Ports vs Roads: Infrastructure, Market Access and Regional Outcomes*

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Abstract

Ports are at the center of international trade's infrastructure network. I provide a framework to estimate the quality of different ports and to estimate trade costs on normal roads and expressways. I apply my framework to India and find that quality varies significantly across Indian ports: the standard deviation in Indian port productivities is equivalent to an ad-valorem trade cost of around 15%. I then build a general equilibrium model of international and internal trade with port and road infrastructure to assess the relative importance of ports versus roads in shaping international market access. Improving all ports to the level of the best port increases average wages by 1% across Indian districts. Reducing international costs as if all roads to ports became expressways increases wages by 0.1%, an order of magnitude less. Making all roads expressways and also changing internal trade cost increases wages by 0.6%. Improvements in ports and roads have different distributional implications. Port improvements increase international market access more and benefit export oriented regions, while improving roads benefits domestically oriented regions.

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1 Introduction

International trade relies on a multifaceted infrastructure network. Ports are at the center of this network, as around 80% of the world's trade in goods is seaborne (UNCTAD, 2018). Accordingly, port quality and easy access to ports are essential to participation in the global economy and investments in ports and access to ports are large.[1] This paper addresses the following question: which part of the infrastructure network, ports or roads to port, is limiting international market access, and what are the regional implications of different types of infrastructure improvements?

The empirical and quantitative setting for this paper is India, a large country with a long coastline and many ports, as well as a rich internal geography.

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 from a novel transaction-level export dataset of Indian exporters. 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 location-sector-destination is not necessarily the closest port to the location, nor the closest to the destination. To rationalize these facts, I assume 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 cost, and a cost of going from the port to the destination. A lower port cost 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. The port fixed effects' structural interpretation is related to their quality: high port share conditional on origin-port and port-destination costs imply an otherwise low cost of using the port. In this estimation, a key parameter governs the port-choice cost elasticity. When the dispersion of idiosyncratic route productivities is low, firms are more likely to switch ports following changes in port costs, which leads to a high elasticity of substitution between ports. For a given port share difference, a large port elasticity implies a small port cost differential, while a small elasticity implies a larger port cost differential. The elasticity also governs

[1] For example, India's Sagarmala Project plans investments of close to 21 billion USD for port modernization, and 31 billion USD for port connectivity between 2015 and 2035. See `http://web.archive.org/web/20170603191904/http://sagarmala.gov.in/projects/projects-under-sagarmala`. For comparison, India's total public infrastructure annual spending scheduled for the fiscal year of 2015-16 according to the 12th Five Year Plan was of around 95 billion.

how changes in some segments of potential export routes affect the aggregate export cost. I show how to estimate that parameter, and along the way 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 internal and international 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, a country where most of international trade is done by sea, using my data on export transactions combined with various road, port and trade data. I estimate that the ratio between the port elasticity and the trade elasticity is around 5.2. Using a commonly used trade elasticity of 4, this means that when the cost of using of a port decreases by 1%, its share of use increases by around 21%. My estimates imply that quality varies significantly across Indian ports: the standard deviation of port quality is equivalent to an ad-valorem trade cost of around 15%. 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 an expressway is equivalent to an ad-valorem trade cost of around 1.5%, while the cost of the same distance on a normal road is around 18% higher.

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 conduct three counterfactuals. The first simulates what would happen if all ports were at the best level. In that case, real wages in India would increase by around 1% on average, with large heterogeneity across districts and a standard deviation of around 0.5%. Inland districts would gain less than coastal regions. Exports as a share of GDP would increase by 3.1 percentage points. The second counterfactual simulates what would happen if all roads to the ports were expressways, while keeping the cost of internal trade constant. In that scenario, average real wages would increase by an order of magnitude less (0.1%) and the increase in exports as share of GDP would be of only 0.3 percentage points. Inland regions with lower connectivity to the coast would benefit more. Those two first counterfactuals imply that ports play a larger role in shaping international market access than roads. The last counterfactual improves all roads to expressways and reduces internal trade costs as well as costs to the port. In that scenario, average wages would increase by 0.6%. Hence the overall welfare impact of bringing all ports to the best level is higher than that of road improvements.

It could be that while improving ports has a larger welfare benefit, it also has a larger cost. I provide estimates of the cost of improving ports and roads, and show that this is not the case. I use data on investment in ports completed between 2015 and 2019 and changes in port share usage to estimate that an additional billion dollar spent on port improvements reduces the iceberg trade cost at the port by around 2.2%. 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 transforming all roads to expressway have a cost of similar magnitude, despite their different welfare implications.

The distributional welfare impact of port and road infrastructure improvements are different. Hence policymakers might still be interested in using road improvements or a combination of road and port if they have specific regions to target in mind even if their aggregate impacts are different. Improving specific ports can also provide a tool to address distributional concerns, and 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 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 and directly compare ports and roads. Previous papers have separately highlighted the importance of road infrastructure (Asturias et al., 2019; Faber, 2014; Alder, 2019; Baldomero-Quintana, 2020; Coşar et al., 2021; Fan et al., 2021) or rail network (Donaldson, 2018; Jaworski et al., 2020; Xu and Yang, 2021). Recently, a limited number of papers have focused on the importance of ports and shipping networks (Ducruet et al., 2020; Ganapati et al., 2021). In this paper, I explicitly model road and port infrastructure, which allows me to assess which type of infrastructure is the bottleneck. In that respect, 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).

Second, 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 the internal and external economy, and by providing a direct comparison between port and road infrastructure. In terms of context, 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 trade costs associated with infrastructure.

Third, I contribute to the fast growing literature on shipping networks that uses heterogeneous shipping costs on an infrastructure network for analytical convenience (Allen and Arkolakis, 2020; Ganapati et al., 2021). In these papers, exporters are assumed to face heterogenous export costs. When the heterogenous component of costs follows a Fréchet distribution, the models typically allow for tractable solutions where a key elasticity governs the changes in route choices following changes in route costs. I provide novel stylized facts based on micro-data that justify the assumption of heterogenous shipping costs and provide a novel estimate of the port route elasticity. 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., 2021). My estimation strategy relies on observing port choices of exporters, as Fan et al. (2021). Compared to that paper, I add a destination dimension that allows me to estimate the port elasticity using fixed effects to capture the cost of going from the origin to the port, and from the port to the destination, without making any assumption on the particular functional form of the cost of going from the origin to the port. Ganapati et al. (2021) also use a closely related model, but in their framework, the parameter governing the route elasticity is the same as the trade elasticity.[3] According to my estimates, the route elasticity is significantly higher than the trade elasticity. To the best of my knowledge, Fan et al. (2021) and Baldomero-Quintana (2020) are the only papers estimating a port elasticity, while other papers (e.g. Allen and Arkolakis, 2019) estimate a road-route elasticity. The value I find is higher than both of these papers, which is consistent with the fact that I control for the destination while they use only one composite rest of the world destination.

Finally, my paper provides a way of measuring port qualities and road costs differential between expressways and normal roads, using only data on port choices and exports. Blonigen and Wilson (2008) uses data on import charges to estimate port productivities. My framework only requires data on port of exit, which is more commonly accessible through customs dataset. Other papers rely on price differentials (Donaldson, 2018) to estimate trade costs, or simply use theoretical relative speed to infer the relative costs on expressways and normal roads (Asturias et al., 2019; Alder, 2019). My framework is closely related to Fan et al. (2021) who also use port choice data to estimate the cost of distance on an expressway relative to normal roads, but don't estimate port cost differentials.

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

[3] In their model, producers in each potential sourcing location draw a random trade cost to other destinations for each variety of a continuum, 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). Hence the trade cost dispersion parameter has the same "trade elasticity" interpretation as in Eaton and Kortum (2002).

The remainder of the paper is organized as follows. Section 2 presents the data and stylized facts about port usage in India, section 3 builds the model of port choice, section 4 shows how to estimate the key parameters and port quality, section 5 shows the estimation results, section 6 builds the full model, and section 7 presents the results of the counterfactuals.

2 Basic facts

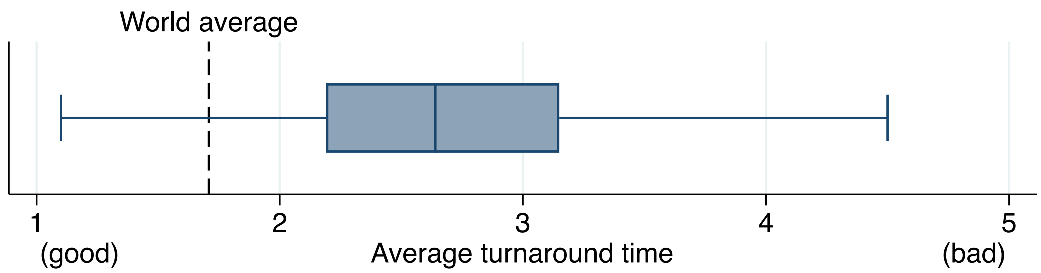
2.1 Data

The main data I use is a novel dataset of firm-level export transactions from India. The dataset construction involves several data sources, web-scraping, and name-matching techniques. I start from obtaining firm-level information from the "India Importer and Exporter Directory" combined with a list of Exporter Status firms published by the Directorate General of Foreign Trade. I then obtain the list of export transactions of those firms and their details from the Custom's National Trade Portal (Icegate). I then merge it with the Economics Census' directory of establishments and data from the Ministry of Corporate Affairs to obtain the firms sectoral classification. Appendix A contains the details of the data construction.

