to the Most Favored

[6]We extract tariff data directly at the ISIC Rev. 3 sectoral level, and use a correspondence to ISIC Rev. 3.1, then ISIC Rev. 4, to match it with the WIOD data classification.

Figure 3.1: US Sectoral Employment, NAFTA Input Share and NAFTA Export Share



Notes: The left panel depicts the US sectoral employment against the share of total input spending in a sector that is sourced from Canada and Mexico. The right panel depicts the US sectoral employment against the share of total output exported to Canada and Mexico. The sector key is in Appendix Table C.2.

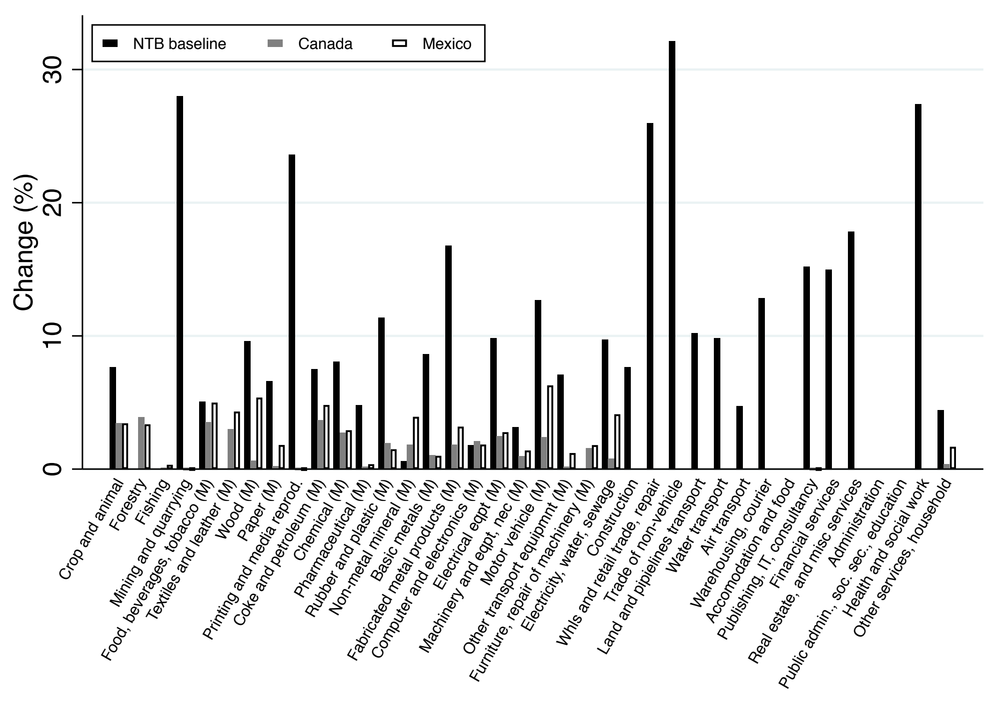
Nation (MFN) for the NAFTA country pairs. The NAFTA members' import tariffs on the rest of the countries do not change in the counterfactual.

Estimates of non-tariff trade barrier (NTB) changes in case of rollback of NAFTA come from Felbermayr et al. (2017). Those authors fit a standard gravity model on bilateral trade flows by industry. In addition to the usual gravity controls, the authors also include a NAFTA dummy. If the NAFTA dummy is positive, it implies that trade is higher than predicted among NAFTA countries conditional on other observables. The procedure interprets this finding as lower NTBs among the NAFTA countries due to NAFTA being in place. Under the assumption that this positive unexplained effect of NAFTA goes away if NAFTA is revoked, Felbermayr et al. (2017) compute the rise in NTBs as the increase in trade costs required for trade to fall by the amount of the estimated NAFTA dummy in each industry. According to this procedure, in a small number of sectors NTBs will actually fall as a result of revoking NAFTA. Since this appears implausible, we set the NTB change to zero in instances where the regression model predicts them to fall if NAFTA is revoked.

Figure 3.2 presents the changes in tariffs and NTBs that we assume would occur if

NAFTA were revoked, expressed in percentage points (Appendix Table C.3 reports the precise numbers). Since we assume that Canada and Mexico would receive MFN treatment if NAFTA disappeared, the tariff changes that would actually occur are by and large in single digit percentage points. The inferred NTB changes are both larger on average, and more broad-based, affecting also a number of service sectors in which tariffs are zero. It is plausible that a revocation of NAFTA will be accompanied by a general deterioration of the relationship between the countries, and that the NTBs will rise in a wide range of sectors.

Figure 3.2: Assumed changes in US tariffs and NTBs on Canada and Mexico if NAFTA is revoked



Notes: This figure reports the change in sectoral tariffs on Mexico and Canada, and the change in the NTBs imposed by the US on Mexico and Canada, if NAFTA is revoked, expressed in percentage points. "(M)" denotes a manufacturing sector.

At the same time, the NTB changes reported in Figure 3.2 are inferred from observed variation in trade flows, rather than measured directly. Direct measurement of NTBs is not feasible. To our knowledge, the only comprehensive NTB database is compiled by UNCTAD, and contains count measures of the number of NTBs in place by sector and country pair. We collected these data and compared the number of NTBs among the NAFTA countries with the number of NTBs that the NAFTA countries impose on non-NAFTA trading partners. It is indeed the case that the within-NAFTA number of NTBs is systematically lower than the number imposed by NAFTA countries on non-NAFTA economies. We computed the bilateral sectoral change in the number of NTBs within NAFTA if each NAFTA country went from the observed number of NTBs to the average that it imposes on the rest of the world. In this exercise, we assumed that after the lower NTBs due to NAFTA are phased out, each NAFTA country treats its NAFTA partners with the same level of NTBs that it imposes on the rest of the world, in each sector. The correlation between the implied change in the number of NTBs and the ad valorem NTB change from Felbermayr et al. (2017) in Figure 3.2 is 0.23 for the US-Mexico NTBs and 0.36 for the US-Canada NTBs. Given the significant caveats associated with simply using the number of NTBs as a measure of their severity, the positive correlation is reassuring that there is some informational content in the NTB values inferred from trade flows and used in the baseline.

Nonetheless, given the large amount of uncertainly surrounding the NTB numbers, throughout we report the results under two additional assumptions. First, we assume that the NTBs don't change following the dismantling of NAFTA, and only tariffs do. This is the most conservative treatment of NTBs, resulting in far smaller overall trade cost increases from dismantling NAFTA. The second alternative we implement is to jettison the sectoral variation in NTB changes, and simply apply a uniform increase in NTBs that is equal to the average change across sectors implied by the

Felbermayr et al. (2017) numbers. This amounts to a 9.62% uniform increase in NTBs when NAFTA is revoked.

3.4 Quantitative results

3.4.1 Calibration

All parameters except the trade elasticity θ can be calibrated directly from the WIOD data. All numbers in the WIOD data are in *basic prices* and therefore ex-tariff. One cell in the the WIOD database is $M_{ij,mn}$, the exports from country m, sector i to country n, sector j, where j could be $j = C$ the final consumption. Denoting by $M_{j,mn} = \sum_{i=1}^{J} M_{ji,mn} + M_{jC,mn}$ the total WIOD value of good j exported from m to n, we have that in terms of our model $M_{j,mn} = \frac{\pi_{j,mn} p_{jn} Q_{jn}}{1+\tau_{j,mn}}$.

The quantities needed to solve the model are:

$$p_{jn} Q_{jn} = \sum_{m=1}^{N} (1 + \tau_{j,mn}) M_{j,mn} \tag{3.16}$$

$$\pi_{j,mn} = \frac{(1 + \tau_{j,mn}) M_{j,mn}}{p_{jn} Q_{jn}} \tag{3.17}$$

$$D_n = \sum_{j=1}^{J} D_{jn} \text{ where } D_{jn} = \sum_{m=1}^{J} M_{j,nm} - \sum_{m=1}^{J} M_{j,mn} \tag{3.18}$$

$$T_n = \sum_{m=1}^{N} \sum_{j=1}^{J} \tau_{j,mn} M_{j,mn} \tag{3.19}$$

$$p_{jn} Y_{jn} = \sum_{m=1}^{N} (1 + \tau_{j,mn}) M_{jC,mn.} \tag{3.20}$$

The production and utility parameters can be calibrated using the optimality conditions described above:

$$\xi_{jn} = \frac{\sum_{m=1}^{N}(1+\tau_{j,mn})M_{jC,mn}}{\sum_{i=1}^{J}\sum_{m=1}^{N}(1+\tau_{i,mn})M_{iC,mn}} \tag{3.21}$$

$$\beta_{jn} = 1 - \frac{\sum_{m=1}^{N}\sum_{i=1}^{J}(1+\tau_{i,mn})M_{ij,mn}}{\sum_{m=1}^{N} M_{j,nm}} \text{ for } j \neq C \tag{3.22}$$

$$\gamma_{ij,n} = \frac{\sum_{m=1}^{N}(1+\tau_{i,mn})M_{ij,mn}}{\sum_{m=1}^{N}\sum_{j'=1}^{J}(1+\tau_{j',mn})M_{ij',mn}} \tag{3.23}$$

$$\alpha_{s,jn} = \frac{labor\_revenue_{s,jn}}{value\_added_{jn}}, \tag{3.24}$$

where skill-specific labor revenue and value added come from the WIOD Socio-Economic Accounts.

In the baseline we set the trade elasticity $\theta = 5$, a common value in the quantitative trade literature (e.g. Costinot and Rodríguez-Clare, 2014). Section 3.6.2 assesses the robustness of the results to alternative θ's.

3.4.2 Sectoral and aggregate effects

Figure 3.3 reports the change in the real wage for each sector following the full revocation of NAFTA. As discussed above, we present three scenarios for NTB changes: (i) baseline depicted in Figure 3.2; (ii) no NTB changes (tariff changes only), and (iii) uniform NTB changes.

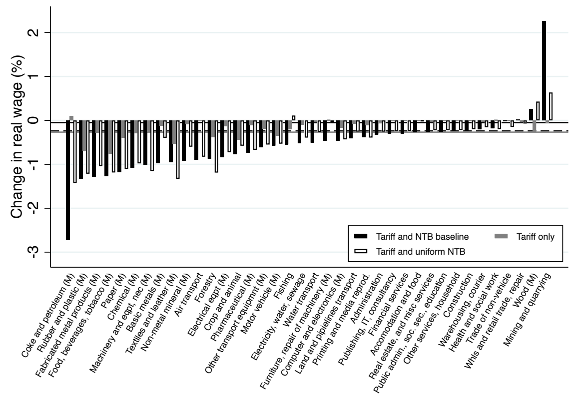
The real wage change is simply the change in the sectoral wage divided by the consumption price index, expressed in net terms: $\widehat{w}_{s,jn}/\widehat{P}_n - 1$. Note that the Cobb-Douglas production function with immobile factors implies that the proportional wage changes are the same across skill types (see equation 3.10), and thus there are no distributional effects across skills within a sector. Section 3.6.1 analyzes instead a model with mobile factors of production, in which the distributional effects are instead across skill types. US sectors experience a range of wage changes from a 2.2% increase in the mining and quarrying sector to a 2.7% decline in the coke and petroleum sector. The large majority of sectors experience wage decreases, with 7 sectors, all in manufacturing, seeing reductions in excess of 1%. With unchanged NTBs, wage decreases are much smaller on average, as would be expected since this scenario involved much smaller trade cost increases. In the United States, overall the uniform NTB case is quite highly correlated with the baseline, with the notable difference for the outlier sectors, where the uniform NTB scenario implies changes smaller in absolute terms. In Canada and Mexico, the range of sectoral wage changes is much greater. Both Mexico and Canada have sectors that experience wage reductions in excess of 10%.

In all three countries, the employment-weighted average wage changes, depicted by the horizontal lines in Figure 3.3, are negative in all three scenarios. The numbers are in the first column of Table 3.2. The average wage fall in the US is an order of magnitude smaller than in Mexico and Canada in all scenarios. However, when computing aggregate welfare changes, we must take into account changes in the capital income and tariff revenue. Proportional changes in capital income are the same as wage income in our framework. Adding tariff revenue, the second column of Table 3.2 reports the overall welfare changes. The US loses 0.22% from the dismantling of NAFTA in the baseline scenario. Canadian and Mexican losses are about ten times larger in proportional terms at around -2%. The numbers are quite similar under a uniform NTB change. When only tariffs change, the US is indifferent, whereas Canadian and Mexican welfare fall by 0.06% and 0.25% respectively.

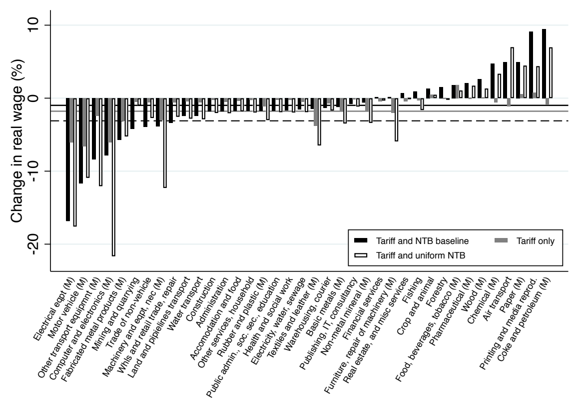
Though proportional changes are smaller in the US, it bears the largest dollar losses from dismantling NAFTA, at about US$40 billion, as reported in the last column. Canada is a close second at US$36 billion, and Mexico at US$22. Our exercise implies that relative price levels (real exchange rates) also move, with the

Figure 3.3: Sectoral wage changes in NAFTA countries due to full rollback of NAFTA

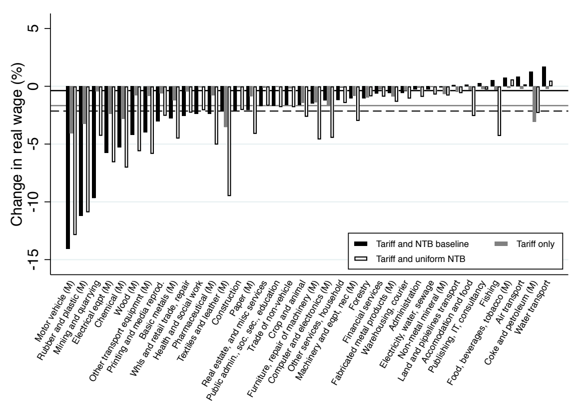
United States



Mexico



Canada



Notes: This Figure depicts sectoral real wage changes due to revocation of NAFTA. Horizontal lines denote the employment-weighted average wage change for the baseline (solid line), tariff only (grey line) and tariff and uniform NTB scenarios (dashed line). "(M)" denotes a manufacturing sector.

Table 3.2: Employment weighted average wage and total welfare changes

	Real wage change, %	Total welfare change, %	in bn. US$
	Tariff and NTB baseline		
Canada	-1.67	-2.15	-36.20
Mexico	-1.79	-1.81	-22.07
United States	-0.27	-0.22	-39.47
	Tariff only		
Canada	-0.37	-0.06	-1.08
Mexico	-0.99	-0.25	-3.06
United States	-0.05	-0.00	-0.20
	Tariff and uniform NTB		
Canada	-2.14	-2.02	-33.95
Mexico	-3.10	-2.03	-24.80
United States	-0.24	-0.22	-38.79

Notes: This table reports the aggregate real wage changes and the total welfare changes, in percentage points and in billion US$, for the NAFTA countries under the three NAFTA revocation scenarios.

US dollar appreciating by 2.3% against the Mexican peso, and by 1.2% against the Canadian dollar in real terms. Table 3.3 presents the percentage changes in trade volume from the rollback of NAFTA relative to world GDP. As expected, NAFTA countries tend to trade less with each other and substitute towards other countries. In the baseline scenario, the fall in NAFTA trade volume is quite large. For example, U.S. exports to Canada and Mexico would fall by 36.9% and 41.8% respectively. When only tariffs change, the changes are smaller but still sizeable, at around 8% and 17.7%.

3.4.3 Geographic distribution

We now move on to the geographic distribution of relative gains and losses. To this end, we aggregate county-level sectoral employment to obtain sectoral employment shares in each congressional district. Then, we construct the weighted average real wage change in a district by applying the sectoral wage changes to district-level sectoral employment shares. In Canada and Mexico, we use province- and state-

Table 3.3: Percentage change in NAFTA country trade volumes due to a full rollback of NAFTA

Tariff and NTB baseline

	Source				
Destination	Canada	Mexico	United States	Other	Total
Canada	0.10	-23.49	-36.91	2.03	-3.25
Mexico	-41.14	-0.34	-41.84	-2.23	-4.14
United States	-36.50	-33.90	0.49	2.13	-0.12
Other	11.58	16.39	0.09	0.19	0.22
Total	-3.23	-4.13	-0.12	0.22	0.03

Tariff only

	Source				
Destination	Canada	Mexico	United States	Other	Total
Canada	0.40	-3.70	-8.01	1.78	-0.28
Mexico	-14.91	0.96	-17.72	0.99	-0.67
United States	-5.60	-11.83	0.09	0.08	-0.07
Other	0.45	1.49	0.35	0.02	0.03
Total	-0.28	-0.67	-0.08	0.03	-0.01

Tariff and NTB average

	Source				
Destination	Canada	Mexico	United States	Other	Total
Canada	0.41	-23.83	-38.01	6.19	-2.79
Mexico	-44.54	-0.40	-45.94	-0.82	-4.43
United States	-32.27	-34.95	0.43	1.46	-0.18
Other	7.60	13.61	0.81	0.20	0.23
Total	-2.78	-4.42	-0.18	0.23	0.03

Notes: This table reports the percentage changes in trade volume between NAFTA countries and other countries relative to world GDP.

level sectoral employment shares, respectively. Let c subscript locations, and let ω_{jc} be the share of sector j employment in total district c employment. The mean real wage change in location c is then

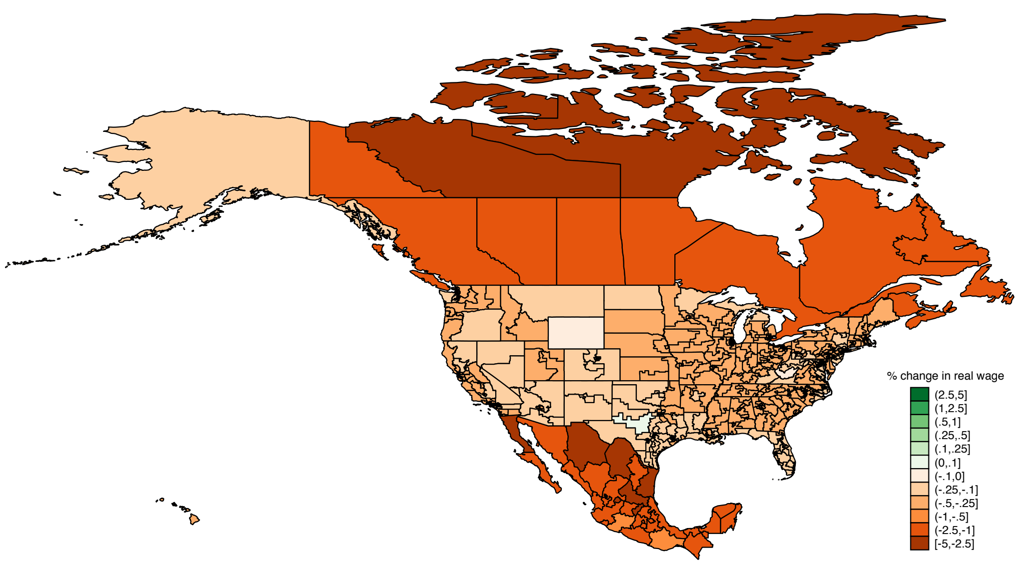
$$\sum_j \omega_{jc} \left(\frac{\widehat{w}_{jn}}{\widehat{P}_n} - 1 \right).$$

Note that we are implicitly assuming that within each country, there are no technology differences and there is costless trade in goods, which equalizes sectoral wages across locations. Thus, our distributional effects across locations are driven purely by sectoral composition differences, and not by differences in wages in the same sector across geographic areas within a country.