The dataset covers a sample of around 16,000 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, the destination country, and whether the export was containerized or not. I also observe the list of a firm's branches with their address and the firms' sectoral classification. For my purposes, I drop exports by air or land, which constitute around 27% of the sample.[4] I also keep only exports that are containerized, as dry or liquid bulk cargo requires more specific type of equipment at the port, and my dataset doesn't contain enough firms that don't use containers to convincingly accommodate this variation. Containerized exports account for around 83% of sea exports in value, over 95% in numbers of firms. I keep all ports used by at least 10 firms in my sample. The resulting sample covers around 11,400 firms located in over 400 different Indian districts, 17 ports and over two hundred destinations. The 17 ports cover over 99% of Indian sea exports. Appendix A shows that the sample is representative of the official aggregate figures for key statistics such as port and destination shares.

[4] The share of land exports is extremely low at 2%. Exports by air are the main alternative to sea and account for around 25% of total exports. Some transactions take place through inland port, used to transit towards actual ports. For these observations, I use the actual sea port of exit.

Figure 1: Port share and port turnaround time



Notes: This figure displays a box-plot of Indian ports' turnaround time in 2018. The vertical dashed line represents the world average turnaround time.

2.2 Stylized facts

In this section, I briefly describe the characteristics of ports in India, and show two stylised facts about port usage that are useful ingredients for modelling port choice.

Fact 1: ports are heterogenous Ports in India have long been underperforming compared to international benchmarks on average (World Bank, 2013). Here, I show that there is also a large heterogeneity across Indian ports according to a common measure of port productivity. Figure 1 displays a box plot of the turnaround time of Indian ports (the average time taken for a ship between entering and exiting the port). The vertical dashed black line represents the world average turnaround time at ports. First, it is apparent that the turnaround time of Indian ports is higher than the world average, implying that India has scope to improve port quality. Second, there is a significant heterogeneity across ports within India. This paper investigates the impact of the overall low port quality on India's international market access, and the relevance of port heterogeneity on regional outcomes.

Other consistent measures of port productivity across ports are scarce and limited to a small subset of ports (see Hussain, 2018, for a review of ports in India). This further motivates the need for a framework to estimate unobservable port quality from more commonly observable data.

Fact 2: firms don't use the closest port If some ports are better than others, firms might be willing to incur additional internal costs to reach a better port. To assess whether this is happening, I measure the road distance between the firm and the port, and compare it with the distance to the closest port. Table 1 shows that firms could save on average 25% of the distance to the port if they used the closest port to their district.[5] The chosen

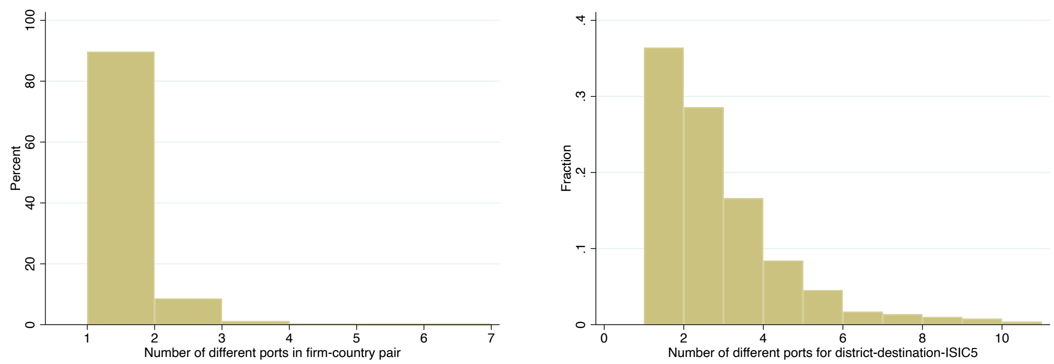
[5] Where the closest port is defined as the closest port for which I observe some containerized transaction.

Table 1: Modal port distances

	origin-port distance			port-destination distance		
	observed port	closest port	$\frac{close-obs}{obs}$	observed port	closest port	$\frac{close-obs}{obs}$
Average	391	265	-25%	5,866	5,451	-12%
Median	208	157	-18%	6,150	5,625	-4%

Notes: The left panel of this table shows the average and median road distance in kilometers between the origin district and the observed and closest ports, as well as the average and median fraction of distance the firm could save by using the closest port. The right panel shows the shortest sea distance between the ports and the destination.

Figure 2: Number of ports per sector-origin-destination



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.

port isn't the closest to the destination either, as the right panel of the table shows that firms could save around 12% of sea distance by using the port located the closest to the destination. This implies that on average, firms seems 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 port of higher quality.

Fact 3: firms use a single port per destination The left panel of Figure 2 shows the histogram of the number of port used within a firm-destination pair. Close to 90% of firms use a unique port to reach a destination.

Fact 4: observably similar firms use different ports I next 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, and origin region as an Indian district, and a destination as a country.[6] To classify each transaction to an origin district for firms that have many branches, I assume that the closest branch to the port shipped the good. This might introduce some spurious heterogeneity in case of misclassification, and I repeat the same exercise using firms that only have one branch in Appendix B with similar findings. The right panel of Figure 2 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.

The emerging literature incorporating ports in international shipping has built on the heterogeneous trade cost model of Allen and Arkolakis (2020) (e.g. Ducruet et al., 2020; Ganapati et al., 2021; Baldomero-Quintana, 2020). In that framework, agents (firms or traders) don't all incur the same cost when using a specific route. While this assumption is usually made for analytical convenience, the facts shown above actually support that hypothesis.

3 A model of port choice

In this section, I present a simple partial-equilibrium model of port choice that rationalises the facts presented above. I will incorporate that model in a full general equilibrium later in section 6. For expositional purposes, I remove any sectoral dimension in this section, and add it later when moving to the data.[7]

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

$$\tau_{io\rho d} = \frac{\tau_{o\rho d}}{\varepsilon_{io\rho d}} \tag{1}$$

where $\tau_{o\rho d}$ captures all the common costs of using port ρ to reach destination d from origin o, and $\varepsilon_{io\rho d}$ 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. For now,

[6] An example of ISIC5 category is 17111 which corresponds to "Preparation and spinning of cotton fiber including blended cotton". Appendix B explores narrower geographical classifications and shows that the patterns remain the same when using postal code as origin region, and discharge port as destination.

[7] Note that since I focus on containerized transactions, the assumption of a single cost for all exporters is not extreme.

I leave the particular form of $\tau_{o\rho d}$ unspecified, and differences $\tau_{o\rho d}$ 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: $\tau_{iod} = \min_\rho \frac{\tau_{o\rho d}}{\varepsilon_{io\rho d}}$. Using the properties of the Fréchet distribution, standard steps show that the probability of choosing port ρ is given by:

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho d}\right)^{-\theta}}{\sum_k \left(\tau_{okd}\right)^{-\theta}}, \tag{2}$$

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:

$$d_{od} = E\left[\min_\rho \frac{\tau_{o\rho d}}{\varepsilon_{io\rho d}}\right] = \kappa \left[\sum_\rho \left(\tau_{o\rho d}\right)^{-\theta}\right]^{-\frac{1}{\theta}}, \tag{3}$$

where κ is a constant involving the Gamma function and θ. Notice that the expected trade cost depends on the same term $\Phi_{od} = \sum_\rho \left(\tau_{o\rho d}\right)^{-\theta}$ as the denominator of the port probability equation (2), and the probability of choosing port ρ can be rewritten in term of expected export cost:

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}},$$

and θ is the elasticity of port share with respect to both the cost of using the port $(\tau_{o\rho d})$ and the expected average trade cost (d_{od}).

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 2 better, and can be incorporated in a standard trade model with firm heterogeneity as shown below in Section 6. The model is also related to the framework of Ganapati et al. (2021) 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 differ from the trade elasticity.

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.

4.1 Port elasticity

To estimate θ, I make two additional assumptions on pricing and demand, and a third assumption on the specific form of $\tau_{o\rho d}$ to show how to combine export value data with port shares to estimate θ.

Assumption 1. *Firms set constant markup prices*

The constant markup assumption is consistent with a variety of common market structures, including perfect competition and monopolistic competition. Under that assumption, the price that firm i in origin o would charge to destination d if it sent through the least-cost port is given by:

$$p_{iod} = \mu c_i \tau_{io\rho d} = \mu c_i \min_{\rho} \frac{\tau_{o\rho d}}{\varepsilon_{io\rho d}} \tag{4}$$

where μ is the markup and c_i is the firm's marginal cost.

Assumption 2. *Demand satisfies constant elasticity of substitution*

Under the CES assumption, the spending on each firm's output in destination d is given by:

$$X_{iod} = (p_{iod})^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}}, \tag{5}$$

where σ is the elasticity of substitution, X_d is total spending at destination d and P_d is the price index. Assumptions (1) and (2) are consistent with a number of common market structures used in the international trade literature, such as monopolistic competition and perfect competition. Under these assumptions, the total exports of firm i to destination d are given by:

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

Taking the expectation over the ε draws, the expected value of export is given by:

$$E\left[X_{iod}\right] = \gamma\left(\mu c_i\right)^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}} \left(d_{od}\right)^{1-\sigma}, \tag{6}$$

where d_{od} is the expected trade cost defined in equation (3), and γ is a constant involving the Gamma function, θ, and σ. Appendix C.1 provides the proof. To estimate θ, I use the fact that the port choice probability also depends on the expected cost as shown above:

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}}.$$

Hence assumptions (1) and (2) allow me to connect two observable quantities (port choice and X_{iod}) to the same expected trade cost d_{od}. The trade cost term $\tau_{o\rho d}$ is unobservable, but giving it enough structure will allow me to recover it from observable trade shares using fixed effects, and use them to estimate the unobservable d_{od} (up to an exponent θ), and use it in the value equation (6) to estimate θ. In particular, I make the following additional assumption:

Assumption 3. *The origin-port-destination trade cost is given by:*

$$\tau_{o\rho d} = \tau_{o\rho}\tau_{\rho}\tau_{\rho d},$$

where $\tau_{o\rho}$ captures the cost of going from the origin to the port, τ_{ρ} captures the cost of handling the shipment at the port, and $\tau_{\rho d}$ captures the cost of shipping the good from the port to the destination.

Under assumption 3, the port choice probability equation becomes

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}}. \tag{7}$$

To take the port choice equation to the data, I use the fact that the expectation of a dummy variable for firm i's choosing port ρ is equal to the probability that it choses port ρ. This gives rise to the following estimation equation:

$$E\left[1_{io\rho d}\right] = \frac{\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}}, \tag{8}$$

where $1_{io\rho d}$ is a dummy variable equal to 1 if firm i located in region o uses port ρ to export to destination d. I estimate equation 8 using a Poisson PMLE procedure and use $o\rho$, ρd

and od fixed effects to capture the unobservable τ terms:

$$E\left[1_{io\rho d}\right] = \exp\left(\underbrace{-\theta\ln\tau_{o\rho} - \theta\ln\tau_{\rho}}_{f_{o\rho}\text{ FE}} - \underbrace{\theta\ln\tau_{\rho d}}_{f_{\rho d}\text{ FE}} + \underbrace{\theta\ln d_{od}}_{od\text{ FE}}\right). \tag{9}$$

The estimated $f_{o\rho}$ and $f_{\rho d}$ fixed effects are estimated up to the port cost τ_{ρ}, and their sum has the structural interpretation of $-\theta\ln\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)$. These fixed effects are consistently estimated as the number of origins O and the number of destinations D grow to infinity while the number of ports stays constant, but the od fixed effect isn't. Intuitively, for each $o\rho$ pair, there is a large number of destinations, and for each ρd, there is a large number of origins. One might be worried that the estimation suffers from the incidental parameter problem, as the dimensionality of the od fixed effect grows with O and D, but Weidner and Zylkin (2021) show that the PPMLE estimator remains consistent in the setting of three-way fixed effects.[8] Armed with a consistent estimate of $-\theta\ln\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)$, I construct the following generated regressor:

$$z_{od} = \sum_{\rho}\exp\left(f_{o\rho} + f_{\rho d}\right). \tag{10}$$

It is straightforward to show that z_{od} converges in probability to $\left(d_{od}\right)^{-\theta}$ since $f_{o\rho} + f_{\rho d}$ converge to $-\theta\ln\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)$.[9] Substituting d_{od} with $\left(z_{od}\right)^{-1/\theta}$ in the value equation (6) gives:

$$\begin{aligned} E\left[X_{iod}\right] &= \gamma\left(\mu c_i\right)^{1-\sigma}\frac{X_d}{P_d^{1-\sigma}}\left(d_{od}\right)^{1-\sigma} \\ &= \alpha_i\beta_d\left(z_{od}\right)^{\frac{\sigma-1}{\theta}}\nu_{od}, \end{aligned} \tag{11}$$

[8] Weidner and Zylkin (2021) study the consistency of the PPMLE estimator in the context of the traditional trade gravity equation and panel data with importer-time, exporter-time and importer-exporter fixed effects. In their setting, the number of periods T is fixed, the number of exporters (i) and importer (j) are both equal to N. They study the consistency of the PPMLE estimator as N grows to infinity, and show that the estimator does not suffer from the incidental parameter problem even if the ij fixed effect has the dimentionality N^2. In my setting, the number of port is fixed and corresponds to T in their setting. The number of origins and destinations is not equal in my setting, but the core of their argument for consistency of the it and jt fixed effects (corresponding to the $o\rho$ and ρd fixed effect in my context) relies on the fact that their dimension only grows with $\sqrt{N}$ as N increases. Although O and D are not equal in my setting, the argument still holds since the dimension of the $o\rho$ and ρd fixed effects also grows with $\sqrt{OD}$ as OD grows.

[9] Remember that the expected trade cost d_{od} is given by

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

where ν_{od} is an error term that vanishes as the sample grows, and α_i, β_d control for the firm specific marginal cost and the destination demand. Hence, equation (11) provides a way to consistently estimate the ratio between the trade elasticity and the port elasticity $((\sigma-1)/\theta)$, by regressing export value on a firm fixed effect, destination fixed effect, and z_{od}.

A final hurdle to solve is that in the data, I observe the *freight-on-board* value of exports, so that the cost of going from the port to the destination is not included in the observed value. To account for this, I assume that I observe $X^*_{iod} = (X_{iod}/\tau_{\rho d})\,\mu_{iod}$, where μ_{iod} is an iid error term. In that case, adding a port-destination (ρd) fixed effect to the regression controls for the fact that I observe only FOB value.[10]

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 estimating origin-port-sector costs.

Assumptions discussion The constant markup and CES demand assumptions (1) and (2) are ubiquitous in the international trade literature, and serve as basis for numerous estimation strategies for the trade elasticity. Hence I don't view them as controversial.

Assumption 3 is less common, although it is also used in other papers where trade takes place along a network. Implicitly, I treat ports as a piece of infrastructure similar to roads, rather than as price-setting actors. An important assumption is that all firms face the same port specific cost τ_ρ up to the iid shock ε.[11] The assumption requires that there is no discrimination on the pricing or treatment of shipments at the port depending on the origin, destination or size of the shipment. A potential deviation from assumption 3 might lead to an inconsistent estimate using my strategy. If the cost $\tau_{o\rho d}$ is not given by $\tau_{o\rho}\tau_\rho\tau_{\rho d}$, but by:

$$\tau_{o\rho d} = \tau_{o\rho}\tau_\rho\tau_{\rho d}\eta_{o\rho d},$$

where $\eta_{o\rho d}$ is an iid shock, which could for example represent $o\rho d$ specific economies of scale that are not captured in the individual segments.[12] If this were the case, the first stage of my estimation strategy would still provide consistent estimate of $\tau_{o\rho}$ and $\tau_{\rho d}$, but the

[10] In more details:

$$E\left[X^*_{iod}\right] = E\left[\frac{X_{iod}}{\tau_{\rho d}}\mu_{iod}\right] = \frac{\alpha_i\beta_d}{\tau_{\rho d}}\left(z_{od}\right)^{\frac{\sigma-1}{\theta}}\nu_{od}$$

[11] This assumption will turn out to be crucial especially in the next section.

[12] For this to happen, it would need to be the case, for example, that economies of scale because of large transits from Delhi to the UAE through the port of Mundra does not translate into lower cost between Delhi and Mundra for non-UAE destinations, nor into lower cost between Mundra and the UAE for non-Delhi origin.

generated regressor would not converge to $d_{od}^{-\theta}$, so that the second stage estimate wouldn't be consistent.[13] However, the residuals in the first stage would be more volatile than if assumption 3 didn't hold. In Appendix C.1.2, I show that the distribution of residuals is close to what one would expect from random Fréchet draws for a sample of the size I use. I conclude that a violation of assumption 3 is unlikely to drive my results.

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 (2) gives:

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

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, I assume that 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:

$$\tau_{o\rho} = \prod_k t_{k(o\rho)} \tag{12}$$

I then assume that the cost on the segment is a function of the distance of the segment and the type of road of the segment:

$$t_k = \exp\left(\tilde{\beta}^{c(k)} dist_k\right). \tag{13}$$

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 expressways separated in the middle (typically four lanes in total with two lanes per direction). The parameter β^c captures the trade cost semi-elasticity with respect to distance on a particular type of road. This parametrization will also allow me to easily run counterfactuals 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

[13]The generated regressor would still converge to $\sum_\rho (\tau_{o\rho}\tau_\rho\tau_{\rho d})^{-\theta}$, but $d_{od}^{-\theta}$ woud be equal to $\sum_\rho (\tau_{o\rho}\tau_\rho\tau_{\rho d})^{-\theta}\,\eta_{o\rho d}$ in this context.

between the port and destination:

$$\ln \tau_{\rho d} = \lambda \ln seadist_{\rho d}$$

Combining the parametrizations leads to the following estimating equation:

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

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:

$$\min_{\{\beta_c\},\beta^{sea},\{\alpha_\rho\},\{\Phi_{od}\}} \left[\ln \pi_{o\rho d} - \min_{r\in R_{o\rho}} \left\{\sum_c \beta^c dist^c_{o\rho}(r)\right\} - \beta^{sea} \ln seadist_{\rho d} - \alpha_\rho - \Phi_{od}\right]^2, \tag{14}$$

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:

$$\beta^* = arg \min_{\{\beta^c\}} \left\{\ln \pi_{o\rho d} - \sum_c \beta^c dist^c_{o\rho}(\beta^*) - \beta^{sea} \ln seadist_{\rho d} - \alpha_\rho - \Phi_{od}\right\}^2, \tag{15}$$

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 15. 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 15 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,[14]
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

[14] Strictly speaking, problem 15 minimizes least-squares via OLS rather than PPMLE. However, using PPMLE allows me to use observations where the share is 0 and is also consistent.

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 (15) is only a necessary condition to being a solution to the minimization problem (14), unless the fixed point is unique. While this cannot be proved, I check that the solution is unique by starting from different initial guesses, and all converge to the same point.[15]

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. Estimating the β^cs directly 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.

5 Estimation Results

This section presents the estimation results.

5.1 Port elasticity

I run the estimation defining an origin as an Indian district and a destination as a foreign country. I estimate θ using different levels sectoral aggregation to ensure that the destination demand fixed effects are sector-specific. I use years 2015-2019 of data, and add a sector-year dimension to all fixed effects mentioned in the estimation strategy. Table 2 displays the results. The standard errors are computed using a bootstrap procedure, clustered at the firm level.

Table 2: Elasticity estimation results

	Pooled	Arg-Min-Man-Other	ISIC2
$\frac{\sigma-1}{\theta}$	0.193	0.262	0.280
	(.033)	(.049)	(.049)
Implied θ with $\sigma - 1 = 4$	21	15	14

Notes: This table shows the results of estimating the elasticity parameter using the strategy outlined in section 4. Standard error are based an 100 cluster-bootstrap samples, with replacements at the firm level.