Figure 3.4 depicts the average real wage changes following the revocation of NAFTA, by geographical region. Darker shades denote larger wage reductions. The first distinctive feature of the figure is that the location-specific real wage changes are overwhelmingly negative throughout North America. Second, the systematically darker colors are outside of the United States: as reported above, wage reductions are greater in Canada and Mexico. The figure highlights the pervasiveness of average wage reductions geographically in Canada and Mexico: though individual sectors sometimes experience wage increases, no region in Canada or Mexico sees real wage gains.

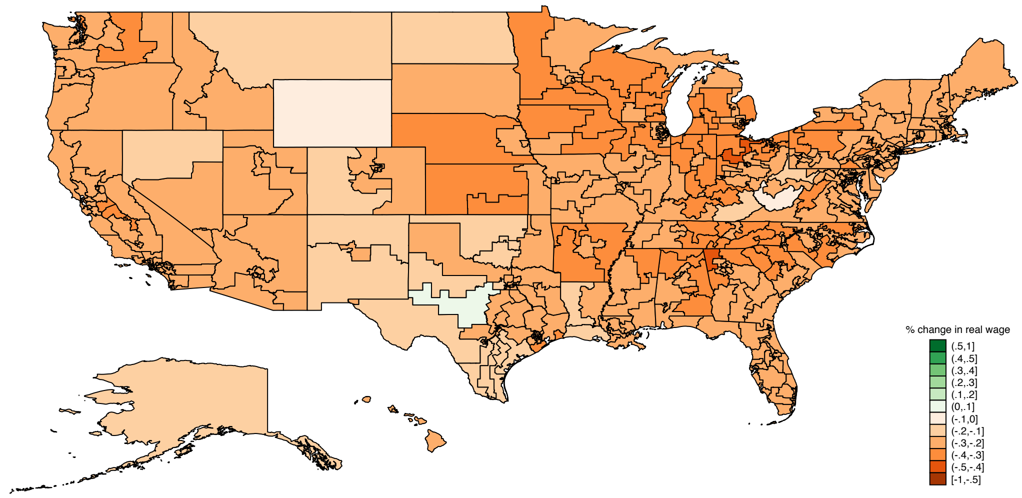
Figure 3.5 zooms in on the United States. In the eastern portion of the country, there are two distinct darker bands in the upper Midwest and the South. The lightest hues (smallest wage decreases) are in mining areas of Texas, West Virginia, and Wyoming.

Figure 3.4: Real wage changes in NAFTA countries following revocation of NAFTA



Notes: This figure depicts the average wage changes by geographic region in North America.

Figure 3.5: Real wage changes in US congressional districts following revocation of NAFTA



Notes: This figure depicts the average wage changes by congressional district in the United States.

3.5 Political correlates of the local economic impact

The quantitative assessment above establishes that the revocation of NAFTA has distributional consequences: real wage changes differ across sectors and geographic locations. This section analyzes the political dimension by correlating the geographic variation in real wage changes with recent voting outcomes. Since proposals to revoke NAFTA originate from the United States, we focus on this country.

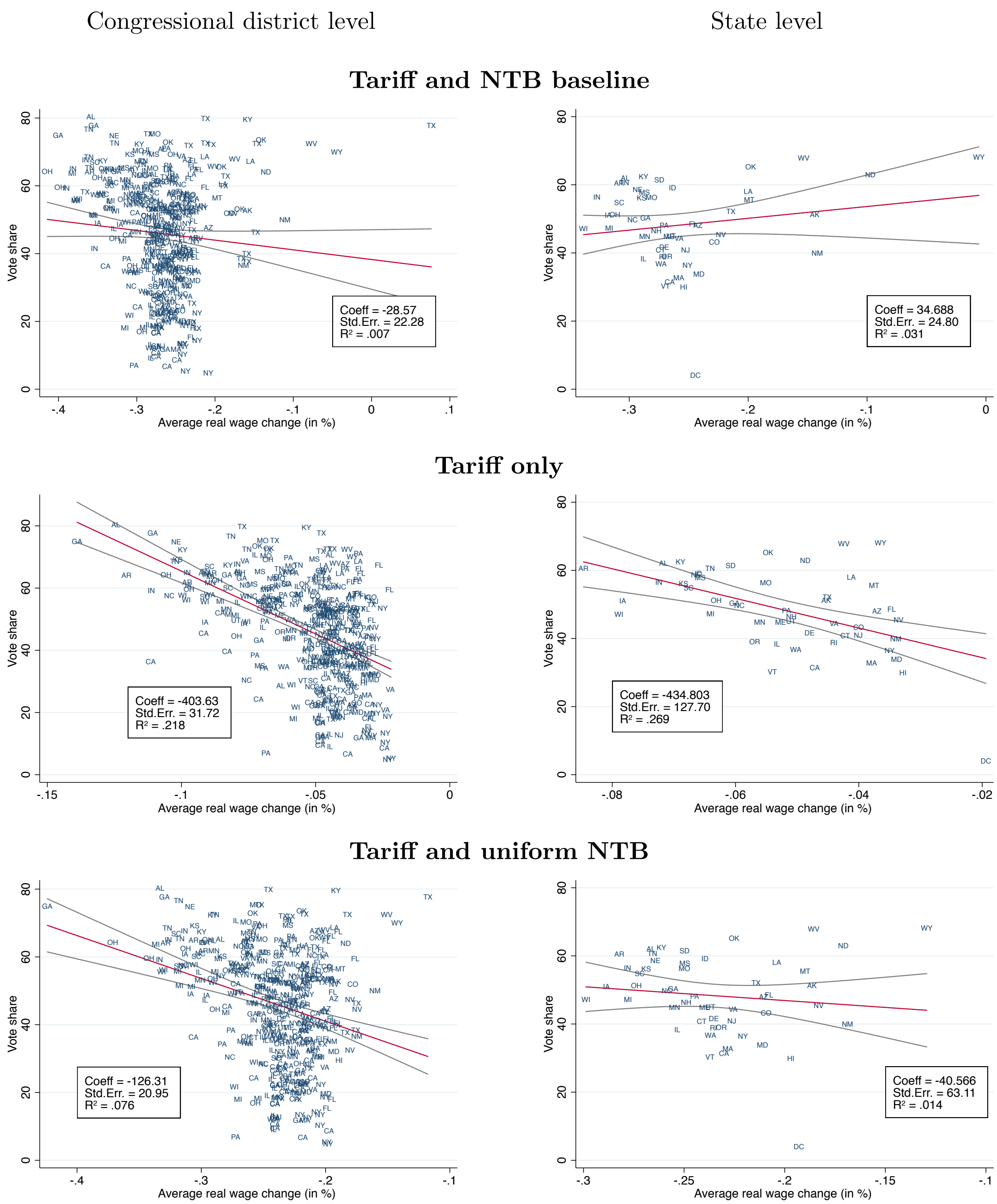
3.5.1 Correlation with Trump vote share

Figure 3.6 presents the scatterplots of the real wage changes due to revocation of NAFTA against the vote share of the then Republican Party presidential nominee Donald Trump in the 2016 US presidential election (henceforth "Trump vote share"). The left panels shows the scatterplots at the congressional district level, and the right panels at the state level. At the district level, the slope of the relationship is negative. It is not significant in the baseline, but becomes significant in the other two scenarios. Looking closer, in the baseline the negative relationship is substantially attenuated by districts with a heavy presence of mining and quarrying, such as Texas 11th district (encompassing central Texas and eastern Texas cities of Midland and Odessa), the state of Wyoming (a single Congressional district), and West Virginia 3rd (roughly the southern half of the state). Since mining and quarrying experiences a large change in NTBs in the baseline, these districts are relatively better off from the policy change, and voted heavily for Trump. Dropping just 2 districts (out of 435) with the highest mining and quarrying employment shares renders the negative bilateral relationship significant at the 1% level. All in all, with the possible exception of heavily mining and quarrying areas, Trump-voting congressional districts would experience systematically larger wage decreases if NAFTA is revoked.

The right side of Figure 3.6 depicts these relationships at the state level. This might be thought of as corresponding to voting for the president and the US Senate. Under the NTB baseline, the slope is positive but not significant. Looking closer at the plot, it is clear that the slope is once again influenced by mining states such as Wyoming, North Dakota, and West Virginia, that voted for Trump but would lose relatively less from the revocation of NAFTA. In the upper left part of the plot are states in the South and the Midwest that voted for Trump but would be hurt the most by NAFTA revocation, with the top 5 largest wage reductions being in Wisconsin, Indiana, Iowa, Michigan, and Ohio. The two alternative NTB scenarios yield a negative slope: Trump-voting states are hurt relatively more by revoking NAFTA.

Appendix Table C.4 shows the top and bottom 10 US congressional districts in terms of mean real wage change. The second column also shows the mean change in real wage and tariff revenue. Under the assumption of uniformly distributed tariff revenue, this can be computed as $IWT_{jn} = w_{jn}L_{jn} + s_{jn}T_n$, where s_{jn} is the share

Figure 3.6: Real wage changes and 2016 Trump vote share



Notes: This figure depicts the scatterplots of the average real wage change from revoking NAFTA and the 2016 Trump vote share by congressional district (left side) and state (right side), along the OLS fit. The boxes report the coefficient, robust standard error, and the R^2 of the bivariate regression.

of employment of sector j in country n, and the mean change in district c is given by:

$$\sum_j \omega_{jc} \left(\frac{\widehat{IWT}_{jn}}{\widehat{P}_n} - 1 \right).$$

3.5.2 Political outcomes and heuristic measures of trade exposure to NAFTA

To better understand the patterns documented above, we next construct heuristic measures of trade exposure to NAFTA and correlate them with the real wage changes and voting patterns. We use three simple observable measures, intended to capture at an intuitive level some of the main driving forces behind the geographic distribution of losses. The specific-factors model delivers the intuition that factors employed in import-competing sectors should benefit from a uniform increase in trade barriers, and sectors with an export orientation should lose. In a model with input-output linkages, factors in a sector employing imported inputs might lose, although that prediction depends on the substitution elasticities in production and demand.

Thus, at the sector level, we define import penetration as the share of imports from NAFTA in total absorption:

$$IMP_j^{NAFTA} = \frac{IMPORTS_j^{NAFTA}}{p_{jn}Q_{jn}},$$

where, as before, $p_{jn}Q_{jn}$ is the total US spending (absorption) in an industry. Define export intensity as the share of output exported to NAFTA countries:

$$EXP_j^{NAFTA} = \frac{EXPORTS_j^{NAFTA}}{\sum_k \pi_{j,nk} p_{jk} Q_{jk}},$$

where $\sum_k \pi_{j,nk} p_{jk} Q_{jk}$ is the total US output/sales in sector j. Define NAFTA input dependency as:

$$INPDEP_j^{NAFTA} = \frac{INTERMIMPORTS_j^{NAFTA}}{INTERMUSE_j},$$

where $INTERMIMPORTS_j^{NAFTA}$ is the value of intermediate imports from the NAFTA countries, and $INTERMUSE_j$ is total spending on intermediate inputs for sector j.

These are aggregated to the congressional district level with employment shares:

$$IMPORT\,EXPOSURE_c = \sum_j \omega_{jc} IMP_j^{NAFTA},$$

$$EXPORT\,ORIENTATION_c = \sum_j \omega_{jc} EXP_j^{NAFTA},$$

and

$$IMPORTED\,INPUT\,INTENSITY_c = \sum_j \omega_{jc} INPDEP_j^{NAFTA}.$$

Thus, a congressional district has a high import exposure, for example, if it has high employment shares in sectors with high import penetration from NAFTA countries, and similarly for other measures.

The top row of Figure 3.7 presents the scatterplot of the real wage change due to the revocation of NAFTA against import exposure (left panel), export orientation (center panel) and imported input intensity (right panel). All three measures have statistically significant negative correlation with the real wage change. This is intuitive in the case of two of the measures: NAFTA export-oriented districts and those that import a lot of NAFTA inputs should lose more from dismantling NAFTA. However, the relationship is also negative for import exposure, which is not intuitive, as locations that compete with NAFTA imports should benefit in relative terms if NAFTA disappeared.

The bottom row reports the bivariate relationships between these three measures and the Trump vote share. All three are positive and significant. This time, the import exposure measure delivers "intuitive" results, as the NAFTA import-competing locations voted more for Trump. But evidently so did those that export a lot to NAFTA countries, or use more NAFTA inputs.

This apparent incoherence is resolved by observing that the three heuristic measures are highly correlated among themselves. Import exposure has a 0.92 correlation with export orientation, and a 0.95 correlation with imported input intensity. Export orientation has a 0.86 correlation with imported input intensity.

The picture that emerges is that US congressional districts differ systematically in their overall trade openness with NAFTA. Locations that compete with NAFTA imports are also the ones that export the most to NAFTA, and use most NAFTA inputs. For these areas, a dismantling of NAFTA represents a larger fall in trade openness compared to locations not engaged with NAFTA, and thus larger real income falls. These are also the locations that on average voted for Trump.

This discussion shows how misleading it can be to rely on simple heuristic measures, especially in isolation. Looking at the strong positive correlation between the widely used import exposure index and the Trump vote share may lead one to conclude that revoking NAFTA does indeed correspond to the economic interests of Trump-voting districts. However, it turns out that the districts with a high import-exposure level are also systematically different along other pertinent dimensions, such as export orientation.

Altogether, the patterns imply that districts with higher import exposure would actually lose systematically more from revoking NAFTA. To further illustrate this point, Table 3.4 shows results of a regression of the real wage changes and vote shares on the three heuristic measures. Columns 1-3 report the regressions underlying the bivariate plots in Figure 3.7. Column 4 uses all three heuristics together. Now, the export orientation and imported input intensity still have same the "intuitive" sign, but the import exposure indicator switches sign and thus also becomes intuitive. Controlling for export orientation and imported input intensity, locations with greater NAFTA import exposure experience relatively positive (less negative) wage changes from revoking NAFTA. Columns 5 through 8 repeat the exercise for the Trump vote share. Here again, when all three heuristics are included together, the sign on the import exposure coefficient is unchanged and remains intuitive, but the sign on the export orientation switches in the expected direction: controlling for import exposure, districts with higher NAFTA export orientation votes less for Trump.

3.6 Extensions and robustness

3.6.1 Mobile factors

All of the above analysis assumes that factors are immobile across sectors, and thus is meant to capture the short-run effects. In this section, we instead allow factors to be mobile across sectors, as is more standard in multi-sector trade models. Since cross-sectoral factor movements are subject to large frictions even at multi-year horizons (Artuç et al., 2010; Dix-Carneiro, 2014), this exercise is meant to capture the long-run effects. Note that in this environment, factor market clearing ensures that factor prices are the same in all sectors, and thus there is a single factor price change for each factor of production (capital and the three types of labor). However, there are still distributional effects across workers according to skill type, and across geographic locations according to the skill composition of the labor force.

Table 3.5 reports the real wage changes by skill type. In the United States, in all scenarios the wage changes increase with skill: more skilled workers are hurt less by the dismantling of NAFTA. Intriguingly, the pattern is U-shaped in Mexico, with the medium-skilled workers hurt the most by NAFTA dissolution in all scenarios.

In Canada, all skill types are worse off, but the relative ranking is not stable across scenarios, indicating sensitivity to assumptions on the pattern of trade cost changes across sectors.

The fourth and fifth columns report the total proportional and dollar amount welfare changes. These are very similar to the baseline, indicating that assumptions on cross-sectoral factor mobility are not crucial for the aggregate welfare. A similar result was found by Levchenko and Zhang (2013).

Turning to the geographic distribution of real wage changes, we construct congressional district average real wage changes by using skill shares in each district, similarly to the immobile factor case:

$$\sum_{s} \omega_{sc} \left(\frac{\widehat{w}_{sn}}{\widehat{P}_n} - 1 \right),$$

where ω_{sc} is the share of skill s in district c. Thus, districts with more skilled workers lose relatively less in the long run from the dismantling of NAFTA, as their wages fall by less. Note that the range of wage changes across skills, at only 0.07 percentage points in the baseline, is far smaller than the range of wage changes across sectors in the specific-factors model, which was about 5 percentage points. Thus, as expected the range of average wage changes across locations is also quite small, about 0.02 percentage points. Figure 3.8 presents the scatterplots of the revocation of NAFTA against the Trump vote share. There is still a systematically negative relationship between the long-run district-level real wage change and the Trump vote share. In fact, in several scenarios this relationship is stronger than in the specific-factors case.

3.6.2 Varying the productivity dispersion parameter

In this robustness check, we repeat the main counterfactuals using alternative values of $\theta = \{2.5; 8\}$. These values represent the typical range of θ used in the trade literature. Table 3.6 shows the employment weighted average wage change for the different values of θ. Table 3.6 presents the aggregate real wage changes and welfare changes. We only report the baseline NTB scenario (the others deliver similar results and are available upon request). The alternative values of θ produce quite similar overall welfare changes. Appendix Figures C.1 and C.2 present the scatterplots of the Trump vote share against real wage changes at the congressional district level for the two alternative values of θ. The overall patterns are the same as in the baseline.

3.6.3 Difference with Romney vote

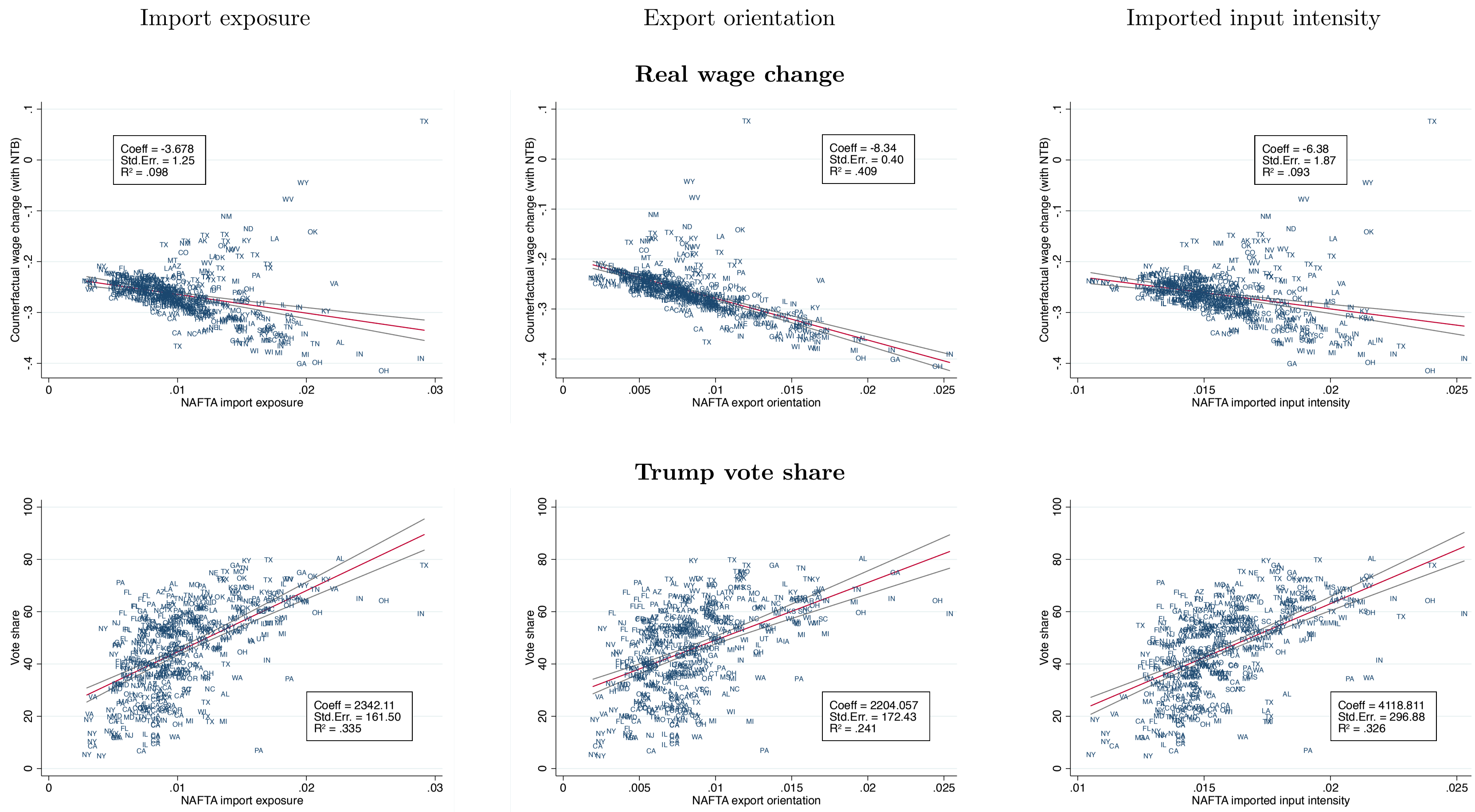
It may be informative to focus on voters that changed their vote in the 2016 election. To this end, Appendix Figure C.3 shows the scatterplots of the difference between the Trump 2016 vote share and the Romney 2012 vote share against the average real wage change at the congressional district level (left panel) and state level (right panel). Negative correlations are if anything more pronounced for the Trump-Romney increment than the Trump vote share itself, especially at the state level.

3.7 Conclusion

Today's global production arrangements will lead to strong spillovers of protectionist policies. Barriers to input trade can reduce the competitiveness of domestic industries as internationally sourced inputs become more expensive. In a global input-output network, a tariff aimed at one specific trade partner or import sector ultimately affects all sectors of the domestic economy, yet very heterogeneously so. It is thus a domestic redistributive policy. In a highly interconnected world economy with supply chains crossing country borders, it is not transparent which workers stand to gain or lose from trade policy changes. In this paper, we undertake a quantitative assessment of both the aggregate and the distributional effects of one proposed trade policy change: revoking NAFTA.

We find that NAFTA revocation lowers real incomes in the large majority of sectors in all three NAFTA countries, and that average wages fall in nearly all US congressional districts, and in all Mexican states and Canadian provinces. Within this range of negative values, however, these are still differences in outcomes across locations. Correlating real wage changes with recent voting patterns, we show that if anything Trump-voting congressional districts would lose relatively more from the revocation of NAFTA. Our results underscore the difficulty of making simple heuristic judgements about who gains and loses from trade policy changes in the current global economy.

Figure 3.7: Heuristic measures, real wage changes and 2016 Trump vote share



Notes: The top row of the Figure depicts the scatterplots of the real wage change at a congressional district level against each of the heuristic measures defined in Section 3.5.2. The bottom row of the Figure depicts the scatterplots of the Trump vote share against each of the heuristic measures defined in Section 3.5.2. The lines through the data are the OLS fit. The boxes report the coefficient, robust standard error, and the R^2 of the bivariate regression.

Table 3.4: Vote shares and heuristic measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	NAFTA rollback wage change				Trump vote share			
Export orientation	-8.341***			-30.88***	2204.1***			-1219.9***
	(0.400)			(0.688)	(172.4)			(469.0)
Import exposure		-3.678***		25.62***		2342.1***		2602.2***
		(1.247)		(0.885)		(161.5)		(671.1)
Imported input intensity			-6.383***	-6.857***			4118.8***	1420.9
			(1.868)	(1.570)			(296.9)	(884.5)
N. obs.	435	435	435	435	435	435	435	435
R^2	0.409	0.098	0.088	0.933	0.241	0.335	0.326	0.351

Notes: Robust standard errors in parentheses. ***: significant at the 1% level; **: significant at the 5% level. In columns (1) to (4), the dependent variable is the percentage wage change caused by a revocation of NAFTA in the congressional district. In columns (5) to (8), the dependent variable is the vote share Donald Trump received during the 2016 presidential election in the congressional district. Variable definitions and sources are described in detail in the text.

Table 3.5: Skill-specific wage and welfare changes

	Real wage change, %				
	High skill	Medium skill	Low skill	Total welfare change, %	in bn. US$
			Tariff and NTB baseline		
Canada	-1.39	-1.29	-0.29	-2.04	-34.38
Mexico	-1.19	-1.90	-0.73	-1.57	-19.20
United States	-0.31	-0.33	-0.38	-0.23	-40.68
			Tariff only		
Canada	-0.27	-0.39	-0.49	-0.05	-0.88
Mexico	-0.33	-0.67	0.02	-0.14	-1.67
United States	-0.05	-0.06	-0.10	-0.01	-2.12
			Tariff and uniform NTB		
Canada	-1.85	-1.99	-1.80	-1.97	-33.12
Mexico	-1.44	-2.56	-1.38	-1.68	-20.53
United States	-0.27	-0.28	-0.31	-0.23	-41.95

Notes: This table reports the aggregate real wage changes for each skill type, and the total welfare changes, in percentage points and in billion US$, for the NAFTA countries under the three NAFTA revocation scenarios.

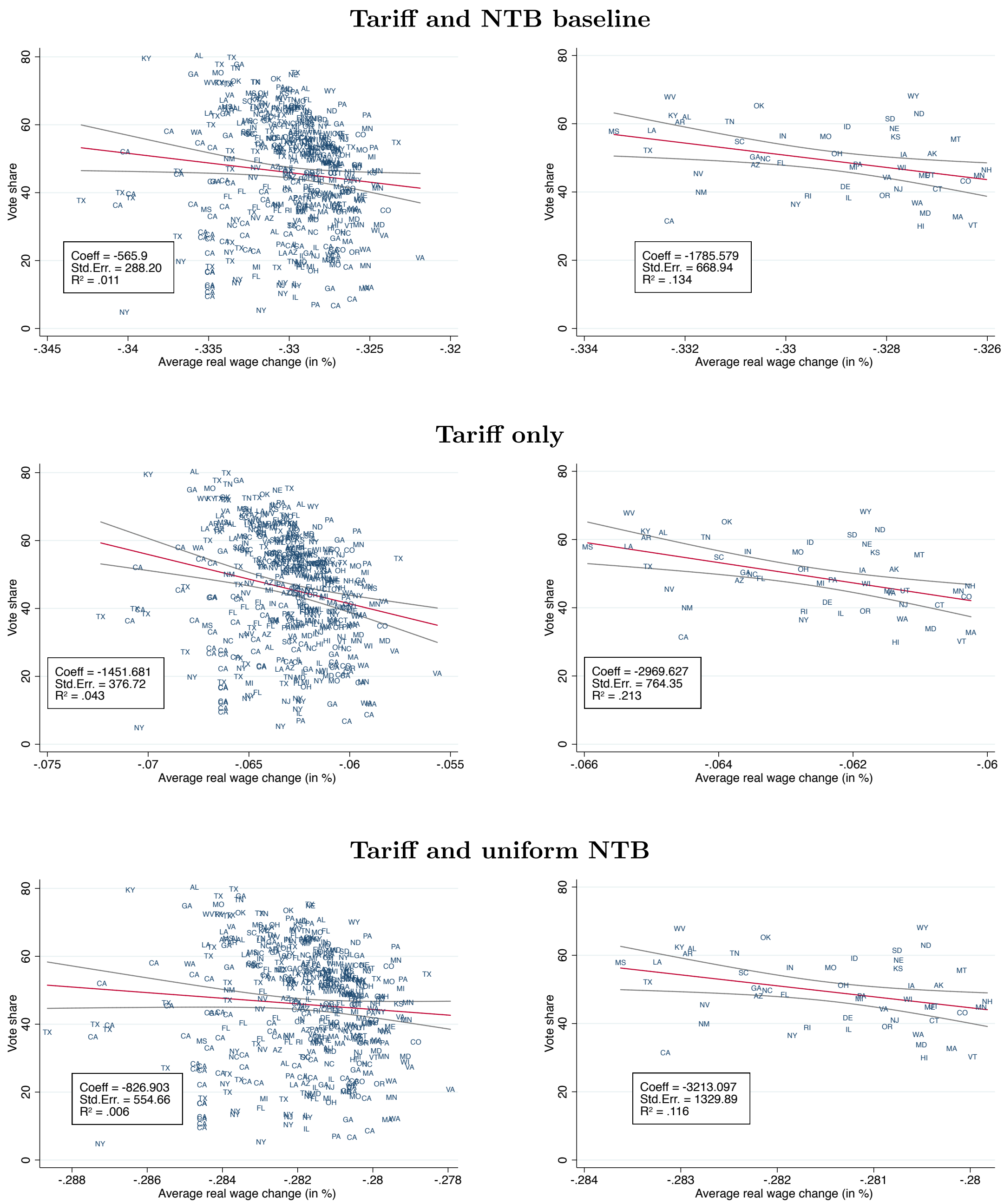
Table 3.6: Aggregate real wage changes and welfare changes for different θ (Tariff and NTB baseline)

	Real wage change, %	Total welfare change, %	in bn. US$
	$\theta = 2.5$		
Canada	-1.93	-2.23	-37.62
Mexico	-1.98	-1.77	-21.65
United States	-0.32	-0.26	-46.75
	$\theta = 8$		
Canada	-1.41	-1.96	-33.01
Mexico	-1.60	-1.73	-21.10
United States	-0.23	-0.19	-34.19

Notes: This table reports the aggregate real wage changes and the total welfare changes, in percentage points and in billion US$, for the NAFTA countries under the two alternative values of θ.

Figure 3.8: Real wage changes and 2016 Trump vote share, mobile factors

Congressional district level State level



Notes: This figure depicts the scatterplots of the average real wage change from revoking NAFTA and the 2016 Trump vote share by congressional district (left side) and state (right side) under the assumption of perfect factor mobility across sectors, along with the OLS fit. The boxes report the coefficient, robust standard error, and the R^2 of the bivariate regression.

APPENDICES

APPENDIX A

Appendices to Chapter 1

A.1 Data

This sections details the sources of the data and addresses potential concerns about its quality.

A.1.1 Trade data

Construction of the trade data

The main dataset in the analysis is the firm-port-destination export dataset. I build this dataset by combining several sources.

India importer-exporter directory I first use the India Importer and Exporter directory published by the Directorate General of Commercial Intelligence and Statistics branch of the Ministry of Commerce and Industry.[1] The directory contains a list of Indian firms involved in importing or exporting in India. To perform any import or export transaction in India, firms need to register to get an Importer-Exporter Code (IEC). The directory contains the details of around twenty thousand firms with their IEC. The coverage includes firms that self-registered, and firms that were added by

[1]The directory can be accessed online at the DGCIS website: `http://dgciskol.gov.in/` under the menu "Trade Directory".

the DGCIS based on observed transactions from the Customs. The additional details are the firms' address and items (HS code) they import or export.

Exporter Status List I complement the list of firms by using the list of IECs of firms with special Exporter Status delivered by the Directorate General of Foreign Trade. Large exporters can obtain a special status that allows them to lower their administrative burden, for example by self-authenticating certificates of origin.

Firms' address and branches I get additional firm details such as addresses of the headquarter and all branches from the Customs National Trade Portal (*icegate*).[2] I get the coordinates of each postal code (*pincode*) from `http://www.geonames.org/`. I complete missing coordinates by manually searching for the postal codes on Google maps.

List of transactions by firm I obtained the list of import and export transaction for each IEC from ICEGATE's "IECwise summary report" form.[3] The list includes the shipping bill number (or for exports the bill of entry number), the date of the transaction and the port of exit (entry). I then obtain additional details of the transactions from the public enquiry "tracking at ICES" form using the shipping bill and bill of entry numbers. The additional details are value, weight, and port of destination as well as other additional dates ("let export", "out of charge"). For export transactions through an Inland port, the details also include the eventual Indian port of exit.

[2]The details used to also be available from the DGFT's website, where I obtained the data for most of the firms. Cross-checks between ICEGATE's data and the DGFT's data ensured that the two are identical.

[3]Until early 2021, that form was publicly available. It has since been made private.

Sectoral classification I merge the list of exporter/importer firms with the Indian Economic Census directories of establishment[4] and with the "Master Details" of registered companies from the Ministry of Corporate Affairs.[5] I use a name-matching algorithm together with postal code matching, to match the firm names in my trade dataset to the firms in those two sources. I can then obtain the NIC code for each firm.[6]

Representativity of the final trade dataset

Firm sample The final sample is comprised of 16,000 firms. Table A.1 lists largest sectors at the NIC-2digits level. The main sectors are the usual manufacturing sectors, as well as wholesale and intermediaries (74 and 51)) that account for around 20% all transactions. Appendix A.2 discuss the robustness of the paper's stylized facts to removing those intermediaries. Table A.2 displays the summary statistics of total export transactions, value, number of destinations, and number of ports used by firm.

Table A.1: Main sectoral composition

NIC 2-digits	Description	Share of obs	Share of value
24	Chemicals and Chemical Products	0.126	0.122
74	Other business activities	0.113	0.094
51	Wholesale trade	0.106	0.127
17	Textiles	0.078	0.059
18	Wearing apparel	0.060	0.030
29	Machinery and equipment NEC	0.056	0.042
27	Basic Metals	0.042	0.061
15	Food and Beverages	0.039	0.040
28	Fabricated Metal Products	0.032	0.027
25	Rubber and Plastic	0.029	0.018

Notes: "NIC" refers to the National Industry Classification, which falls under the general International Standard Industry Classification (ISIC). One observation is a transaction.

[4]These lists are available from the Ministry of Statistics and Programme Implementation at `http://www.mospi.nic.in`

[5]That data is available from the MCA's website at `http://www.mca.gov.in/`.

[6]NIC stands for "National Industry Classification", which is a sectoral classification consistent with the UN's International Standard Industry Classification (ISIC).

Table A.2: Firm level summary statistics

	Value (log)	Number of ports	Number of destinations
Average	13.83	1.64	7.72
Median	14.13	1	4
p25	12.41	1	1
p75	15.45	2	10

Notes: The table shows summary statistics of total (log) exports in USD, number of ports used, and number of destination served per firm for the year 2019.

The total exports in my dataset for the year of 2019 are around 90.9 USD billion, against 324 billion in the aggregate official statistics. Below, I show that even though my sample only covers around 29% percent of total exports, it is representative in terms of port usage and destinations.

Port and country shares To check how my sample compares to the aggregate in terms of ports and country shares, I download the port-country level exports from the Directorate General of Commercial Intelligence and Statistics.[7] The left panel of Figure A.1 plots the share of each port in my sample against the share in the full dataset. The dots are located along a 45 degree line, indicating that my sample is representative in this key dimension. The right panel of Figure A.1 repeats the same exercise at the country level. Again, all dots are close to the 45 degree line.