The results show that the port elasticity is significantly higher than the trade elasticity

[15] In particular, I 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.

by a factor of around 3.5-5.2. Using a common value of trade elasticity of 4 (Simonovska and Waugh, 2014), the baseline pooled estimate implies a port elasticity of around 21, with a 95% confidence interval between around 15 and 30. This implies that if a port's cost increases by 1%, its share would decrease by around 21%.

To the best of my knowledge, only two papers estimate the port elasticity. Fan et al. (2021) estimate a value of around 6.7 and Baldomero-Quintana (2020) finds values around 4. My estimate is higher than both estimates. Both papers focus on domestic infrastructure's impact on port choice and only have a composite rest-of-the-world destination region. Hence, the destination dimension that my paper explicitly incorporates is included in the idiosyncratic shock in their framework which increases its volatility. As a result, their port elasticity is lower, because a lower θ is needed to accommodate the higher volatility.[16] My estimate is the first port elasticity estimate that explicitly controls for the destination and allows the port elasticity to differ from the trade elasticity.

Other papers that explicitly incorporate different destinations either calibrate the port elasticity from other route elasticity estimates (Ducruet et al., 2020) or frame their model such that the route elasticity is equal to the trade elasticity, and hence use common values of trade elasticity for the θ parameter (e.g. Ganapati et al., 2021).

5.2 Infrastructure quality

I use the national highway network extracted from Open Street Map (OSM) to compute the fastest routes.[17] 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, 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 (14) using yearly 2015-19 origin-port-destination shares and adding sector-year dimension to all fixed effects and shares. Appendix A.3 discusses the potential issues with the road data and compares it with official statistics. I also add a dummy for whether the origin district is in the same state as the port, to capture potential inter-state border crossing frictions common in India. Table 3 displays the results of the estimation.

The results are similar regardless of the sectoral aggregation, reflecting the fact that all transactions considered are containerized and most firms are manufacturing firms.

[16] In an elasticity interpretation, the port choices are less sensitive to the domestic trade costs, because it is driven by the unobserved cost from the ports to the destination.

[17] 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.

Table 3: Road parameters and port quality estimation

	$\ln \pi_{o\rho d,sy}$		
	Pool	Agr-Min-Man-Other	ISIC 2
Normal road	-0.378	-0.400	-0.394
(100km)	(.01)	(.01)	(.01)
Expressway	-.320	-0.344	-0.336
(100km)	(.01)	(.01)	(.01)
$\ln seadist_{\rho d}$	-0.679	-0.695	-0.692
	(.039)	(.041)	(.035)
Same state port	0.754	0.642	0.640
	(.015)	(0.014)	(.011)
Port FE	yes	yes	yes
odsy FE	yes	yes	yes
odsy Cluster	yes	yes	yes
N	1,133,760	1,354,660	2,459,060

Notes: The table shows the estimates of the PPML estimation regressing the port shares (computed at the origin-destination-sector-year level) on the road and sea distances, using the least-cost route road distances after convergence of the cost parameters.

Ports Table 4 shows the estimates of $-\ln \tau_\rho$ relative to the best port for the 10 largest Indian container ports and some summary statistics over the 17 ports in my sample. The variation across ports is large: the standard deviation across ports is between 21% and 11% depending on the port elasticity value, with a value of 15% for my central estimate. This number can be interpreted as an ad-valorem trade costs of 14%: improving a port by one standard deviation decreases trade cost by 15%.

The left panel of Figure 4 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.

To ensure that the estimated fixed effect really captures changes in costs, Figure 3 displays the scatterplot of the estimated port fixed effect estimates against 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

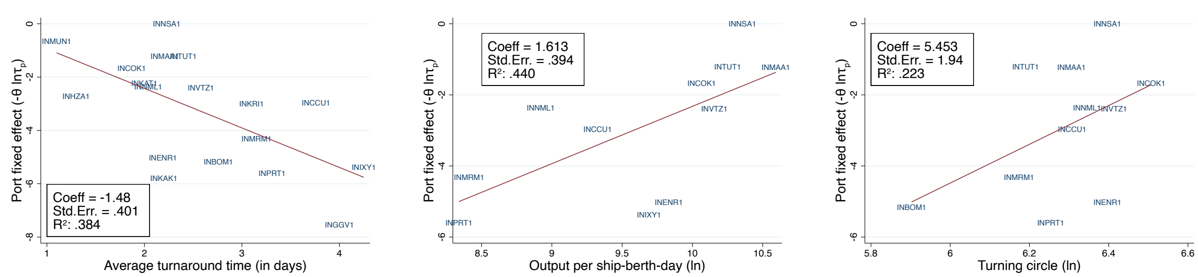
Table 4: Estimated port quality

Port Name	Port fixed effect	Implied quality		
	$(-\theta \; ln\hat{\tau}_\rho)$	$(\theta = 15)$	$(\theta = 21)$	$(\theta = 30)$
Nava Sheva	0.00	0.00	0.00	0.00
Mundra	-0.81	-0.05	-0.04	-0.03
Chennai	-1.34	-0.09	-0.06	-0.04
Kolkata	-3.05	-0.20	-0.15	-0.10
Tuticorin	-1.39	-0.09	-0.07	-0.05
Kochi	-1.79	-0.12	-0.09	-0.06
Vizag	-2.59	-0.17	-0.12	-0.09
Kattupalli	-2.83	-0.19	-0.13	-0.09
Hazira	-3.25	-0.22	-0.15	-0.11
Pipavav	-3.03	-0.20	-0.14	-0.10
Average	-3.76	-0.25	-0.18	-0.13
Median	-3.03	-0.20	-0.14	-0.10
Std deviation	3.19	0.21	0.15	0.11

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.

ships need a wider turning circle, and ports with higher fixed effect are able to accommodate larger ships.

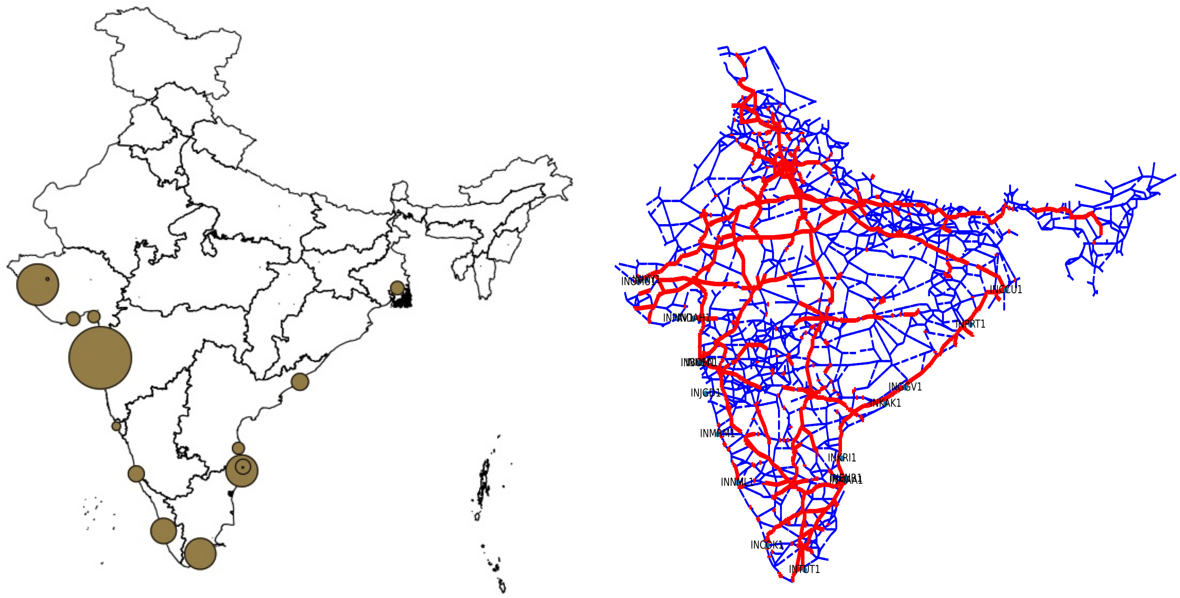
Figure 3: Port quality estimates and observables



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.

Figure 4: 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.

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. An additional 100km on normal road distance to a port decreases the probability of using that port by 0.378, while the same distance on an expressway decreases it by 0.32. 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 18% higher than that of traveling on an expressway. My estimate is consistent with existing estimates: Fan et al. (2021) find a difference of around 20% for the difference between expressways and regular roads in China.

Remember that the coefficient on the road distances have the structural interpretation of $\theta * \beta^c$. Using $\theta = 21$ consistent the port elasticity estimated above, this implies that an additional 100km on an expressway is equivalent to an ad-valorem trade cost of around 1.5%. Further, interpreting β^c as the (inverse) average speed on the category multiplied by the cost of time and assuming a speed of 60km/h on the expressway ($\beta^c = 1/60 * costtime = .00320/21$) implies that the semi-elasticity of trade cost to an additional hour of travel time is around 0.01 ($.00320 * 60/21 \approx .009$). This implies that an additional hour of travel time is equivalent to a 1% ad-valorem trade cost. This is lower, but in the same order of magnitude, as the estimate of 7% from Allen and Arkolakis (2019) for the US. A lower value is to be expected given the lower cost of labor in India.

To illustrate the heterogenous road quality across Indian regions, the right panel of Figure 4 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 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.

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 districts or foreign countries.

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, α_d is the share of goods in consumption, and G_d is a CES aggregate of a continuum of goods, with elasticity of substitution σ:

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

Each region is endowed with L_d units of labor, supplied inelastically and perfectly mobile across the two sectors.[18] Assuming balanced trade, labor income is the only source of revenue and the consumer must satisfy the following budget constraint:

$$P_d^G G_d + P_d^S S_s = w_d L_d,$$

[18] This assumption reflects the fact that my counterfactuals are designed to study long-term effects of infrastructure changes.

where w_d is the wage rate in region d.