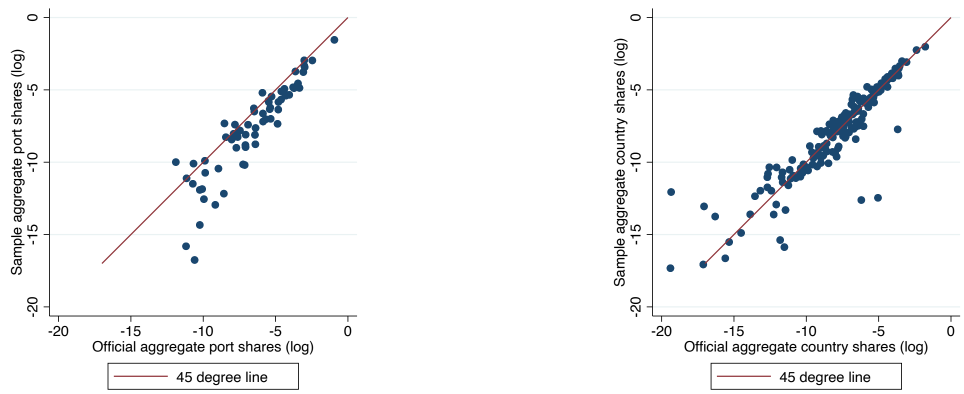
A.1.2 Port data and sea distance

Ports coordinates I use the UN/LOCODE database to get the coordinates of Indian and foreign ports.[8] For some Indian ports, coordinates are missing. I manually add them by searching for the port on Google maps.

Ports characteristics I use the annual "Basic Ports Statistics of India" published by the Transport Research Wing of the Shipping Ministry to get data on port to-

[7] That data is available from the "Data dissemination portal" on the DGCIS' website at `http://dgciskol.gov.in/`.
[8] The data is available at `https://unece.org/trade/uncefact/unlocode`

Figure A.1: Port and country shares representativity



Port shares   Country shares

Notes: The left panel displays the fit between the share of Indian exports through each port between my sample and the official aggregate data. The right panel displays the fit between the share of Indian exports to each destinations between my sample and the official aggregate data.

pography (minimum depth), equipment (number of berth, handling equipment) and capacity.[9] The same report also contains measures of port productivity (turnaround time, pre-berthing wait time, output per ship berth-day).

Sea distance I compute the sea distance between each port and foreign port destination using the *searoute* package from Eurostat.[10] I then use the average distance between the port and all foreign ports (weighted by number of transactions) in the country of destination as my measure of port-destination sea distance.

A.1.3 Road data

Highway data My main source of data for the road network is Open Street Map (OSM). OSM is a crowd-sourced map of the world, that includes details on roads among many other things. Each road is classified by category of importance, and highways with a separation in the middle are marked as oneway. Further, information

[9]The reports are available at `http://shipmin.gov.in/division/transport-research`

[10]The package is available at `https://github.com/eurostat/searoute` and allows to compute the sea distance between two points by specifying their coordinates.

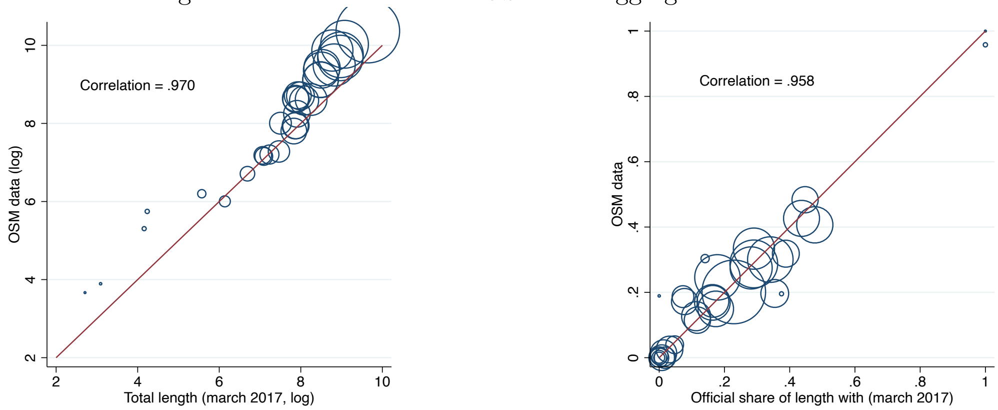
on the number of lanes is available for a subset of the roads. I use the oneway classification, the lane number, and additional category classification (motorway, trunk road) in the OSM data to construct two categories of highway: four or more lanes (more than 2 lanes per direction, with a physical separation in the middle, which I label as "expressway"), or twoway highways (no separation in the middle, the majority of which have 2 lanes in total, shared for both directions, which I label as "normal road").

I extract all large roads from OSM using the following rule. I first extract any road segment from OSM that are either tagged as "NHXX", where NH stands for "National Highway" and XX for the relevant number. Then, because some states also have high quality state highways, I also keep any segment that matches the tag "motorway", "trunk", or "motorroad=yes".[11]

One concern regarding this source of data is that it is user-based and might miss some information. However, information on large highways (which constitute the part of the infrastructure used in the analysis) are less likely to be missing. Finally, my classification fits the official data well at the state level. The left panel of Figure A.2 shows the scatter plot of the length by category at the state level in my final data and against the official 2017 statistics. The right panel shows the share of "expressway" against the share of national highways with 4 or more lanes (in total for both directions) in the state. The dots lie along the 45 degree line, and the correlation is large and highly significant. In the aggregate, the road network in my data contains around 54,900 km of "expressway" and 164,500 km of "normal road".

[11] See `https://wiki.openstreetmap.org/wiki/Tagging_Roads_in_India` for the guidelines that users are invited to follow when tagging Indian roads on OSM. I also keep "link" segments between motorways and trunk roads.

Figure A.2: Match between OSM and aggregate data



Length

Quality composition

Notes: The figure compares my final data to the data from the "Basic Road Statistics of India 2016-2017". The left panel displays the total length of road in my data in a given state (in logs), against the official state aggregate. The right panel displays the share of road (by length) that I classify as "expressway" on the y axis, against the official share of national highway with 4 lanes of more. The size of the circle is proportional to total road length in the state.

Least-cost distance To compute the least-cost route between an origin district and a port, I first compute the centroid of the district based on the map files provided by the Data{Meet} Community Maps Project.[12] I then find the closest point of the centroid on the highway network, and use that point as the starting point of routes from the district to the ports. I also place the ports on their closest point on the network.

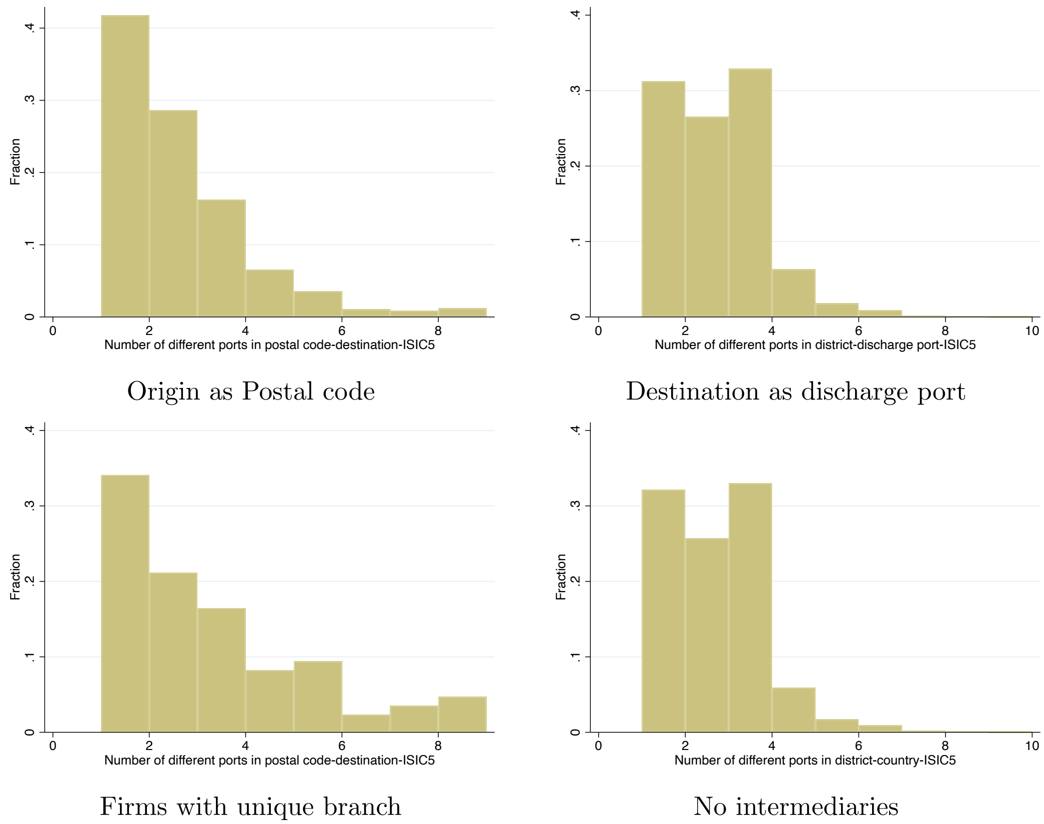
I compute the least-cost route to each port according to equations (1.10) and (1.11), by fist weighting the edges of the highway network using their distance multiplied by the cost parameters β^c, and then using the Dijkstra algorithm. I compute the district-district road distances in the same way.

A.2 Stylized facts robustness

Figure A.3 displays the number of ports per sector-origin-destination triplet for different aggregation of origin and destination, and for different firm subsamples. In

[12] See `http://projects.datameet.org/maps/districts/`.

Figure A.3: Number of ports per sector-origin-destination



Origin as Postal code — Destination as discharge port

Firms with unique branch — No intermediaries

Notes: The top left panel displays the histogram of the number of ports per origin-sector-destination triplet, where the origin is a 6-digit postal code. The top right panel defines a destination as a discharge port rather than a country. The bottom left panel defines a destination as a discharge port. The bottom right panel removes firms whose ISIC code could refer to intermediaries (51 and 74). Only triplets with more than one firm are kept to avoid artificial ones.

all cases, there is more than one port for the majority of triplets.

A.3 Estimation

In this section, I provide more details about the estimation procedure for θ, and additional robustness checks.

A.3.1 Elasticity estimation

Moment condition derivation To derive the moment condition, it is useful to present first the following result to calculate the expectation of the minimum trade cost ($\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}$), to the power of any λ:

$$E\left[\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^\lambda\right] = \left[\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{\lambda}{\theta}} \Gamma\left(1+\frac{\lambda}{\theta}\right),$$

where Γ is the Gamma function. To prove this, notice that the CDF of the minimum trade cost is given by:

$$\begin{aligned} P\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}} < t\right) &= 1 - P\left(\frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}} > t, \forall\rho\right) \\ &= 1 - \prod_\rho \exp\left(-\left(\frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{t}\right)^{-\theta}\right) \\ &= 1 - \exp\left(-\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^\theta\right). \end{aligned}$$

So the PDF of the trade cost is given by:

$$f(t) = \exp\left(-\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^\theta\right) \theta \sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^{\theta-1},$$

and the expectation of interest is given by:

$$\begin{aligned} E\left[\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^\lambda\right] &= \int_0^\infty t^\lambda \exp\left(-\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^\theta\right) \theta \sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^{\theta-1} dt \\ &= \int_0^\infty \exp\left(-\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^\theta\right) \theta \sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^{\lambda+\theta-1} dt. \end{aligned}$$

Using $x = \sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta} t^\theta$ to do a change of variable yields:

$$E\left[\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^\lambda\right] = \left[\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{\lambda}{\theta}} \int_0^\infty \exp(-x)\, x^{\frac{\lambda}{\theta}} dx,$$

and using the fact that $\Gamma(\alpha) = \int x^{\alpha-1} e^{-x} dx$ gives the desired result:

$$E\left[\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^\lambda\right] = \left[\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{\lambda}{\theta}} \Gamma\left(1+\frac{\lambda}{\theta}\right).$$

To get equation (1.6), remember that $p_{iod} = \mu c_i \left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)$, so using the previous result, the expectation of the ratios of values with respect to the Fréchet draws is given by:

$$
\begin{aligned}
E\left[\frac{X_{iod}}{X_{io\delta}}/\frac{X_{jo'd}}{X_{jo'\delta}}\right] &= E\left[\left(\frac{p_{iod}}{p_{io\delta}}/\frac{p_{jo'd}}{p_{jo'\delta}}\right)^{(1-\sigma)}\right] \\
&= E\left[\left(\frac{\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)}{\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho\delta}}{\varepsilon_{io\rho\delta}}\right)}/\frac{\left(\min_\rho \frac{\tau_{o'\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{jo'\rho d}}\right)}{\left(\min_\rho \frac{\tau_{o'\rho}\tau_\rho\tau_{\rho\delta}}{\varepsilon_{jo'\rho\delta}}\right)}\right)^{(1-\sigma)}\right] \\
&= \Gamma\left(1+\frac{1-\sigma}{\theta}\right)^2\Gamma\left(1-\frac{1-\sigma}{\theta}\right)^2 \\
&\quad * \left(\frac{\sum_\rho\left(\tau_{o\rho}\tau_\rho\tau_{\rho\delta}\right)^{-\theta}}{\sum_\rho\left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}}/\frac{\sum_\rho\left(\tau_{o'\rho}\tau_\rho\tau_{\rho\delta}\right)^{-\theta}}{\sum_\rho\left(\tau_{o'\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}}\right)^{\frac{1-\sigma}{\theta}},
\end{aligned}
$$

where I used the previous results with $\lambda = (1-\sigma)$ for the terms in the nominator and $\lambda = (\sigma-1)$ for the terms in the denominator. The law of iterated expectation and the independence of ε across firms, ports and destination allows to solve for the expectation of each term separately.

Robustness Table A.3 shows the results of the estimation of the port elasticity θ when using shares of transactions as a measure for $\pi_{o\rho d}$, and Table A.4 shows the results of the estimation of the port elasticity θ when using shares of value as a measure for $\pi_{o\rho d}$.

Table A.3: Elasticity estimation results (share of transactions)

	District level			Postal code level		
	Pooled	ISIC3	ISIC5	Pooled	ISIC3	ISIC5
$\frac{\sigma-1}{\theta}$	0.826	0.855	0.839	0.889	0.867	0.853
	(.002)	(.001)	(.002)	(.001)	(.001)	(.002)
N	2,587,540	289,036	134,536	9,394,312	686,531	219,800
Cluster	destination pair					

Notes: This table shows the results of estimating the elasticity parameter using the strategy outlined in section 1.4.

Table A.4: Elasticity estimation results (share of FOB value)

	District level			Postal code level		
	Pooled	ISIC3	ISIC5	Pooled	ISIC3	ISIC5
$\frac{\sigma-1}{\theta}$	0.745	0.788	.7759	0.747	0.795	0.780
	(.003)	(.003)	(.004)	(.005)	(.009)	(.0045
N	2,587,540	289,036	134,536	9,394,312	686,531	219,800
Cluster	destination pair					

Notes: This table shows the results of estimating the elasticity parameter using the strategy outlined in section 1.4.

A.4 Model appendix

A.4.1 Model calibration data

The calibration approach uses the following Lemma, taken from Eckert (2019):

Lemma A.1. *Consider the mapping defined as:*

$$A_i = \sum_j B_j \frac{\lambda_i K_{ij}}{\sum_k \lambda_k K_{kj}}$$

For any strictly positive $A_i \gg 0$, $B_i \gg 0$ such that $A_i = B_i$, and strictly positive matrix $K > 0$, there exist a unique (to scale), strictly positive vector of $\lambda_i \gg 0$.

Proof. See Eckert (2019). □

Lemma A.1 implies that given d_{od} and $\alpha_d X_d$, there is a unique (to scale) vector of λ_o that satisfies equation (1.24). To further fit the observable country-level trade share exactly, I set up the following problem.

Find λ_o, a_d^{exp}, a_o^{imp} such that the following model equilibrium condition is satisfied:

$$\alpha_o X_o = \sum_d \frac{\lambda_o \left(\tau_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(\tau_{kd}\right)^{1-\sigma}} \alpha_d X_d,$$

the model-implied aggregate India share in destination d's expenditure matches the data:

$$\sum_{o \in IND} \pi_{od} = \sum_{o \in IND} \frac{\lambda_o \left(\tau_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(\tau_{kd}\right)^{1-\sigma}} = \pi_{IND,d}^{DATA},$$

and the model-implied share of origin o in India's total expenditure matches the data:

$$\sum_{d \notin IND} \frac{X_{d,IND}}{X_{IND}} = \frac{\sum_{d \in IND} \lambda_o \left(\tau_{od}\right)^{1-\sigma} \alpha_d X_d}{\sum_k \sum_{d \in IND} \lambda_k \left(\tau_{kd}\right)^{1-\sigma} \alpha_d X_d} = \pi_{o,IND}^{DATA},$$

where:

$$\tau_{od} = \begin{cases} 1 & \text{if } o = d \\ \exp\left(\sum_c \beta^c dist_{od}^c\right) & \text{if } o, d \in IN \\ a_d^{exp} \underbrace{\left[\sum_\rho \left(\exp\left(\sum_c \beta^c dist_{o\rho}^c\right) \tilde{\tau}_\rho \left(seadist_{\rho d}\right)^\gamma\right)^{-\theta}\right]^{-\frac{1}{\theta}}}_{\tilde{\tau}_{od}} & \text{if } o \in IN, d \notin IN \\ a_o^{imp} \left[\sum_\rho \left(\exp\left(\sum_c \beta^c dist_{o\rho}^c\right) \tilde{\tau}_\rho \left(seadist_{\rho d}\right)^\gamma\right)^{-\theta}\right]^{-\frac{1}{\theta}} & \text{if } o \notin IN, d \in IN \\ \tau_{od} & \text{if } o, d \notin IN \end{cases}$$

The normalization constants a_d^{exp} and a_o^{imp} allow me to match the aggregate Indian shares $\pi_{IND,d}^{DATA}$ and $\pi_{o,IND}^{DATA}$ exactly, while the relative costs $\tilde{\tau}_{od}$ drive the within-India regional variation. I use the following iterative algorithm to solve for λ:

1. Guess a vector of λ and compute the corresponding τ_{od} to match the observable trade shares exactly:

   (a) Foreign-foreign shares:

   $$\frac{\tau_{od}}{\tau_{dd}} = \left(\frac{\frac{\pi_{od}^{DATA}}{\lambda_o}}{\frac{\pi_{dd}^{DATA}}{\lambda_d}}\right)^{1-\sigma}, \forall o, d \notin IND,$$

   (b) India to foreign flows:

   $$\left(a_d^{exp}\right)^{1-\sigma} = \frac{\pi_{IND,d}^{DATA} / \sum_{o \in IND} \lambda_o \left(\tilde{\tau}_{od}\right)^{1-\sigma}}{\pi_{d,d}^{DATA} / \lambda_d},$$

   (c) Foreign to India flows:

   $$\left(a_o^{imp}\right)^{1-\sigma} = \frac{\pi_{o,IND}^{DATA} / \sum_{d \in IND} \lambda_o \left(\tilde{\tau}_{od}\right)^{1-\sigma} X_d}{\pi_{IND,IND}^{DATA} / \sum_{o \in IND} \sum_{d \in IND} \lambda_o \left(\tau_{od}\right)^{1-\sigma} X_d}.$$

2. Solve for new λ solving $X_o = \sum_d \frac{\lambda_o \tau_{od}^{1-\sigma}}{\sum_k \lambda_k \tau_{kd}^{1-\sigma}} X_d$, normalizing $\lambda_1 = 1$.