Optimality implies that consumers spend $X_d^G = \alpha_d w_d L_d$ on manufacturing goods, and $X_d^S = (1 - \alpha_d) w_d L_d$ on services. 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.

6.2 Production

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

$$y_d^S = A_d^S L_d^S, \tag{16}$$

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 equal to labor costs and given by $Y_d^S = w_d^S L_d^S$.

Goods The production of manufacturing goods is similar to Krugman (1980). 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) and repeated here for convenience:

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

Hence firm i's cost of exporting to region d is given by $\tilde{d}_{od}(i) = \min_\rho \frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}$. A firm in a foreign region o shipping to an other foreign country d faces an iceberg trade cost 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. The firms only learn their idiosyncratic port-route productivities $\varepsilon_{io\rho d}$ after paying the fixed entry cost.

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

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

and variable profits are given by:

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

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:

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

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:

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

Total exports from o to d are given by:

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

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

Labor demand from firm i is given by:

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

and aggregate labor demand is given by:

$$N_o^f \left(\frac{\sigma}{\sigma - 1} \right)^{-1} \frac{\sigma}{w_o} \underbrace{\frac{1}{\sigma} \sum_d \left(\frac{\sigma}{\sigma - 1} \frac{w_o}{A_o} d_{od} \right)^{1-\sigma} \frac{X_d}{P_d^{1-\sigma}}}_{\text{equal to expected variable profits}} + N_o^f f_o.$$

Because of free entry and the fact that firms pay the entry cost before learning their idiosyncratic draw, expected profits are equal to 0 and variable profits are equal to the fixed cost $w_o f_o$. Plugging that in the total labor demand from the goods sector gives the following demand for labor in the goods sector L_o^G:

$$L_o^G = \sigma N_o^f f_o.$$

6.3 Equilibrium

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

$$\begin{aligned} Y_o^S &= X_o^S \\ w_o L_o^S &= (1-\alpha_o)\, w_o L_o, \end{aligned}$$

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 o. Since services are non-tradable, balanced trade implies that total goods consumption equals total goods sales:

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

and total service sales equals total service consumption

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

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

$$\alpha_o L_o = \sigma N_o^f f_o \tag{17}$$

$$\left(1-\alpha_o\right) L_o = L_o^S \tag{18}$$

- Budget constraint and balanced trade in goods

$$X_d = w_o L_o \tag{19}$$

$$\sum_d X_{od}^G = w_o L_o^G \tag{20}$$

- Optimal consumption choices

$$\alpha_o X_o = \sum_d X_{od}^G \tag{21}$$

$$X_{od}^G = N_o^f \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o} d_{od}\right)^{1-\sigma} \frac{\alpha_d X_d}{\left(P_d^G\right)^{1-\sigma}}, \tag{22}$$

where

$$\left(P_d^G\right)^{1-\sigma} = \sum_o N_o^f \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o} d_{od}\right)^{1-\sigma} \tag{23}$$

and

$$d_{od} = \begin{cases} 1 & \text{if } o = d \\ \tilde{d}_{od} & \text{if } o, d \in IN \text{ or } o, d \notin IN \\ \left[\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{1}{\theta}} & \text{if } o \in IN \text{ and } d \notin IN\text{, or } d \in IN \text{ and } o \notin IN \end{cases} \tag{24}$$

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 ($\tau_{o\rho}$).

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 E.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 4 (Simonovska and Waugh, 2014), corresponding to $\sigma = 5$, and a value for $\theta = 4/0.193$, 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, port-level cost estimates, and sea distance estimates using the parametrization described in section 4.2:

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}}{\sum_k \left(\tau_{ok}\tau_k\tau_{kd}\right)^{-\theta}}, \tag{25}$$

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). 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 (22), (21) and (23), the following equation holds:

$$\underbrace{\alpha_o X_o}_{\text{data}} = \sum_d \frac{\lambda_o \left(d_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(d_{kd}\right)^{1-\sigma}} \underbrace{\alpha_d X_d}_{\text{data}}, \tag{26}$$

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 (26) is useful to calibrate the model, because there is a unique vector of λ_o consistent with data on X_o and trade frictions d_{od} (see the useful Lemma 1 in Appendix D.1). Since data on trade across Indian districts and between districts and foreign countries is not readily available, I use equation (26) to recover the λ_o from data on district and foreign country level GDPs as well as from my estimates of road, port and sea costs 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. 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 D.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.

Baseline real wage 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:

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

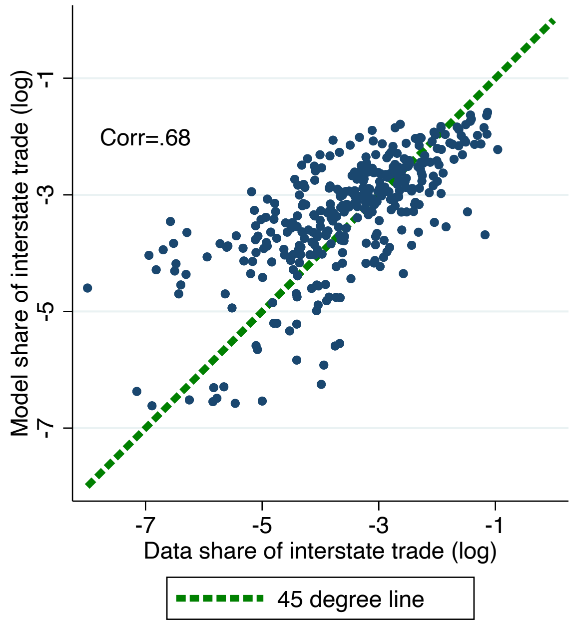
$$\log\frac{X_d/L_d}{P_d} = \alpha_d \underbrace{\log\frac{X_d}{L_d}}_{data} - \alpha_d \underbrace{\log P_d^G}_{model+data} + (1-\alpha_d)\underbrace{\log A_d^S}_{unknown}.$$

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. In the counterfactuals, 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).[19] 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

[19] 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.

Figure 5: 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.

Asher et al. (2021) to predict GDP per capita based on these observables.[20] 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 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 0.903.

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.

Model calibration fit Figure 5 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 refers to the 2015-16 flows published in the 2016-2017 Indian Economic Survey. The correlation is around 0.7.

[20]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.

7.2 Counterfactuals cost changes

7.2.1 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 diminish.

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

$$\hat{\tau}_\rho = \frac{\min_p \tau_p}{\tau_\rho}, \tag{27}$$

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:

$$\hat{\tau}_{o\rho}^{CF} = \exp\left(\left[\beta^{expressway} - \beta^{normal}\right] dist_{o\rho}^{normal}\right) \tag{28}$$

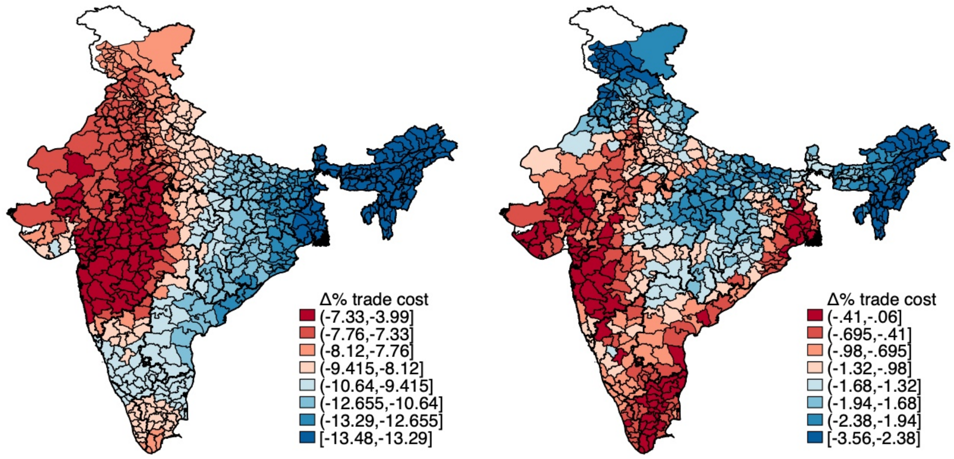
This measure removes the effect of road improvement on internal trade costs. This is useful to isolate the international market access component of changes in infrastructure. I also run the road improvement counterfactual allowing for internal trade costs to change when the roads are improved, where the formula of district-to-district trade cost changes is the same as in equation 28.

Figure (6) displays the average export cost changes by Indian districts in the two counterfactuals, where blue indicates a larger trade cost decrease. The left panel shows changes when all ports are brought to the best level and the right panel shows changes when all roads are brought to the best level. Blue districts experience a larger trade cost fall. It is clear that regions located on the east coast, where ports are on average of lower quality, benefit from larger cost decrease when ports are improved. When roads are improved, regions along the Golden Quadrilateral experience lower changes in export costs, as they are already connected to ports with an expressway.

7.2.2 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 change in real wages. In practice, I improve reduce each port's iceberg cost by 10% and compute the

Figure 6: Counterfactual trade cost changes



Equal ports Equal road to port

Notes: This figure displays the change in average export costs faced by each Indian district in the counterfactuals. The left panel shows changes when all ports are brought to the best level and the right panel shows changes when all roads are brought to the best level. Blue districts experience a larger trade cost fall.

counterfactual real wage change for all regions. This also allows me to compute which port is the bottleneck for different districts in India.

7.3 Counterfactual results

Table 5 shows the results of the counterfactuals. It shows summary statistics of the absolute change in export share of GDP and percent 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.

Improvements in ports increases the export share of GDP by around 3.1%, from a baseline average of 7.1%. The change in export share is an order of magnitude smaller when the road component of export costs is improved. This indicates that ports have a larger potential for increasing international market access than roads. The change in the export share is muted when internal trade costs are also allowed to change when roads are improved, since domestic trade also benefits from the road improvements.