3. Go back to 1 with the new guess for λ until convergence.

A.5 Counterfactuals appendix

A.5.1 Equilibrium in changes

The equilibrium in changes is a set of trade share changes $\hat{\pi}_{od}$, wage changes $\hat{w}_d$, and price index change $\hat{P}_d$ that satisfy:

$$\hat{\pi}_{od} = \frac{\left(\hat{w}_o \hat{d}_{od}\right)^{1-\sigma}}{\sum_k \underbrace{\pi_{kd}}_{\text{data}} \left(\hat{w}_k \hat{d}_{kd}\right)^{1-\sigma}},$$

$$\hat{w}_o = \sum_d \hat{\pi}_{od} \hat{w}_d \underbrace{\frac{X_{od}^G}{\alpha_o X_o}}_{\text{data}},$$

$$\hat{P}_d = \left(\sum_k \underbrace{\pi_{kd}}_{\text{data}} \left(\hat{w}_k \hat{d}_{kd}\right)^{1-\sigma}\right)^{\frac{\alpha_d}{1-\sigma}} \left(\hat{w}_d\right)^{1-\alpha_d},$$

where the changes in trade costs $\hat{d}_{od}$ are exogenous and given by:

$$\hat{d}_{od} = \begin{cases} 1 & o, d \text{ foreign} \\ \left[\sum_\rho \pi_{o\rho d} \left(\hat{\tau}_{o\rho} \hat{\tau}_\rho\right)^{-\theta}\right]^{-\frac{1}{\theta}} & o \text{ indian district, } d \text{ foreign} \\ \left[\sum_\rho \pi_{o\rho d} \left(\hat{\tau}_\rho \hat{\tau}_{\rho d}\right)^{-\theta}\right]^{-\frac{1}{\theta}} & o \text{ indian district, } d \text{ foreign} \\ 1 & o, d \text{ indian districts} \end{cases}$$

and $\hat{\tau}_{o\rho}$ and $\hat{\tau}_\rho$ are as specified in section 1.7.2.

APPENDIX B

Appendices to Chapter 2

B.1 Simplified model derivation

Start from the labor market clearing equation:

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

Define P_n as the total population of region n: $P_n = \frac{\alpha\gamma_n + (1-\alpha)\beta_n}{1-\alpha} L$ if $n \in US$, and $P_{RW} = R - \frac{\alpha}{1-\alpha} L$. We have that:

$$w_n P_n = \sum_i \pi_{ni} w_i P_i$$

Before taking the derivative of equation (B.1), consider first the partial derivatives with respect to α of P_n and π_{ni}.

$$\frac{\partial P_n}{\partial \alpha} = \frac{1}{(1-\alpha)^2} \gamma_n L,$$

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

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

Regarding the trade shares, we have:

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

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

$$\frac{\partial \pi_{ni}}{\partial \alpha} = \pi_{ni}\Bigg[-\frac{\theta}{w_n}\frac{\partial w_n}{\partial \alpha} + \theta\sum_k \pi_{ki}\frac{\partial w_k}{\partial \alpha}\frac{1}{w_k} + \theta\eta\frac{1}{\alpha}\frac{1-migsh_n}{1-\alpha} - \theta\eta\frac{1}{\alpha}\sum_{k\in US}\pi_{ki}\frac{1-migsh_k}{1-\alpha}\Bigg], i = RW$$

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

$$\frac{dw_n}{d\alpha}P_n + w_n\frac{dP_n}{d\alpha} = \sum_i \frac{d\pi_{ni}}{d\alpha}w_iP_i + \pi_{ni}\frac{dw_i}{d\alpha}P_i + \pi_{ni}w_i\frac{dP_i}{d\alpha}$$

Plug in for trade share change:

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

and rearange:

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

Plug in for change in population:

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

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

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

Divide by $w_n L_n = X_n$ and rearange:

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

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

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

Realize that $\frac{w_{RW}}{X_n} \frac{MIGPOP}{(1-\alpha)} = \frac{w_{RW} L_n}{X_n} \frac{migsh_n}{(1-\alpha)} = \frac{migsh_n}{(1-\alpha)}$:

$$\begin{aligned}
\left(\xi_n^w - \sum_i \xi_i \frac{X_{ni}}{X_n} \right) + \theta \left(\xi_n - \sum_{i,k} \pi_{ki} \xi_k \frac{X_{ni}}{X_n} \right) = -\frac{migsh_n}{(1-\alpha)} + \sum_{i \in US} \frac{X_{ni}}{X_n} \frac{migsh_i}{(1-\alpha)} \\
+ \frac{1}{1-\alpha} \frac{X_{nRW}}{X_n} \left(\theta \eta \left(1 - migsh_n - \sum_{k \in US} \pi_{kRW} \left(1 - migsh_k \right) \right) - \frac{MIGPOP}{RWPOP} \right),
\end{aligned}$$

which is equation (2.4).

B.2 Additional regression results

Table B.1 displays the full results of the regression presented in the main body of the paper. All first stage results are strong, and the sign of bilateral controls are as expected.

Table B.1: Full Results and First Stage Regressions

	log $(exports)$				First stage		
	OLS		IV		ln(mig)	ln(HSmig)	ln(LSmig)
$\ln(migrants)$	0.152***		0.208***				
	(.059)		(.065)				
$\ln(HSmig)$		0.091+		0.308***			
		(.052)		(.105)			
$\ln(LSmig)$		0.057		-0.056			
		(.038)		(.077)			
ln($distance$)	-1.377**	-1.387**	-1.325**	-1.342**	-0.364+	-0.752+	-0.443
	(.621)	(.622)	(.595)	(.593)	(0.213)	(.377)	(.282)
Adjacency	0.348***	0.346***	0.304***	0.289***	0.097	0.513***	0.345
	(0.164)	(.161)	(0.164)	(.168)	(0.180)	(.087)	(.224)
$\ln(instr.)$					0.753***		
					(0.026)		
$\ln(instr.HS)$						0.520***	
						(.058)	
$\ln(instr.LS)$							0.404***
							(.027)
KP F-Stat			791.3	140.7			
Imp. and exp. FE	✓	✓	✓	✓	✓	✓	✓
Country clust. SE	✓	✓	✓	✓	✓	✓	✓
N	2511	2511	2511	2511	2511	2511	2511

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

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

Table B.2: Robustness results

	(1)	(2)	(3)	(4)	(5)	(6)
	PPMLE		$migrants = 1 + mig$		Extended sample	
$\ln(migrants)$	0.275***		0.204***		0.141***	
	(.056)		(.054)		(0.033)	
$\ln(HSmig)$		0.489***		0.305***		0.316***
		(.127)		(.099)		(.064)
$\ln(LSmig)$		-0.121		-0.041		-0.098**
		(.090)		(.067)		(.047)
KP F-Stat			586.2	99.2	2387.5	352.9
Imp. and exp. FE	✓	✓	✓	✓	✓	✓
Standard Errors	robust	robust	imp. clust.	imp. clust.	imp. clust.	imp. clust.
N	2719	2517	2704	2552	5918	5150

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

B.3 Skill and imperfect substitutability model

B.3.1 Model details

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

On the goods market, the trade shares satisfy

$$\pi_{ni}^{trade} = \frac{A_n (d_{ni} C_n)^{-\theta}}{\sum_s A_s (d_{si} C_s)^{-\theta}},$$

where the labor bundle cost C_n is given by:

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

and each skill labor bundle cost is itself given by:

[1] In the bigger sample, there are a total of 135 countries, but not all states export to them. Due to convergence issues, the PPMLE standard errors are not clustered at the importing country level.

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

where the labor bundle costs are derived from the firm's profit maximization problem.

Total revenue is equal to total output:

$$X_n = \sum_i \pi_{ni}^{trade} X_i.$$

On the labor market, for each skill s:

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

where labor supply from migration choices implies that:

$$L_{nn}^s = \left(B_{nn}^s\right)^{\frac{1}{\varepsilon}} \left(\pi_{nn}^{s,mig}\right)^{\frac{\varepsilon-1}{\varepsilon}} N_n^s \gamma,$$

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

where $\gamma = \Gamma(\frac{\varepsilon-1}{\varepsilon})$ and $\Gamma(.)$ is the gamma function. And total revenue is equal to total labor revenue:[2]

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

[2]For expositional convenience, I am omitting the fact that when $n \in US$, workers from every US states get wage w_n^{sd}. In that case, one would have:

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

The migration shares satisfy

$$\pi_{in}^{s,mig} = \frac{B_{in}^s \left(\frac{\left(w_n^{sd}\right)^{(i=n)} (w_n^{sm})^{(i \neq n)}}{P_n \kappa_{in}^s} \right)^{\varepsilon}}{\sum_k B_{ik}^s \left(\frac{\left(w_k^{sd}\right)^{(i=k)} \left(w_k^{sm}\right)^{(i \neq k)}}{P_k \kappa_{ik}^s} \right)^{\varepsilon}},$$

where

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

Finally, the trade costs are given by

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

where

$$N_{in}^s = \pi_{in}^{s,mig} N_i^s.$$

Equilibrium in changes

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

$$\hat{\pi}_{in}^{s,mig} = \frac{\hat{B}_{in}^s \left(\frac{\left(\hat{w}_n^{sd}\right)^{(i=n)} (\hat{w}_n^{sm})^{(i \neq n)}}{\hat{P}_n \hat{\kappa}_{in}} \right)^{\epsilon}}{\sum_k \hat{B}_{ik}^s \left(\frac{\left(\hat{w}_k^{sd}\right)^{(i=n)} \left(\hat{w}_k^{sm}\right)^{(i \neq n)}}{\hat{P}_k \hat{\kappa}_{ik}^s} \right)^{\varepsilon} \pi_{ik}^{s,mig}}$$

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

$$\hat{P}_n = \left(\frac{\hat{A}_n (\hat{C}_n)^{-\theta}}{\hat{\pi}_{nn}^{trade}} \right)^{-\frac{1}{\theta}}$$

$$\hat{C}_n = \left[\left(\hat{C}_n^L \right)^{1-\rho} \sum_i \Theta_{in}^L + \left(\hat{C}_n^H \right)^{1-\rho} \sum_i \Theta_{in}^H \right]^{\frac{1}{1-\rho}},$$

where Θ_{in}^s is the initial share of the wage bill going to s-skill workers from i, in country n ($\Theta_{in}^s = \frac{w_n^{sm} L_{in}^s}{X_n}$ if $i \neq n$, $\Theta_{nn}^s = \frac{w_n^{sd} L_{in}^s}{X_n}$), and when $n \notin US$:

$$\hat{C}_n^s = \left[\left(\hat{w}_n^{sd} \right)^{1-\lambda} \frac{\Theta_{nn}^s}{\sum_i \Theta_{in}^s} + \left(\hat{w}_n^{sm} \right)^{1-\lambda} \frac{\sum_{i \neq n} \Theta_{in}^s}{\sum_i \Theta_{in}^s} \right]^{\frac{1}{1-\lambda}},$$

When $n \in US$:

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

Trade cost changes are given by:

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

$$\hat{X}_n X_n = \sum_i \hat{\pi}_{in}^{trade} \pi_{in}^{trade} \left(\hat{X}_i X_i \right)$$

$$\hat{X}_n = \hat{C}_n^H \hat{L}_n^H \sum_i \Theta_{in}^H + \hat{C}_n^L \hat{L}_n^L \sum_i \Theta_{in}^L$$

$$\hat{C}_n^H \hat{L}_n^H = \hat{C}_n^L \hat{L}_n^L \left(\frac{\hat{C}_n^H}{\hat{C}_n^L} \right)^{1-\rho}$$

For $n \notin US$:[3]

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

[3]When $n \in US$

$$\frac{\hat{w}_n^{sd}}{\hat{w}_n^{sm}} = \frac{\left(\sum_{i \notin US} \hat{L}_{in}^s \frac{\Theta_{in}^s}{\sum_{k \neq n} \Theta_{kn}^s} \right)^{-\frac{1}{\lambda}}}{\left(\sum_{i \in US} \hat{L}_{in}^s \frac{\Theta_{in}^s}{\sum_{k \neq n} \Theta_{kn}^s} \right)^{-\frac{1}{\lambda}}}$$

For $n \notin US$:[4]

$$\hat{C}_n^s \hat{L}_n^s = \hat{w}_n^{sd} \hat{L}_{nn}^s \frac{\Theta_{nn}^s}{\sum_k \Theta_{kn}^s} + \hat{w}_n^{sm} \sum_{i \neq n} \hat{L}_{in}^s \frac{\Theta_{in}^s}{\sum_k \Theta_{kn}^s}$$

Solving the model in changes enables me to solve for counterfactual quantities given exogenous changes in technology A, B, and migration and trade costs κ and τ, by using only data on trade, migration, and age bill shares (π_{ik}^{trade}, $\pi_{ik}^{s,mig}$, X_i, N_{ik}^{sd}, N_{ik}^{sm}, Θ_{in}^s), as well as parameter values for ε, θ, ρ, λ and η^s. Subsection B.3.2 details how to map these objects into the data.

B.3.2 Calibration of the skill model

Table B.3 lists the value of the parameters and their source. The following subsections provide additional details on the link between the data and the model.

B.4 Data and calibration

B.4.1 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).[5] 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

[4] When $n \in US$

$$\hat{C}_n^s \hat{L}_n^s = \hat{w}_n^{sd} \sum_{i \in US} \hat{L}_{in}^s \frac{\Theta_{in}^s}{\sum_k \Theta_{kn}^s} + \hat{w}_n^{sm} \sum_{i \in US} \hat{L}_{in}^s \frac{\Theta_{in}^s}{\sum_k \Theta_{kn}^s}$$

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

Table B.3: Link between the model and the data

	Description	Value	Source
Parameter			
ϵ	migration elasticity	2.3	Caliendo et al. (2017)
ρ	Elasticity of substitution between skill	1.6	Katz and Murphy (1992)
λ	Elasticity of substitution between native and migrant work	20	Ottaviano and Peri (2012)
θ	trade elasticity	4	Simonovska and Waugh (2014)
η^s	migration-elasticity of trade costs	$\eta^H = 0.3/\theta$ $\eta^L = 0$	own estimate
Exogenous object			
$\hat{A}_n$, $\hat{B}_{in}^s$,$\hat{\tau}_{in}$		1	keep constant
$\hat{\kappa}_{in}^s$	migration costs		Uniformly increased to target a reduction of 50% in total migrant stock living in the US
Data			
$\pi_{in}^{s,mig}$, N_{in}^s	population data		ACS, World Bank, OECD
π_{in}^{trade}, X_n	trade data (including services)		Census data on state level exports and imports, WIOD, CFS
Θ_{in}^s	initial wage bill shares		ACS, IPMUS-International

Notes: see below for details on the sources and exact mapping between the data and the model objects.

model) as:

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

For i or j in the US, I first use the ACS to construct $N_{i,US}$, which I define as the total population born in state i and residing in the US ($N_{i,US} = \sum_{j \in US} N_{ij}$, where N_{ij} comes 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[6]) and compute the skill share: $shskill_{ij}^s = \frac{IPUMS_{ij}^s}{IPUMS_{ij}}$. When $i \in US$, there is no information on the state of origin. In that case, I use the ACS data to apportion the skilled and unskilled by state i: $shskill_{ij}^s = \frac{\frac{ACS_{iUS}^s}{\sum_{n \in US} ACS_{nUS}^s} IPUMS_{USj}^s}{\frac{ACS_{iUS}}{\sum_{n \in US} ACS_{nUS}} IPUMS_{USj}}$.

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

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.[7]. 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.

B.4.2 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

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

from the state.

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

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

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

If $i, j \in US$:

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

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.[8] In Appendix B.5, I check the robustness of my results to this assumption by assuming that the same fraction of service output that is exported by the US to the rest of the world is also traded within the US. More precisely, define the share of tradable in services as $\sigma = X_{US,ROW}^{SERVICE} / \left(X_{US,US}^{SERVICES} + X_{US,ROW}^{SERVICES} \right)$. Then when computing X_{ij} for $i \neq j$, $i, j \in US$, use that same share to compute trade flows:

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

where I use sectoral employment data to attribute the service production to each state. For own-state flow, I use:[9]

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

[8] In the ICIO data, the share of US exports in US service output is around 5%, while it is around 15% for non-services. I define services as anything that is not agriculture, mining or manufacturing.

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

B.4.3 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_{in} in the main model, Θ^s_{in} in the skill model) directly from the survey data also used to construct the migration shares.[10] This ensures that the migration and wage bill data are consistent with each other.

For other countries where survey data is not readily available, I simply use migrant population shares to input the wage bill shares. This assumes that the average wage of all workers in the country is the same, which ignores selection into migration. However, when using the same method to impute wage bill shares for US states, Canada and Mexico, the correlation is high at 0.99. Furthermore, the counterfactual will mostly affect the US, Canada and Mexico to a lesser extent, and the rest of the world much less. Hence the parameters for the rest of the world imputed from US, Canada and Mexican data don't have a significant quantitative importance.

B.4.4 List of regions in the model

Table B.4 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 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.

[10] 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.

Table B.4: 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

B.5 Robustness checks

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

Main model Table B.5 displays the average changes in trade costs, export as share of output, and welfare for alternative calibration for the main counterfactual. Overall, the results are fairly stable when changing the migration elasticity. The change in export trade costs is sensitive to the trade elasticity, because I calibrate $\eta = 0.2/\theta$, but the effect on exports as share of output is stable. The change in welfare is larger for a small trade elasticity, as wages need to fall by more to achieve the same change in exports. Figure B.1 shows the average changes in real wages across US states, decomposed into the average own-state effect, internal market access effect, and international market access, for the same set of robustness checks. In all cases, the own-state effect is positive, because the reduced labor supply is not offset by a larger reduction in market access when only migrant population in the state is reduced. The intra- and international market access effects are negative throughout.

Skill and imperfect substitutability model Table B.6 displays the average changes in trade costs, export as share of output, and welfare for alternative calibration for the main counterfactual with the skill and substitutability model. Figure B.2 shows the average changes in real wages across US states, decomposed into the average own-state effect, internal market access effect, and international market access. The native/migrant elasticity of substitution plays an important role in determining wether the own-state effect (driven mainly by the labor supply effect) is positive or

Table B.5: Sensitivity analysis for the main model

	Migration elasticity $\varepsilon = 1.5$	$\varepsilon = 3$	Trade elasticity $\theta = 2$	$\theta = 6$	Less tradable services
Change in state export costs (exports weighted)	3.67%	3.69%	7.52%	2.44%	3.68%
	(.16)	(.16)	(.34)	(.10)	(0.16)
Change in exports as share of output	-4.97%	-4.27%	-4.06%	-4.62%	-4.59%
	(0.92)	(1.10)	(1.00)	(1.08)	(1.18)
Change in natives' welfare	-0.13%	-0.13%	-0.23%	-0.09%	-0.07%
	(0.06)	(0.10)	(0.14)	(0.06)	(0.05)

Notes: The table shows the percentage changes, after reducing the share of migrants in the US population by half. Numbers are average across US states, with standard deviation in parenthesis. See section B.4.2 for details on the "Less tradable services" scenario.

Figure B.1: Real wage change decomposition: robustness

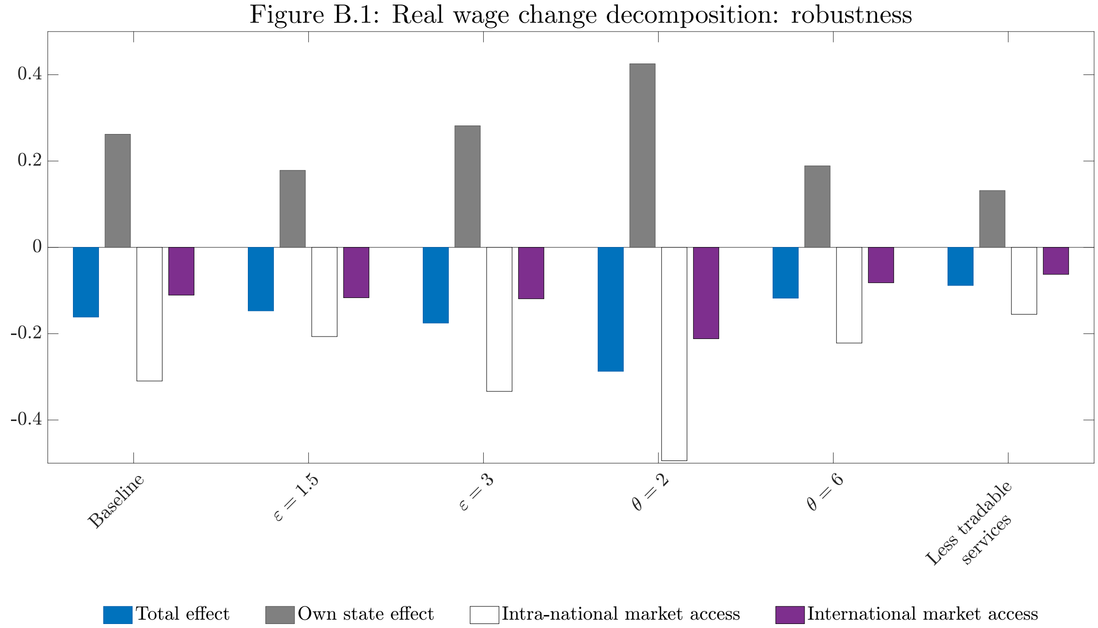


Table B.6: Sensitivity analysis for the skill and imperfect substitutability model

	Native/migrant substitutability		Skill substitutability	Less tradable services
	$\lambda = 5$	$\lambda = 100$	$\rho = 50$	
Change in state export costs	5.44%	5.50%	5.49%	5.48%
(exports weighted)	(0.22)	(0.23)	(0.23)	(0.23)
Change in exports	-6.82%	-7.22%	-7.09%	-7.35%
as share of output	(1.35)	(1.34)	(1.34)	(1.39)
Change in US low-skill welfare	-0.84%	-0.21%	-0.36%	-0.25%
	(0.24)	(0.21)	(0.06)	(0.16)
Change in US college welfare	-0.93%	-0.23%	-0.36%	-0.30%
	(0.19)	(0.07)	(0.05)	(.07)

Notes: The table shows the percentage changes, after reducing the share of migrants in the US population by half. Numbers are average across US states, with standard deviation in parenthesis. See section B.4.2 for details on the "Less tradable services" scenario.

negative. With a low elasticity of substitution, the effect of the reduction in migration is large and negative, while a high substitutability moves the results closer to the main model.[11] The skill substitutability matters less. Overall, both the intra- and international market access effects stay large and negative, regardless of the production function elasticities.

B.6 Algorithms

B.6.1 Algorithm for the main model

This section describes how to solve the model in changes. This solution allows for trade deficits D_n to exist, hence the relevant income for location is not wage w_n but $v_n = w_n + D_n/L_n$.[12] Results in the paper come from first creating a deficit-free

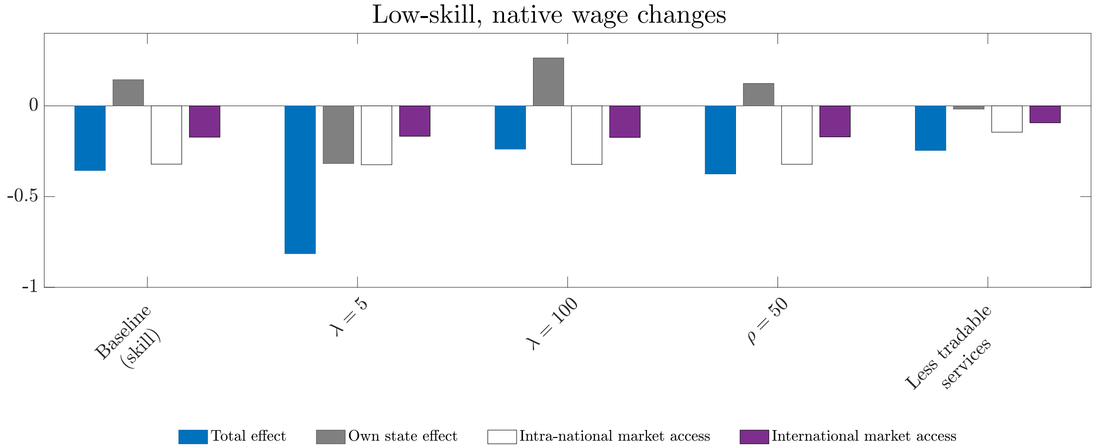
[11] The baseline model without skills and imperfect native-migrant substitutability does not produce exactly the same results as the refined model even when both λ and ρ are set to infinity, because of the different migration shares of skilled and unskilled workers. Since the model interprets high migration shares as reflecting a high B^s_{in}, the fall in effective labor supply is different in the two models even with infinite substitutability.

[12] That is, I assume that the deficit is redistributed uniformly to each efficiency unit of labor. Using the following equation, one can solve for $\hat{v}_n$:

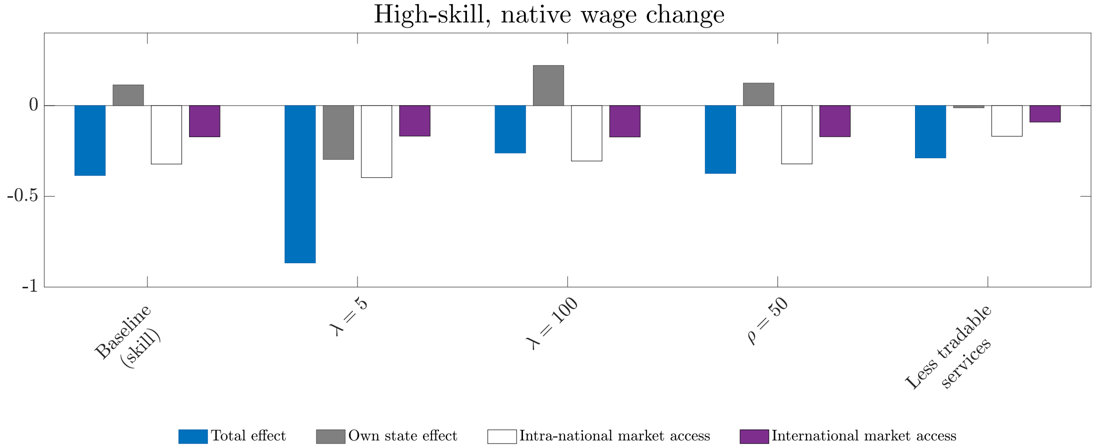
$$X_n^{cons} v_n \sum_i L_{in} = X_n^{outp} + D_n$$

Figure B.2: Imperfect substitutability scenario robustness: decomposition

Low-skill, native wage changes



High-skill, native wage change



equilibrium by solving the system of equation below setting $\hat{D}_n = 0$ while keeping other exogenous variables constant, and then using the resulting trade, migration and wage bill shares to solve for a counterfactual change in migration costs.[13]

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

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

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

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

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

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

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

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

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

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

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

   (c) Solve for $\hat{w}_n$ using

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

$$\hat{v}_n\sum_i \hat{L}_{in}\frac{v_nL_{in}}{X_n^{outp}} = \hat{X}_n^{outp} + \frac{D_n}{X_n^{outp}}\hat{D}_n$$

$$\hat{v}_n\sum_i\left(\hat{B}_{in}\right)^{\frac{1}{\varepsilon}}\left(\hat{\pi}_{in}^{mig}\right)^{\frac{\varepsilon-1}{\varepsilon}}\hat{N}_i\Theta_{in}\frac{X_n^{cons}}{X_n^{outp}} = \hat{X}_n^{outp} + \frac{D_n}{X_n^{outp}}\hat{D}_n$$

[13]The new wage bill shares can be computed as:

$$\Theta_{in}^{'} = \frac{w_n'L_{in}'}{X_n'} = \frac{\hat{w}_n\hat{L}_{in}}{\hat{X}_n}\Theta_{in} = \frac{\hat{w}_n\left(\hat{B}_{in}\right)^{\frac{1}{\varepsilon}}\left(\hat{\pi}_{in}^{mig}\right)^{\frac{\varepsilon-1}{\varepsilon}}\hat{N}_i}{\hat{X}_n}\Theta_{in}$$

(d) Go back to (a) using updated $\hat{w}_n$

4. Solve for $\hat{v}_n$,$\hat{P}_n$ and $\hat{\pi}_{in}^{mig}$ using:

$$\hat{v}_n \sum_i \left(\hat{B}_{in}\right)^{\frac{1}{\varepsilon}} \left(\hat{\pi}_{in}^{mig}\right)^{\frac{\varepsilon-1}{\varepsilon}} \hat{N}_i \Theta_{in} \frac{X_n^{cons}}{X_n^{outp}} = \hat{X}_n^{outp} + \frac{D_n}{X_n^{outp}} \hat{D}_n$$

$$\hat{P}_n = \left(\frac{\hat{A}_n (\hat{w}_n)^{-\theta}}{\hat{\pi}_{nn}^{trade}}\right)^{-\frac{1}{\theta}}$$

$$\hat{\pi}_{in}^{mig} = \frac{\hat{B}_{in}\left(\frac{\hat{v}_n}{\hat{P}_n \hat{\kappa}_{in}}\right)^{\epsilon}}{\sum_k \hat{B}_{ik}\left(\frac{\hat{v}_k}{\hat{P}_k \hat{\kappa}_{ik}}\right)^{\varepsilon} \pi_{ik}^{mig}}$$

5. Go back to 1 using updated $\hat{\pi}_{in}^{mig}$

B.6.2 Algorithm for the skill model

This section describes how to solve the model in changes. This solution allows for trade deficits D_n to exist, hence the relevant income for location is not wage w_n^{sm} or w_n^{sd} but v_n^{sm} or v_n^{sd}, where I assume that deficits are redistributed proportionally to income.[14] Results in the paper come from first creating a deficit-free equilibrium by solving the system of equation below setting $\hat{D}_n = 0$ while keeping other exogenous variables constant, and then using the resulting trade and migration shares to solve for a counterfactual change in migration costs.

1. Guess $\hat{\pi}_{in}^{s,mig}$

[14] That is:

$$L_{nn}^s v_n^{sd} = L_{nn}^s w_n^{sd} + \Theta_{nn}^s D_n = \Theta_{nn}^s \left(X_n^{outp} + D_n\right)$$

$$L_{in}^s v_n^{sm} = L_{in}^s w_n^{sm} + \Theta_{in}^s D_n = \Theta_{in}^s \left(X_n^{outp} + D_n\right)$$

In changes:

$$\hat{L}_{nn}^s \hat{v}_n^{sd} = \hat{\Theta}_{nn}^s \frac{\left(\hat{X}_n^{outp} X_n^{outp} + \hat{D}_n D_n\right)}{\left(X_n^{outp} + D_n\right)} = \frac{\hat{w}_n^{sd} \hat{L}_{nn}^s}{\hat{X}_n^{outp}} \frac{\left(\hat{X}_n^{outp} X_n^{outp} + \hat{D}_n D_n\right)}{\left(X_n^{outp} + D_n\right)}$$

so:

$$\hat{v}_n^{sd} = \frac{\hat{w}_n^{sd}}{\hat{X}_n^{outp}} \frac{\left(\hat{X}_n^{outp} X_n^{outp} + \hat{D}_n D_n\right)}{\left(X_n^{outp} + D_n\right)}, \ \hat{v}_n^{sm} = \frac{\hat{w}_n^{sm}}{\hat{X}_n^{outp}} \frac{\left(\hat{X}_n^{outp} X_n^{outp} + \hat{D}_n D_n\right)}{\left(X_n^{outp} + D_n\right)}.$$

2. Solve for $\hat{N}^s_{in}$, $\hat{L}^s_{in}$ and $\hat{d}_{ni}$ using

$$\hat{N}^s_{in} = \hat{\pi}^{s,mig}_{in}$$

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

$$\hat{d}_{ni} = \hat{\tau}_{ni} \prod_{s \in L,H} \left[1\left(i \mid n \notin US\right) \left(\frac{1 + \hat{N}^s_{in} N^s_{in}}{1 + N^s_{in}} \right) \left(\frac{\sum_j \hat{N}^s_{jn} N^s_{jn}}{\sum_{s,j} N^s_{jn}} \right) + 1\left(i, n \in US\right) \right]^{-\eta^s}$$

3. Solve for $\hat{w}^{sd}_n$, $\hat{w}^{sm}_n$: guess $(\hat{w}^{sd}_n, \hat{w}^{sm}_n)$

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

$$\hat{C}^s_n = \left[\left(\hat{w}^{sd}_n\right)^{1-\lambda} \frac{\Theta^s_{nn}}{\sum_i \Theta^s_{in}} + \left(\hat{w}^{sm}_n\right)^{1-\lambda} \frac{\sum_{i \neq n} \Theta^s_{in}}{\sum_i \Theta^s_{in}} \right]^{\frac{1}{1-\lambda}},$$

$$\hat{C}_n = \left[\left(\hat{C}^L_n\right)^{1-\rho} \sum_i \Theta^L_{in} + \left(\hat{C}^H_n\right)^{1-\rho} \sum_i \Theta^H_{in} \right]^{\frac{1}{1-\rho}}.$$

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

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

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

$$\hat{X}^{outp}_n X^{outp}_n = \sum_j \hat{\pi}^{trade}_{nj} \pi^{trade}_{nj} \left(\hat{X}^{outp}_j X^{outp}_j + \hat{D}_j D_j \right)$$

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

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

   (d) Compute $\hat{w}^{sd}_n$,$\hat{w}^{sm}_n$ using:

$$\hat{C}^L_n \hat{L}^L_n = \hat{X}_n / \left(\sum_i \Theta^L_{in} + \left(\frac{\hat{C}^H_n}{\hat{C}^L_n} \right)^{1-\rho} \sum_i \Theta^H_{in} \right)$$

$$\hat{C}^H_n \hat{L}^H_n = \hat{C}^L_n \hat{L}^L_n \left(\frac{\hat{C}^H_n}{\hat{C}^L_n} \right)^{1-\rho}$$

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

$$\hat{C}_n^s \hat{L}_n^s = \hat{w}_n^{sd} \hat{L}_{nn}^s \frac{\Theta_{nn}^s}{\sum_k \Theta_{kn}^s} + \hat{w}_n^{sm} \sum_{i\neq n} \hat{L}_{in}^s \frac{\Theta_{in}^s}{\sum_k \Theta_{kn}^s}$$

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

4. Solve for $\hat{v}_n^{sd}$, $\hat{v}_n^{sm}$, $\hat{P}_n$ and $\hat{\pi}_{in}^{s,mig}$ using:

$$\hat{v}_n^{sd} = \frac{\hat{w}_n^{sd}}{\hat{X}_n^{outp}} \frac{\left(\hat{X}_n^{outp} X_n^{outp} + \hat{D}_n D_n\right)}{\left(X_n^{outp} + D_n\right)}, \ \hat{v}_n^{sm} = \frac{\hat{w}_n^{sm}}{\hat{X}_n^{outp}} \frac{\left(\hat{X}_n^{outp} X_n^{outp} + \hat{D}_n D_n\right)}{\left(X_n^{outp} + D_n\right)}.$$

$$\hat{P}_n = \left(\frac{\hat{A}_n (\hat{w}_n)^{-\theta}}{\hat{\pi}_{nn}^{trade}}\right)^{-\frac{1}{\theta}}$$

$$\hat{\pi}_{in}^{s,mig} = \frac{\hat{B}_{in}^s \left(\frac{\left(\hat{v}_n^{sd}\right)^{(i=n)} \left(\hat{v}_n^{sm}\right)^{(i\neq n)}}{\hat{P}_n \hat{\kappa}_{in}}\right)^{\epsilon}}{\sum_k \hat{B}_{ik}^s \left(\frac{\left(\hat{v}_k^{sd}\right)^{(i=n)} \left(\hat{v}_k^{sm}\right)^{(i\neq n)}}{\hat{P}_k \hat{\kappa}_{ik}^s}\right)^{\varepsilon} \pi_{ik}^{s,mig}}$$

5. Go back to 1 using the updated $\hat{\pi}_{in}^{s,mig}$

APPENDIX C

Appendices to Chapter 3

C.1 Solution algorithm

To solve equations (3.8) to (3.15) start by guessing $\{\hat{w}_{jn}, \hat{r}_{jn}\}$ and use the following algorithm.