Overall, changes in average real wage are large when ports are improved, with an increase in real wage of about 1%. 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 0.12% 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. When internal costs are reduced

Table 5: Counterfactuals results

	Change in export share of GDP (%)		
	Equal ports (τ_ρ)	Equal road to ports ($\tau_{o\rho}$)	Equal roads (incl. internal)
Average	3.05	0.33	0.13
Median	3.16	0.33	0.15
Std.	0.81	0.16	0.14

	Real wage change (%)		
	Equal ports (τ_ρ)	Equal road to ports ($\tau_{o\rho}$)	Equal roads (incl. internal)
Average	1.00	0.12	0.58
Median	1.02	0.12	0.53
Std.	0.46	0.08	0.34

Notes: This table shows summaries of the percentage change in export share and real wages across Indian districts in the counterfactuals. "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 ports and between districts) to the level they would be at if all roads where expressways.

as a result of road improvement, the average welfare change of road improvement increases to around 0.6%, but remains lower than the impact of port improvement.

The distributional impact of these counterfactual is also large: the standard deviation across districts is almost half of the average effect. Figure 7 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.

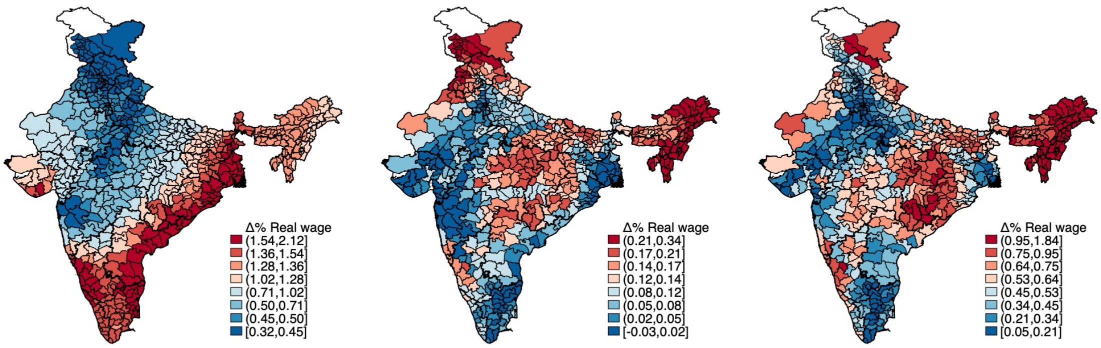
The left panel shows the real wage change when all ports are brought to the best level. Regions near the coast benefit more from the lower port costs. Within coastal regions, there is also heterogeneity in how much districts gain, with a direct link to the map of estimated port quality in Figure 4. Districts 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 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 7, to compare with the road network displayed in Figure 4). 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 seen 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.

The regional heterogeneity might have either positive or negative impact on regional inequality, depending on whether regions that benefit more had originally higher or lower welfare. Figure 8 displays the binscatter plot of the change in district real wage against the initial relative real wage. In the ports improvement scenario, there is no clear relationship between wage change and initial wage, thereby keeping regional inequality fairly constant. In the road improvement scenarios, however, regions with lower initial wage tend to gain more than richer regions. As a result, the standard deviation in log real wages drops by around 0.5% in the full road improvement counterfactual.

Overall, the counterfactual results show that port improvements are an order of magnitude more important than road improvements in terms of international market access.

Figure 7: District-level counterfactual real wage changes



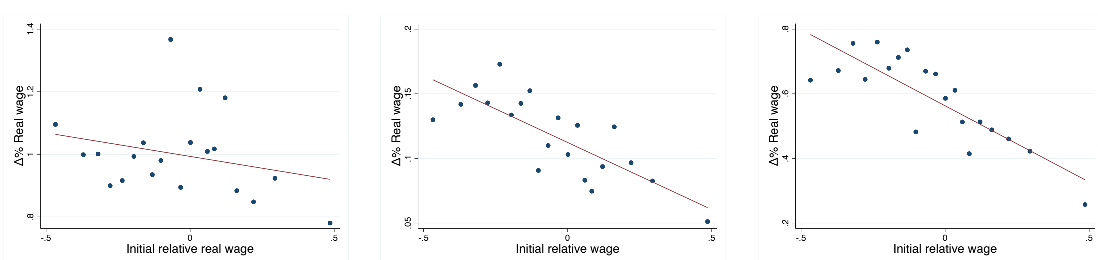
Equal ports | Equal Road to Port | Equal roads

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.

Even taking into account the internal trade cost impact on internal trade, port improvement still produces higher aggregate welfare gains. The two infrastructure improvement have different regional implications. Port improvement tends to favor coastal regions, while road improvements favor inland regions. Since the distributional impacts are different for port and road improvements, policymakers might find a combination useful to balance the effect 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 9 makes this point clear by plotting the bottleneck port for each district. The bottleneck port is de-

Figure 8: Real wage change against initial relative real wage

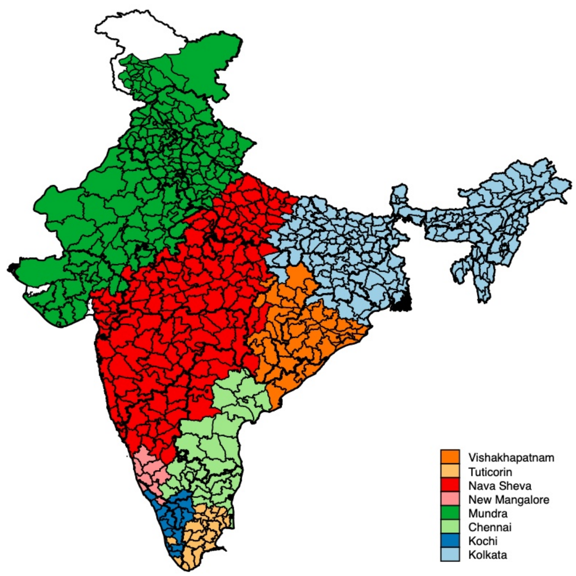


Ports | Roads (to port) | Roads (incl. internal)

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

fined 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 9: District-level bottleneck port



District-level bottleneck port

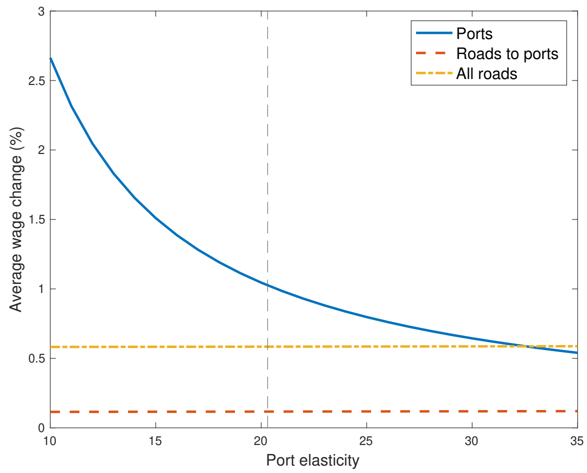
Notes: The figure displays the port that has the largest effect on the district's real wage when improved.

7.4 Sensitivity analysis

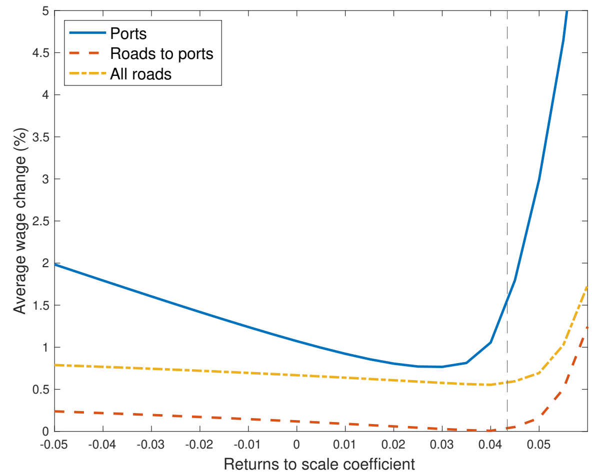
7.4.1 Varying port elasticity

The value of the port elasticity impact my results in two ways. First, a large elasticity implies that the estimated port fixed effects translate into smaller port cost differentials. Hence, the higher θ, the lower the implied difference between the worse and best ports, which decreases the magnitude of port cost changes in my counterfactual and lowers welfare gains. Second, a large port elasticity leads to larger second order impact on export costs because more firms switch to the lowest cost port. The net impact of these two effects is a-priori unclear. The left panel of Figure 10 displays the changes in average welfare for the range of values of θ estimated above. Clearly, the first effect dominates: as the port elasticity increases, the welfare gains of improving ports to the best level decreases, because the high elasticity of substitution implies that the observed fixed effect don't reflect large port cost differences. For all values of θ inside my estimated the confidence interval from section 5.1 (15-30), the

Figure 10: Port elasticity sensitivity and impact of economies of scale



Sensitivity to port elasticity (θ)



Economies of scale

Notes: The left panel plots the average real wage change across district under different port elasticities. The dashed vertical line represents the point estimate for θ. The right panel plots the average real wage change across districts, when all ports are brought to the best level accounting for the presence of economies of scale at the port. The dashed vertical line represents the value implied by the OLS regression of τ_ρ on port volume.

port improvement counterfactual results in higher gains than the road counterfactual.[21]

7.4.2 Economies of scale

Ports and sea shipping may be subject to congestions or economies of scale (Ganapati et al., 2021). In that case, the port cost estimates recovered in section 4.2 are inclusive of economies of scales.[22] More precisely, assume that the iceberg trade cost at the port is given by:

$$\tau_\rho = t_\rho \left(x_\rho\right)^{-\lambda},$$

where t_ρ is a port specific productivity, and x_ρ is the total (export) quantity transiting through port ρ. The parameter λ governs the economies of scale (or congestion if it is negative). In that case, the value of τ_ρ estimated in section 4.2 also includes the scale term $(x_\rho)^{-\lambda}$, and the counterfactuals in the previous section exogenously changes τ_ρ inclusive of the scale economies, rather than changing t_ρ and letting τ_ρ change endogenously with the

[21] When the port improvements are kept constant, increasing the port elasticity θ unambiguously increases the welfare gains. Figure 14 in the Appendix illustrates this by plotting the effect of improving a single port by 10% under different port elasticities.

[22] Because I control only for sea distance between the port and the destination, potential scale economies between large ports and all destinations are also loaded on the port fixed effect. Here I also load it on the port cost to allow for them to be taken into account in a reduced form way.

scale economies. The presence of scale economies has two consequences on the impact of changes in port costs. First, when port costs are equalized, the volume at bad ports tends to increase at the expense of the volume at good ports, which reduces the gains from economies of scales at the good ports and tends to decrease the welfare gains from port equalization. Second, the scale economies magnify the port improvements through increased port volume. Which effect dominates is a-priori unclear.

To assess the extent to which the presence of scale economies might impact the counterfactual results, I recompute the welfare gains allowing for scale economies with different values of λ. I first take the estimated τ_ρ and compute t_ρ based on data on the aggregate volume at the port and the value of λ. Then, I equalize all t_ρ to the best level and solve for the counterfactual changes, allowing for τ_ρ to evolve endogenously with volume. The right panel of Figure 10 shows the average wage change across Indian districts for different values of λ for all counterfactuals. For large negative values of λ (congestion), the welfare gains are higher, because the volumes at the port is redistributed across ports, lowering the congestion costs at large ports. For small positive values, welfare gains are lower because the redistribution across ports diminishes the scale economies. But for larger values, the larger volume at the port leads to higher scale economies and higher welfare gains. Overall, however, the ranking of the counterfactuals is preserved: port improvements lead to larger welfare gains than road improvements for all values of scale economies or congestion forces.

To put an upper bound on the value for λ, I run a simple OLS regression of the estimated τ_ρ on value at the port. The estimated λ is upward biased, since the value at the port is negatively correlated with the unobservable t_ρ. The vertical dashed line in figure 10 displays the scale economy implied by the OLS coefficient. [23]

7.4.3 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 road cost estimates are constrained to observables.

As a robustness check, I rerun the port counterfactual by first projecting the port fixed effects on the port-level turnaround time. I then use the estimated coefficient to predict changes in port cost by bringing all turnaround time to the shortest observed turnaround

[23] In practice, I regress the estimated port fixed effect, whose structural interpretation is $-\theta \ln \tau_\rho$, on the (log) total aggregate export volume at the port, measured in weight. The coefficient has a structural interpretation of $\theta\lambda$, and I use $\theta = 21$ to recover $\lambda = 0.043$. For comparison, Ganapati et al. (2021) find an elasticity of 0.07 for economies of scale in leg-level shipping.

time.[24] The resulting counterfactual wage changes are around 0.6% on average, lower than the baseline results. However, they remain larger or equal to the road improvement results. The conclusion that port improvements lead to larger or equal gains than road improvement remains.

7.5 Infrastructure improvement costs

The previous section shows that the welfare gains from port improvements are larger than or equal to those of road improvements on aggregate. 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 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.[25]

Taking log-differences of the port share equation (2) between 2015 and 2019 gives:

$$\ln \pi_{o\rho d,2019} - \ln \pi_{o\rho d,2015} = \theta \Delta \ln \tau_\rho + \theta \Delta \ln \tau_{o\rho} + \theta \Delta \ln \tau_{\rho d} + \alpha_{od}. \tag{29}$$

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

$$\ln \pi_{o\rho d,2019} - \ln \pi_{o\rho d,2015} = \theta \beta^{invest} invest_\rho^{portimp.} + \alpha_{od} + u_{o\rho d}. \tag{30}$$

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. Note that investments targeting a port because of anticipated increase in the traffic between o and d that is likely to translate in a higher traffic at port ρ won't be correlated with the error term because of the α_{od} fixed effect.[26] To assess the relevance of the identification

[24] Precisely, I regress the estimated port cost on the turnaround time as in the left panel of Figure 3. I then feed in changes in τ_ρ such that $d \ln \tau_\rho = \hat{\beta}^{turnaround} (\min_{\rho'} turnaround_{\rho'} - turnaround_\rho)$.

[25] 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`.

[26] For example, the Sagarmala Final Report presents detailed predictions of which destination markets might grow, which ports are used to serve these destinations, and justifies port improvements accordingly. These types of investment targeting are absorbed in the *od* fixed effect.

threat, I run 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 (29), 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 6 shows the results of the estimation. Reassuringly, planned investments are not positively correlated with port share growth.

Table 6: Effects of improvement investments

	Change in port share			
Completed	0.460***			0.801***
	(.163)			(.190)
Under completion		0.146		-0.104
		(.211)	(.141)	
Planned			0.048	-0.307***
			(.116)	(.068)
origin-dest FE	yes	yes	yes	yes
N	26,240	26,240	26,240	26,240
Port cluster	yes	yes	yes	yes

Notes: The table shows the estimates of the PPML regression of the ratio of 2019 to 2015 port shares on investments at the port (equation 30). Standard errors are reported in parenthesis and clustered at the port level.

The estimate in the first column 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 2.2% (0.46/21), using my estimate of $\theta = 21$. 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 about 4.3, the total cost of the port improvement counterfactual is around 195 billion USD.[27]

[27] 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 6 is also divided by θ. However, to compare it to the counterfactual results, the same θ must hold true for the 2015-2019 regression as for the long-run scenario of the model. Since the port elasticity is likely to be smaller in the short run period of 5 years, the reduced port costs induced by observed investments between 2015 and 2019 are likely smaller than those in the long-run. As a consequence, my estimate of the effect of spending on port cost reduction is likely a lower bound, and my cost estimate is likely an upper bound.

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, potential gains from port improvement are greater than or similar to those of road improvement, and their cost is of similar magnitude. Still, their distributional impacts are different and policymakers might prefer using both tools.

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 leads to higher improvements in international market access, and greater or similar aggregate welfare impact as road improvements for comparable costs. I show that their regional distributional implication are different: port improvements benefit coastal regions relatively more, while road improvements benefit inland regions. Policymakers 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.

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A Data

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

A.1 Trade data

A.1.1 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.[28] 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 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*).[29] 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.[30] The list includes the shipping bill number, the date of the transaction and the port of exit. I then obtain additional details

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

[29] 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.

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

of the transactions from the public enquiry "tracking at ICES" form using the shipping bill 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. The details also include a container number. If that is missing, I assume that the export was not containerized. Cross checking the share of containerized transaction by port with port descriptions shows that this way of imputing if the transaction was containerized is accurate.[31]

Sectoral classification I merge the list of exporter/importer firms with the Indian Economic Census directory of establishments[32] and with the "Master Details" of registered companies from the Ministry of Corporate Affairs.[33] 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.[34]

A.1.2 Representativity of the final trade dataset

Firm sample The final sample is comprised of around 11,400 firms. Table 7 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 B discuss the robustness of the paper's stylized facts to removing those intermediaries. Table 8 displays the summary statistics of total export transactions, value, number of destinations, and number of ports used by firm.

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.[35] The left panel of Figure 11 plots the share of each port in my sample against the share in the full dataset. The dots are located

[31]For example, virtually all the transactions at the Jawaharlal Nehru Port Trust are containerized, both in official statistics and in my data. On the contrary, virtually all transactions at the Mumbai Port Trust, which specializes in bulk cargo, are not containerized.

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

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

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

[35]That data is available from the "Data dissemination portal" on the DGCIS' website at `http://dgciskol.gov.in/`.

Table 7: 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.

Table 8: 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.

along a 45 degree line, indicating that my sample is representative in this key dimension. The right panel of Figure 11 repeats the same exercise at the country level. Again, all dots are close to the 45 degree line.

A.2 Port data and sea distance

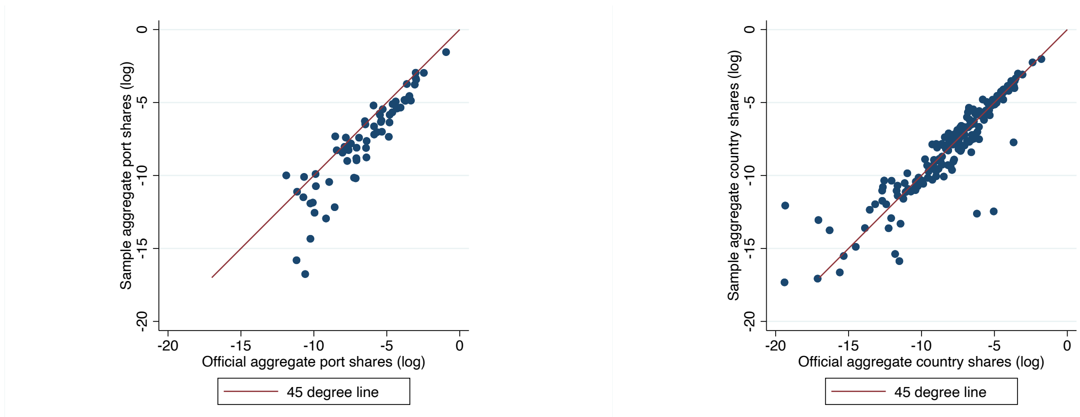
Ports coordinates I use the UN/LOCODE database to get the coordinates of Indian and foreign ports.[36] For some Indian ports, coordinates are missing. I manually add them by searching for the port on Google maps.