1. Solve for $\hat{p}_{jn}$ using equations (3.14) and (3.12):

$$\hat{p}_{jn} = \left(\sum_{m=1}^{N} \pi_{j,mn} (\hat{c}_{jm} \hat{\kappa}_{j,mn})^{-\theta} \right)^{-\frac{1}{\theta}}$$

$$\hat{p}_{jn} = \left[\sum_{m=1}^{N} \pi^{j}_{j,mn} \left(\left(\hat{w}_{jm}^{\alpha_{jm}} \hat{r}_{jm}^{1-\alpha_{jm}} \right)^{\beta_{jm}} \left(\prod_{i=1}^{J} (\hat{p}_{im})^{\gamma_{ij,m}} \right)^{1-\beta_{im}} \hat{\kappa}_{j,mn} \right)^{-\theta} \right]^{-\frac{1}{\theta}}$$

which can be solved iteratively. Then use $\hat{p}_{jn}$ to solve for $\hat{c}_{jn}$ and $\hat{P}_n$:

$$\hat{c}_{jn} = (\hat{w}_{jn}^{\alpha_{jn}} \hat{r}_{jn}^{1-\alpha_{jn}})^{\beta_{jn}} \left(\prod_{i=1}^{J} (\hat{p}_{in})^{\gamma_{ij,n}} \right)^{1-\beta_{jn}}$$

$$\hat{P}_n = \prod_{j=1}^{J} \left(\hat{p}_{jn} \right)^{\xi_{jn}}$$

2. Solve for $\hat{\pi}_{j,mn}$ using equation (3.11) and $\hat{c}_{jn}$:

$$\hat{\pi}_{j,mn} = \frac{(\hat{c}_{jm} \hat{\kappa}_{j,mn})^{-\theta}}{\sum_{m'=1}^{N} \pi_{j,m'n} (\hat{c}_{jm'} \hat{\kappa}_{j,m'n})^{-\theta}}$$

3. Use equations (3.8) and (3.9) to solve for $\hat{Y}_{jn}$ and $\hat{Q}_{jn}$:

$$
\begin{aligned}
\hat{p}_{jn}\hat{Y}_{jn} &= \sum_{i=1}^{J} \widehat{w}_{in} SL_{in} + \sum_{i=1}^{J} \widehat{r}_{in} SK_{in} \\
&\quad + \sum_{m\neq n}\sum_{i=1}^{J} \frac{\tau'_{i,mn}\widehat{\pi}_{i,mn}\widehat{p}_{in}\widehat{Q}_{in}}{1+\tau'_{i,mn}} \frac{\pi_{i,mn} p_{in} Q_{in}}{I_n} + \widehat{D}_n SD_n
\end{aligned}
$$

and

$$
\begin{aligned}
\hat{p}_{jn}\hat{Q}_{jn}(p_{jn}Q_{jn}) &= \hat{p}_{jn}\hat{Y}_{jn}(p_{jn}Y_{jn}) \\
&\quad + \sum_{i=1}^{J}(1-\beta_{in})\gamma_{ji,n}\Big(\sum_{m=1}^{N} \frac{\hat{\pi}_{i,nm}\pi_{i,nm}\hat{p}_{im}\hat{Q}_{im}(p_{im}Q_{im})}{(1+\tau'_{i,nm})} \Big)
\end{aligned}
$$

4. update the next guess for $\hat{w}_{jn}$, $\hat{r}_{jn}$ from the labor market clearing condition

$$
\widehat{w}_{jn} = \widehat{r}_{jn} = \frac{\sum_{m=1}^{N} \frac{\widehat{\pi}_{j,nm}\widehat{p}_{jm}\widehat{Q}_{jm}\pi_{j,nm}p_{jm}Q_{jm}}{1+\tau'_{j,nm}}}{\sum_{m=1}^{N} \frac{\pi_{j,nm}p_{jm}Q_{jm}}{1+\tau_{j,nm}}}.
$$

the solution is defined up to a numeraire, and in updating the $\hat{w}_{jn}$ and $\hat{r}_{jn}$'s, re-set a numeraire country's $\hat{w}_1 = 1$ (where country 1, sector 1 is the numeraire). Then the actual next guess to be returned to step 1 is:

$$
\begin{aligned}
\hat{w}_{jn}^{next} &= \frac{\hat{\hat{w}}_{jn}^{next}}{\hat{\hat{w}}_{11}^{next}} \\
\hat{r}_{jn}^{next} &= \frac{\hat{\hat{r}}_{jn}^{next}}{\hat{\hat{w}}_{11}^{next}}
\end{aligned}
$$

C.2 Robustness figures

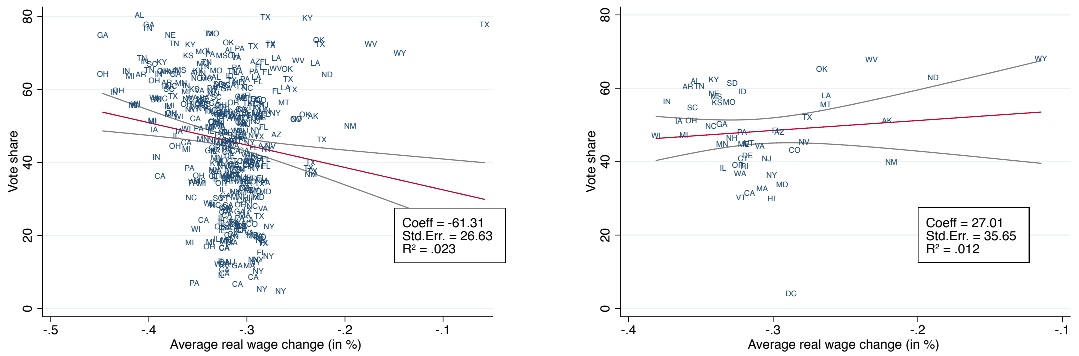
Figure C.1 plots the real wage changes against the Trump vote share when the trade elasticity is equal to 2.5. Figure C.2 plots the real wage changes against the Trump vote share when the trade elasticity is equal to 8.

Figure plots the real wage changes against the difference between 2016 Trump and 2012 Romney vote.

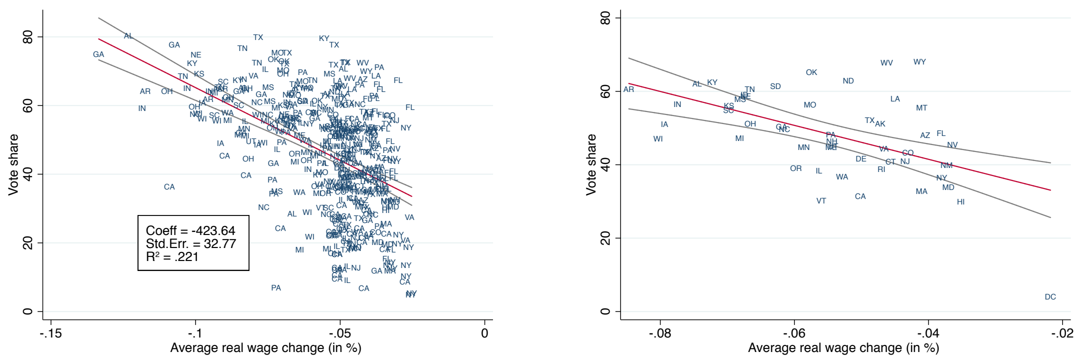
Figure C.1: Real wage changes and 2016 Trump vote share, $\theta = 2.5$

Congressional district level | State level

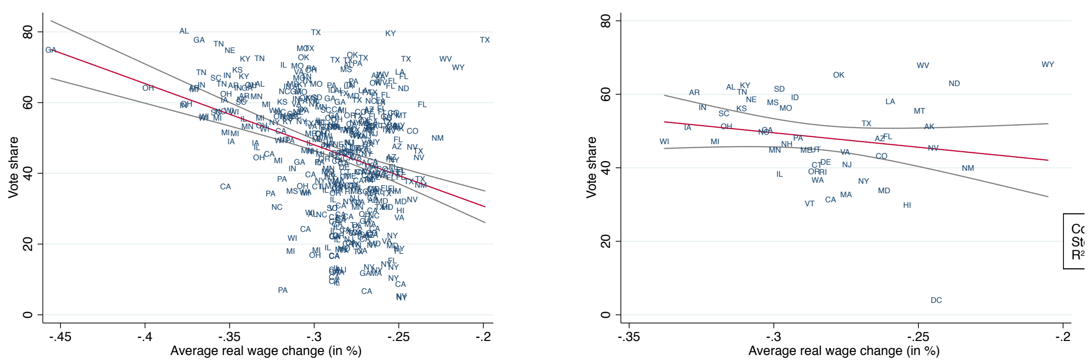
Tariff and NTB baseline



Tariff only

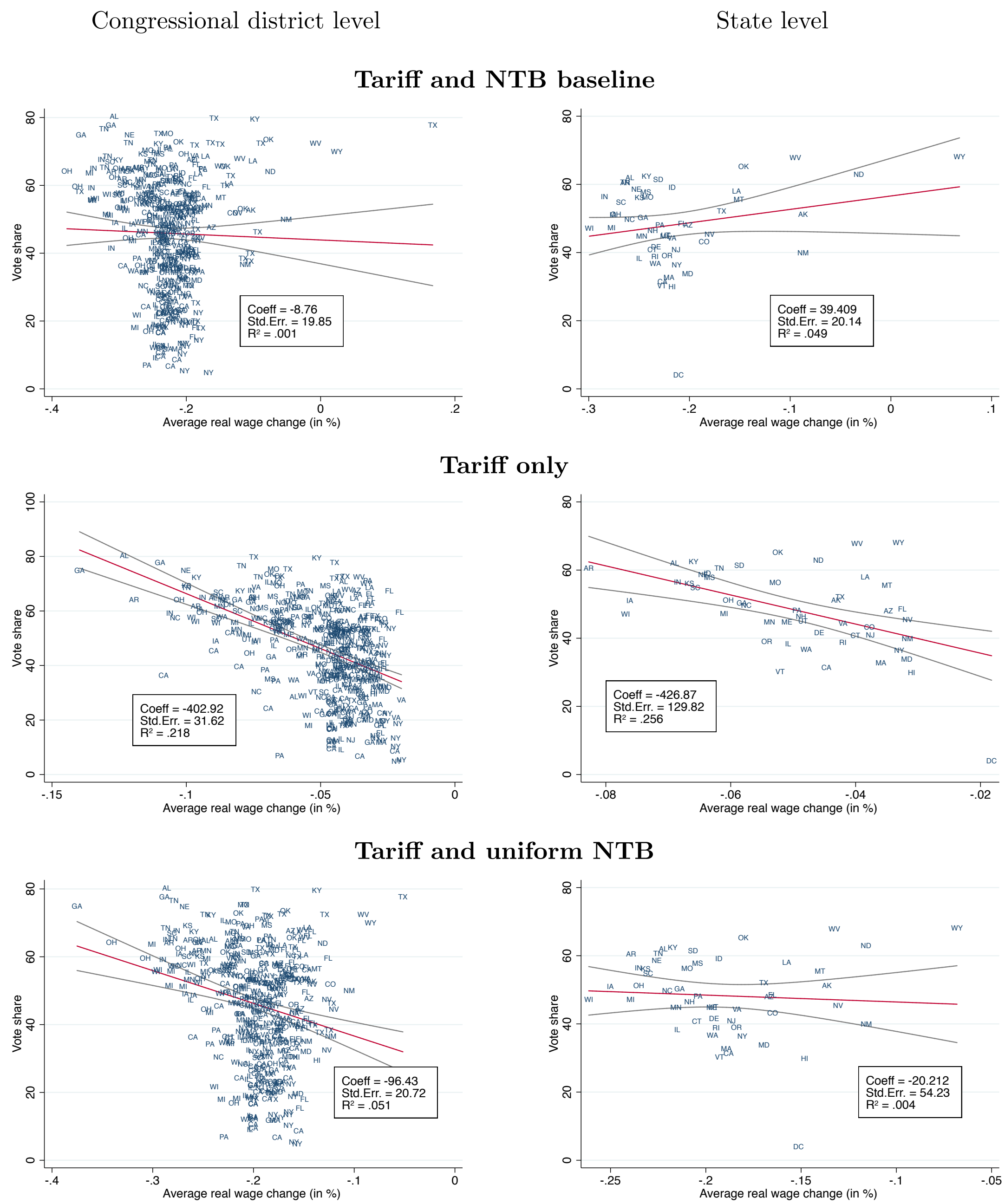


Tariff and uniform NTB



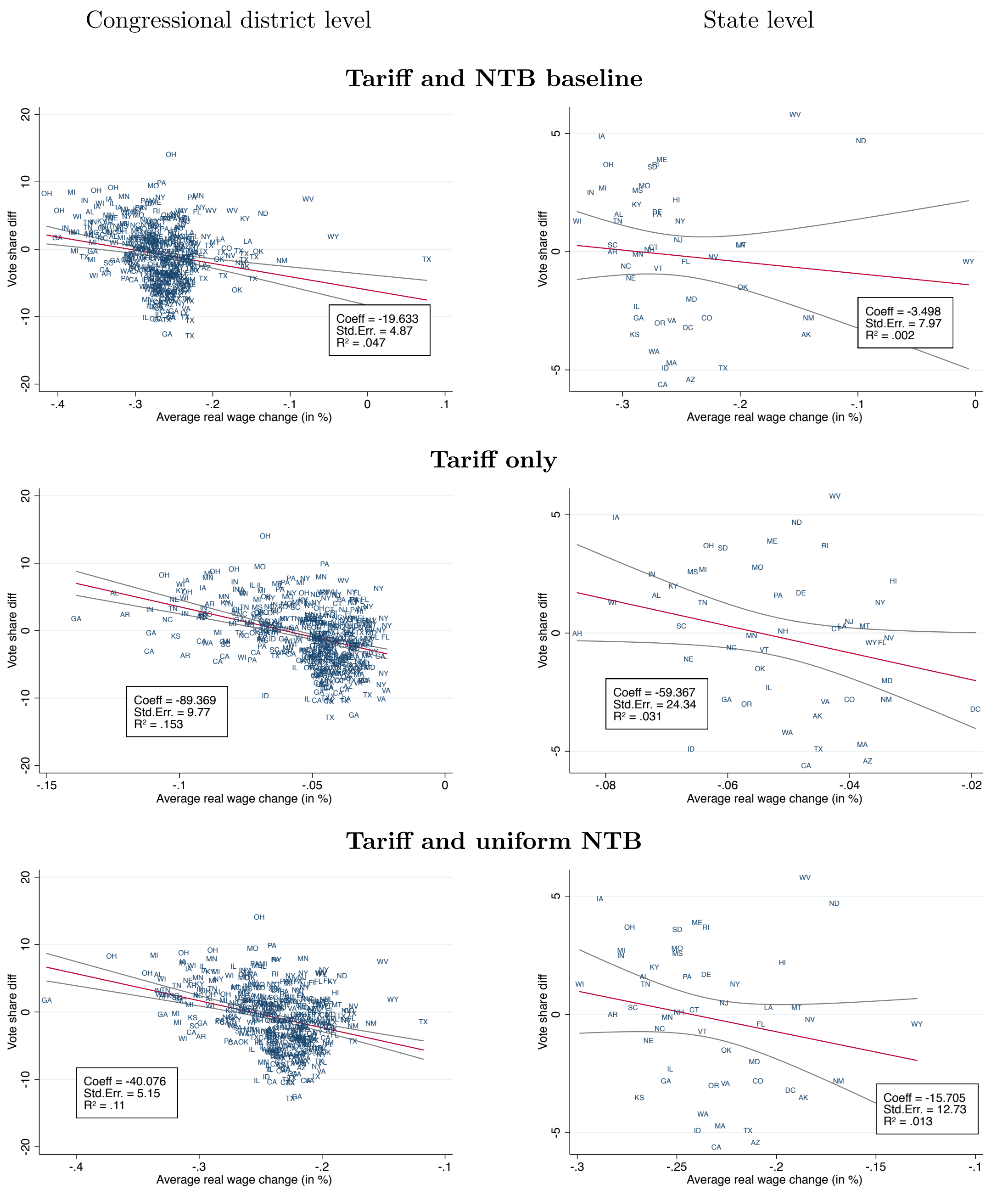
Notes: This figure depicts the scatterplots of the average real wage change from revoking NAFTA and the 2016 Trump vote share by congressional district (left side) and state (right side), along the OLS fit. The boxes report the coefficient, robust standard error, and the R^2 of the bivariate regression. The model is solved under $\theta = 2.5$.

Figure C.2: Real wage changes and 2016 Trump vote share, $\theta = 8$



Notes: This figure depicts the scatterplots of the average real wage change from revoking NAFTA and the 2016 Trump vote share by congressional district (left side) and state (right side), along the OLS fit. The boxes report the coefficient, robust standard error, and the R^2 of the bivariate regression. The model is solved under $\theta = 8$.

Figure C.3: Real wage changes and the difference between 2016 Trump vote share and the 2012 Romney vote share



Notes: This figure depicts the scatterplots of the average real wage change from revoking NAFTA and the difference between the 2016 Trump vote share and the 2012 Romney vote share by congressional district (left side) and state (right side), along the OLS fit. The boxes report the coefficient, robust standard error, and the R^2 of the bivariate regression.

C.3 Additional tables

Table C.1 displays the countries in the quantitative model, Table C.2 shows the sectors in the model, Table C.3 displays the assumed tariff and NTB changes, and Table C.4 displays the bottom and top 10 districts in terms of real wage change.

Table C.1: List of countries

Country	Country code
Australia	AUS
Austria	AUT
Belgium	BEL
Bulgaria	BGR
Brazil	BRA
Canada	CAN
Switzerland	CHE
China	CHN
Cyprus	CYP
Czech Republic	CZE
Germany	DEU
Denmark	DNK
Spain	ESP
Estonia	EST
Finland	FIN
France	FRA
United Kingdom	GBR
Greece	GRC
Croatia	HRV
Hungary	HUN
Indonesia	IDN
India	IND
Ireland	IRL
Italy	ITA
Japan	JPN
Korea	KOR
Lithuania	LTU
Latvia	LVA
Mexico	MEX
Netherlands	NLD
Norway	NOR
Poland	POL
Portugal	PRT
Romania	ROU
Slovakia	SVK
Slovenia	SVN
Sweden	SWE
Taiwan	TWN
United States	USA
Rest of the World	ROW

Table C.2: List of sectors

Sector description	WIOD sector
Crop and animal production, hunting	1
Forestry and logging	2
Fishing and aquaculture	3
Mining and quarrying	4
Manufacture of food products, beverages and tobacco products	5
Manufacture of textiles, wearing apparel and leather products	6
Manufacture of wood and of products of wood and cork, except furniture	7
Manufacture of paper and paper products	8
Printing and reproduction of recorded media	9
Manufacture of coke and refined petroleum products	10
Manufacture of chemicals and chemical products	11
Manufacture of basic pharmaceutical products and pharmaceutical preparations	12
Manufacture of rubber and plastic products	13
Manufacture of other non-metallic mineral products	14
Manufacture of basic metals	15
Manufacture of fabricated metal products, except machinery and equipment	16
Manufacture of computer, electronic and optical products	17
Manufacture of electrical equipment	18
Manufacture of machinery and equipment n.e.c.	19
Manufacture of motor vehicles, trailers and semi-trailers	20
Manufacture of other transport equipment	21
Other manufacturing, repair and installation of machinery and equipment	22-23
Energy, AC; Water ; Sewerage and waste management services	24-26
Construction	27
Wholesale and retail trade	28-29
Retail trade, except of motor vehicles and motorcycles	30
Land transport and transport via pipelines	31
Water transport	32
Air transport	33
Warehousing and support activities for transportation; Postal activities	34-35
Accommodation and food service activities	36
Publishing, telecommunications, computer, information service	37-40
Financial and insurance service activities and auxiliaries	41-43
Real estate, legal, accounting, consultancy, scientific, veterinary activities	44-49
Administrative and support service activities	50
Public admin. and defense; compulsory social security; Education	51-52
Human health and social work activities	53
Other service activities; Activities of households as employers	54

Table C.3: Assumed changes in US tariffs and NTB on Canada and Mexico if NAFTA is revoked

WIOD Sector	$\Delta\tau_{j,CAN\,USA}$	$\Delta\tau_{j,MEX\,USA}$	$\Delta\eta_{j,mUSA}$
1	3.447	3.440	7.651
2	3.898	3.362	0
3	0.088	0.324	0
4	0.003	0.006	27.997
5	3.526	4.992	5.076
6	3.006	4.323	0
7	0.620	5.371	9.606
8	0.225	1.812	6.609
9	0.020	0.001	23.593
10	3.677	4.815	7.506
11	2.741	2.918	8.056
12	0.176	0.370	4.795
13	1.962	1.491	11.365
14	1.816	3.927	0.606
15	1.043	0.999	8.637
16	1.844	3.190	16.779
17	2.094	1.846	1.782
18	2.482	2.772	9.840
19	0.982	1.400	3.134
20	2.406	6.288	12.682
21	0.188	1.206	7.074
22-23	1.573	1.803	0
24-26	0.800	4.118	9.734
27	0	0	7.660
28-29	0	0	25.964
30	0	0	32.112
31	0	0	10.204
32	0	0	9.840
33	0	0	4.741
34-35	0	0	12.830
36	0	0	0
37-40	0.004	0.002	15.182
41-43	0	0	14.974
44-49	0	0	17.838
50	0	0	0
51-52	0	0	0
53	0	0	27.396
54	0.364	1.677	4.424

Notes: This Table reports the change in sectoral tariffs on Mexico and Canada, and the change in the NTBs imposed by the US on Mexico and Canada, if NAFTA is revoked, expressed in percentage points. The sector key is in Table C.2.

Table C.4: Top and bottom 10 U.S. districts (Tariff and NTB baseline)

	Top 10	
District	Real wage change, %	Wage+tariff revenue, %
Texas, 11th	0.08	0.19
Wyoming (at large)	-0.04	0.07
West Virginia, 3rd	-0.08	0.05
New Mexico, 2nd	-0.11	0.01
North Dakota (at large)	-0.13	-0.02
Oklahoma, 3rd	-0.14	-0.02
Texas, 19th	-0.15	-0.02
Texas, 23rd	-0.15	-0.02
Louisiana, 3rd	-0.15	-0.04
Kentucky, 5th	-0.16	-0.03
	Bottom 10	
District	Real wage change, %	Wage+tariff revenue, %
Ohio, 4th	-0.41	-0.30
Georgia, 14th	-0.40	-0.27
Ohio, 5th	-0.40	-0.28
Indiana, 2nd	-0.39	-0.28
Michigan, 10th	-0.38	-0.26
Indiana, 3rd	-0.38	-0.26
Michigan, 2nd	-0.38	-0.26
Wisconsin, 6th	-0.38	-0.26
Wisconsin, 8th	-0.37	-0.26
Texas, 14th	-0.37	-0.24
Average	-0.27	-0.15
Median	-0.27	-0.15
Standard deviation	0.05	0.05

Notes: This Table reports the real wage changes of the top 10 and bottom 10 US congressional districts with the largest/smallest real wage changes.

BIBLIOGRAPHY

Ran Abramitzky and Leah Boustan. Immigration in American Economic History. *Journal of Economic Literature*, 55(4):1311–45, 2017.

Simon Alder. Chinese Roads in India: The Effect of Transport Infrastructure on Economic Development. mimeo, UNC, 2019.

Treb Allen and Costas Arkolakis. The Welfare Effects of Transportation Infrastructure Improvements. Working Paper 25487, National Bureau of Economic Research, January 2019.

Treb Allen and Costas Arkolakis. The Welfare Effects of Transportation Infrastructure Improvements. Working Paper 25487, National Bureau of Economic Research, December 2020.

Erhan Artuç, Shubham Chaudhuri, and John McLaren. Trade Shocks and Labor Adjustment: A Structural Empirical Approach. *American Economic Review*, 100(3):1008–45, June 2010.

Sam Asher, Tobias Lunt, Ryu Matsuura, and Paul Novosad. Development Research at High Geographic Resolution: An Analysis of Night Lights, Firms, and Poverty in India using the SHRUG Open Data Platform. World Bank Economic Review, 2021.

Jose Asturias, Manuel García-Santana, and Roberto Ramos. Competition and the Welfare Gains from Transportation Infrastructure: Evidence from the Golden Quadrilateral of India. *Journal of the European Economic Association*, 17(6):1881–1940, 2019.

David Atkin and Dave Donaldson. Who's Getting Globalized? The Size and Implications of Intranational Trade Costs. Technical report, National Bureau of Economic Research, 2015.

David H. Autor, David Dorn, and Gordon H. Hanson. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–68, October 2013.

Michael Bailey, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert J Richmond, and Johannes Stroebel. International Trade and Social Connectedness. Working Paper 26960, National Bureau of Economic Research, April 2020.

Luis Baldomero-Quintana. How Infrastructure Shapes Comparative Advantage. mimeo, Michigan, 2020.

Bruce A. Blonigen and Wesley W. Wilson. Port Efficiency and Trade Flows. *Review of International Economics*, 16(1):21–36, 2008.

Gharad Bryan and Melanie Morten. The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy*, 127(5):2229–2268, 2019.

Konrad B Burchardi, Thomas Chaney, and Tarek A Hassan. Migrants, Ancestors, and Foreign Investments. *The Review of Economic Studies*, 86(4):1448–1486, 2019.

Ariel Burstein, Gordon Hanson, Lin Tian, and Jonathan Vogel. Tradability and the Labor-Market Impact of Immigration: Theory and Evidence From the United States. *Econometrica*, 88(3): 1071–1112, 2020.

Lorenzo Caliendo and Fernando Parro. Estimates of the Trade and Welfare Effects of NAFTA. *Review of Economic Studies*, 82(1):1–44, 2015.

Lorenzo Caliendo, Luca David Opromolla, Fernando Parro, and Alessandro Sforza. Goods and Factor Market Integration: A Quantitative Assessment of the EU Enlargement. Working Paper 23695, National Bureau of Economic Research, August 2017.

Lorenzo Caliendo, Maximiliano Dvorkin, and Fernando Parro. Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. *Econometrica*, 87(3):741–835, 2019.

David Card. The Impact of the Mariel Boatlift on the Miami Labor Market. *ILR Review*, 43(2): 245–257, 1990.

Miguel Cardoso. The Trade-Creation Effect of Migrants: a Multi-Country General Equilibrium Analysis. mimeo, Brock University, 2019.

Miguel Cardoso and Ananth Ramanarayanan. Immigrants and Exports: Firm-Level Evidence from Canada. mimeo, Brock University, 2019.

Pierre-Philippe Combes, Miren Lafourcade, and Thierry Mayer. The Trade-Creating Effects of Business and Social Networks: Evidence from France. *Journal of International Economics*, 66 (1):1–29, 2005.

Arnaud Costinot and Andrés Rodríguez-Clare. Trade Theory with Numbers: Quantifying the Consequences of Globalization. In Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, editors, *Handbook of International Economics*, volume 4, chapter 4, pages 197–261. Elsevier, 2014.

Alonso de Gortari. Disentangling Global Value Chains. mimeo, Dartmouth, May 2019.

Alan V. Deardorff and Robert M. Stern. *Computational Analysis of Global Trading Arrangements*. The University of Michigan Press, Ann Arbor, 1990.

Robert Dekle, Jonathan Eaton, and Samuel Kortum. Global Rebalancing with Gravity: Measuring the Burden of Adjustment. *IMF Staff Papers*, 55(3):511–540, 2008.

Swati Dhingra, Hanwei Huang, Gianmarco Ottaviano, João Paulo Pessoa, Thomas Sampson, and John Van Reenen. The Costs and Benefits of Leaving the EU: Trade Effects. *Economic Policy*, 32(92):651–705, October 2017.

Julian Di Giovanni, Andrei A. Levchenko, and Francesc Ortega. A Global View of Cross-Border Migration. *Journal of the European Economic Association*, 13(1):168–202, 2015.

Anne-Célia Disdier and Keith Head. The Puzzling Persistence of the Distance Effect on Bilateral Trade. *The Review of Economics and statistics*, 90(1):37–48, 2008.

Raphael Dix-Carneiro. Trade Liberalization and Labor Market Dynamics. *Econometrica*, 83(3): 825–885, May 2014.

Dave Donaldson. Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *American Economic Review*, 108(4-5):899–934, 2018.

César Ducruet, Réka Juhász, Dávid Krisztián Nagy, and Claudia Steinwender. All Aboard: The Effects of Port Development. Technical report, National Bureau of Economic Research, 2020.

James A. Dunlevy. The Influence of Corruption and Language on the Protrade Effect of Immigrants: Evidence from the American States. *Review of Economics and Statistics*, 88(1):182–186, 2006.

Jonathan Eaton and Samuel Kortum. Technology, Geography, and Trade. *Econometrica*, 70(5): 1741–1779, 2002.

Fabian Eckert. Growing Apart: Tradable Services and the Fragmentation of the US Economy. mimeo, Yale University, 2019.

Benjamin Faber. Trade Integration, Market Size, and Industrialization: Evidence from China's National Trunk Highway System. *Review of Economic Studies*, 81(3):1046–1070, 2014.

Pablo Fajgelbaum and Stephen Redding. Trade, Structural Transformation and Development: Evidence from Argentina 1869-1914. *NBER Working Paper*, 20217, 2018.

Pablo D Fajgelbaum and Edouard Schaal. Optimal Transport Networks in Spatial Equilibrium. *Econometrica*, 88(4):1411–1452, 2020.

Gabriel Felbermayr, Volker Grossmann, and Wilhelm Kohler. Migration, International Trade, and Capital Formation: Cause or effect? In *Handbook of the Economics of International Migration*, volume 1, pages 913–1025. Elsevier, 2015.

Gabriel Felbermayr, Marina Steininger, Erdal Yalcin, et al. Global Impact of a Protectionist US Trade Policy. *ifo Forschungsberichte*, 2017.

James Feyrer. Distance, trade, and income-the 1967 to 1975 closing of the suez canal as a natural experiment. Technical report, National Bureau of Economic Research, 2009.

Simon Galle, Andrés Rodríguez-Clare, and Moises Yi. Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade. mimeo, BI Norwegian Business School, UC Berkeley, and US Census Bureau, August 2017.

Sharat Ganapati, Woan Foong Wong, and Oren Ziv. Entrepôt: Hubs, Scale, and Trade Costs. Technical report, CESifo Working Paper, 2020.

David M Gould. Immigrant Links to the Home Country: Empirical Implications for US Bilateral Trade Flows. *The Review of Economics and Statistics*, pages 302–316, 1994.

Glenn W. Harrison, Thomas F. Rutherford, and David G. Tarr. Quantifying the Uruguay Round. *The Economic Journal*, 107(444):1405–1430, 1997.

J Vernon Henderson, Adam Storeygard, and David N Weil. Measuring Economic Growth from Outer Space. *American economic review*, 102(2):994–1028, 2012.

Thomas W. Hertel, editor. *Global Trade Analysis: Modeling and Applications*. Cambridge University Press, New York, 1997.

Chang-Tai Hsieh, Erik Hurst, Charles I Jones, and Peter J Klenow. The Allocation of Talent and US Economic Growth. *Econometrica*, 87(5):1439–1474, 2019.

Ronald Jones. A Three-Factor Model in Theory, Trade, and History. In Jagdish Bhagwati, editor, *Trade, Balance of Payments, and Growth: Papers in International Economics in Honor of Charles P. Kindleberger*. North Holland, Amsterdam, 1971.

Lawrence F Katz and Kevin M Murphy. Changes in Relative Wages, 1963–1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1):35–78, 1992.

Paul Krugman. Scale Economies, Product Differentiation, and the Pattern of Trade. *The American Economic Review*, 70(5):950–959, 1980.

David Lagakos and Michael E Waugh. Selection, Agriculture, and Cross-Country Productivity Differences. *American Economic Review*, 103(2):948–80, 2013.

Andrei A. Levchenko and Jing Zhang. The Global Labor Market Impact of Emerging Giants: a Quantitative Assessment. *IMF Economic Review*, 61(3):479–519, August 2013.

Andrei A. Levchenko and Jing Zhang. The Evolution of Comparative Advantage: Measurement and Welfare Implications. *Journal of Monetary Economics*, 78:96–111, April 2016.

Marc J Melitz. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6):1695–1725, 2003.

Nicolas Morales. High-Skill Migration, Multinational Companies and the Location of Economic Activity. *SSRN 3336003*, 2019.

MPC. Integrated Public Use Microdata Series, International: Version 7.2. Technical report, Minnesota Population Center, 2019.

Michael Mussa. Tariffs and the Distribution of Income: The Importance of Factor Specificity, Substitutability, an Intensity in the Short and Long Run. *Journal of Political Economy*, 82: 1191–1203, 1974.

Gianmarco Ottaviano and Giovanni Peri. Rethinking the Effect of Immigration on Wages. *Journal of the European Economic Association*, 10(1):152–197, 2012.

Gianmarco Ottaviano, Giovanni Peri, and Greg Wright. Immigration, Trade and Productivity in Services: Evidence from UK Firms. *Journal of International Economics*, 112:88–108, 2018.

Christopher Parsons and Pierre-Louis Vézina. Migrant Networks and Trade: The Vietnamese Boat People as a Natural Experiment. *The Economic Journal*, 128(612):F210–F234, 2018.

Giovanni Peri and Francisco Requena-Silvente. The Trade Creation Effect of Immigrants: Evidence from the Remarkable Case of Spain. *Canadian Journal of Economics/Revue canadienne d'économique*, 43(4):1433–1459, 2010.

Stephen J. Redding. Goods Trade, Factor Mobility and Welfare. *Journal of International Economics*, 101:148–167, 2016.

Marta Santamaria. Reshaping Infrastructure: Evidence from the division of Germany. Technical report, Competitive Advantage in the Global Economy (CAGE), 2020.

JMC Santos Silva and Silvana Tenreyro. The Log of Gravity. *The Review of Economics and statistics*, 88(4):641–658, 2006.

Ina Simonovska and Michael E Waugh. The Elasticity of Trade: Estimates and Evidence. *Journal of international Economics*, 92(1):34–50, 2014.

Sebastian Sotelo. Domestic Trade Frictions and Agriculture. *Journal of Political Economy*, 128(7): 2690–2738, 2020.

Walter Steingress. The Causal Impact of Migration on US Trade: Evidence from Political Refugees. *Canadian Journal of Economics/Revue canadienne d'économique*, 51(4):1312–1338, 2018.

Marcel P. Timmer, Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J. de Vries. An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. *Review of International Economics*, 23(3):575–605, August 2015.

UNCTAD. Review of Maritime Transport, 2018. Technical report, Geneva, 2018.

Eva Van Leemput. A Passage to India: Quantifying Internal and External Barriers to Trade. *Journal of International Economics*, 131:103473, 2021. ISSN 0022-1996.

WEF. The Global Enabling Trade Report 2016. *World Economic Forum*, 2016.