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 topography (minimum depth), equipment (number of berth, handling equipment) and capacity.[37] The

[36] The data is available at `https://unece.org/trade/uncefact/unlocode`

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

Figure 11: 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.

same report also contains measures of port productivity (turnaround time, pre-berthing wait time, output per ship berth-day).

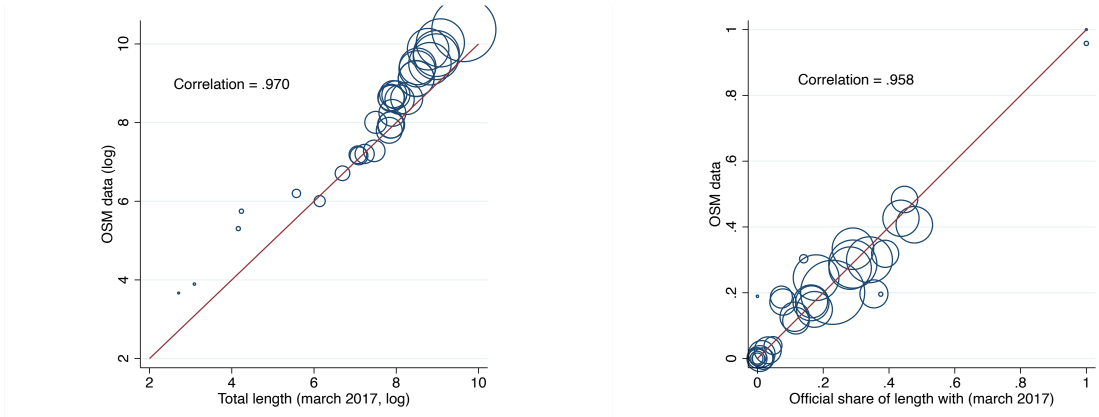
Sea distance I compute the sea distance between each port and foreign port destination using the *searoute* package from Eurostat.[38] I then use the average distance between the port and all foreign ports (weighted by number of transactions) in the country of destination as my measure of port-destination sea distance.

A.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 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").

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

Figure 12: 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.

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".[39]

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 12 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".

[39] 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.

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.[40] 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 (13) and (**??**), 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.

B Stylized facts robustness

Figure 13 displays the number of ports per sector-origin-destination triplet for different aggregation of origin and destination, and for different firm subsamples. In all cases, there is more than one port for the majority of triplets.

C Estimation

In this section, I provide more details about the estimation procedure for the port elasticity θ, and additional robustness checks for its estimation and the infrastructure costs estimation.

C.1 Elasticity estimation

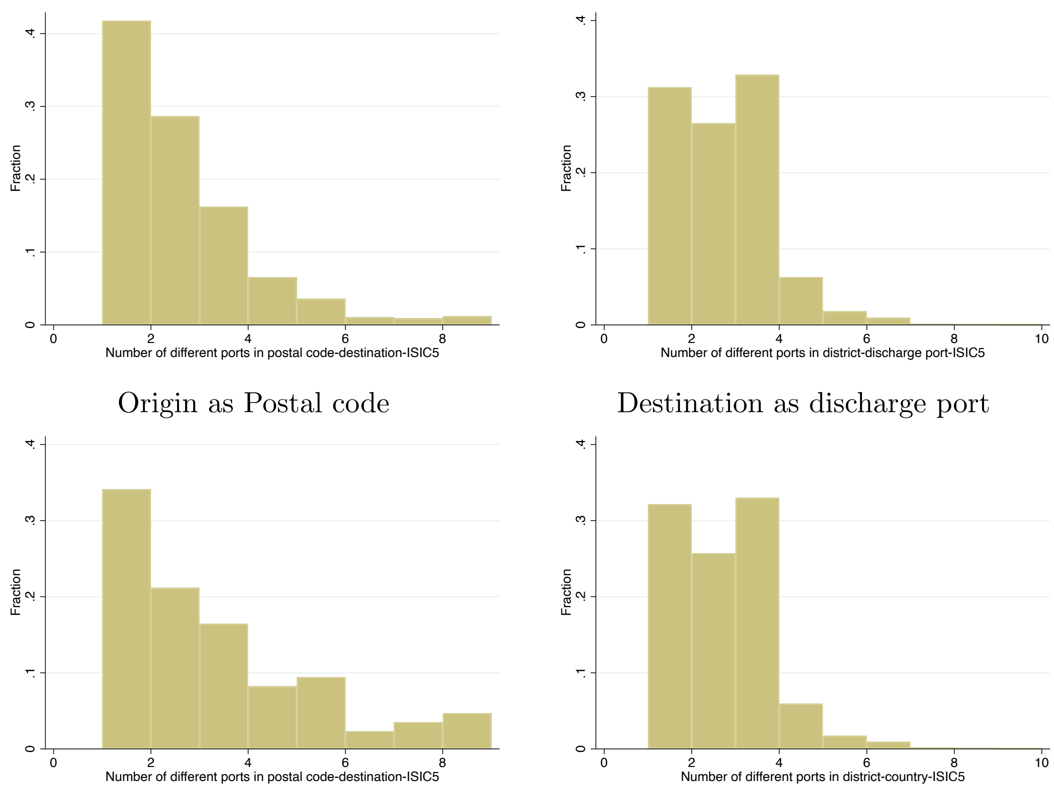
C.1.1 Expected export value derivation

To derive the expected value of exports conditional on the firm choosing its least-cost port, it is useful to present first the following result: 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, is given by:

$$E\left[\left(\min_\rho \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^\lambda\right] = \left[\sum_\rho \left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{\lambda}{\theta}} \Gamma\left(1+\frac{\lambda}{\theta}\right), \tag{31}$$

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

Figure 13: Number of ports per sector-origin-destination (postal code)



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.

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:

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

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:

$$
E\left[\left(\min_{\rho}\frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^{\lambda}\right] = \left[\sum_{\rho}\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{\lambda}{\theta}}\int_{0}^{\infty}\exp\left(-x\right)x^{\frac{\lambda}{\theta}}dx,
$$

and using the fact that $\Gamma\left(\alpha\right)=\int x^{\alpha-1}e^{-x}dx$ 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 (3), simply plug-in $\lambda=1$. To get the expected value of export (equation 6) remember that $p_{iod}=\mu c_{i}\left(\min_{\rho}\frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)$, and the demand is CES, so:

$$
E\left[X_{iod}\right]=\gamma\left(\mu c_{i}\right)^{1-\sigma}\frac{X_{d}}{P_{d}^{1-\sigma}}E\left[\left(\min_{\rho}\frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}\right)^{1-\sigma}\right]
$$

where I used the previous results with $\lambda=(1-\sigma)$ and the fact that the idiosyncratic Fréchet draw is iid, and in particular independent on the firm marginal cost and the destination aggregate demand.

C.1.2 Robustness

Fit of first stage As explained in section 4.1, Assumption 3 is crucial for the identification of the port elasticity, and if the trade cost $\tau_{o\rho d}$ cannot be exactly separated into an origin-port, port, and port-destination component, but also includes an origin-port-destination unobservable error term, the resulting estimate of θ might not be consistent. If the cost is given by:

$$\tau_{o\rho d} = \tau_{o\rho}\tau_{\rho}\tau_{\rho d}\eta_{o\rho d},$$

the port share would be given by

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\eta_{o\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}}$$

instead of

$$\pi_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}}.$$

In that case, regressing the port shares on a set of $o-\rho$, $\rho-d$ and $o-d$ fixed effect would leave $\eta_{o\rho d}$ in the residual error term instead of simply reflecting measurement error in the port share. As a consequence, the residual would be more volatile. Remember that the measurement error comes from the fact that I observe a finite number of firms per $o-d$ pair. Given values for $\tau_{o\rho}$, τ_{ρ} and $\tau_{\rho d}$ (or composites up to τ_{ρ}), and a value of θ, I can simulate Fréchet draws and the resulting port choices for the same number of firms as in my data. I can then use this simulated dataset to regress the first stage. In that regression on the simulated dataset, the only source of the error term comes from measurement error. Hence comparing the volatility of the residuals in the simulated dataset and the actual data is informative on how volatile the potential η term might be. Table 9 displays summary statistics of the data residual and simulated residuals. It turns out that the simulated residuals have a similar volatility as in the data, and that adding an η term to the simulation increases the volatility to more than what is in the data.

Table 9: First stage fit and residual volatility

	Data residuals	Simulation residuals (no η)	Simulation residuals (with η)
Average	0	0	0
Median	-.003	-.003	-.062
SD	0.20	0.21	0.31
p25	-.018	-.019	-.130
p75	-.0006	-.0004	-.0224

D Model appendix

D.1 Model calibration data

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

Lemma 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 1 implies that given d_{od} and $\alpha_d X_d$, there is a unique (to scale) vector of λ_o that satisfies equation (26). 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:

$$\alpha_o X_o = \sum_d \frac{\lambda_o \left(\tau_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(\tau_{kd}\right)^{1-\sigma}} \alpha_d X_d, \tag{32}$$

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

$$\sum_{o \in IND} \pi_{od} = \sum_{o \in IND} \frac{\lambda_o \left(\tau_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(\tau_{kd}\right)^{1-\sigma}} = \pi_{IND,d}^{DATA}, \tag{33}$$

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

$$\sum_{d \notin IND} \frac{X_{d,IND}}{X_{IND}} = \frac{\sum_{d \in IND} \lambda_o \left(\tau_{od}\right)^{1-\sigma} \alpha_d X_d}{\sum_k \sum_{d \in IND} \lambda_k \left(\tau_{kd}\right)^{1-\sigma} \alpha_d X_d} = \pi_{o,IND}^{DATA}, \tag{34}$$

where:

$$\tau_{od} = \begin{cases} 1 & \text{if } o = d \\ \exp\left(\sum_c \beta^c dist^c_{od}\right) & \text{if } o, d \in IN \\ a^{exp}_d \underbrace{\left[\sum_\rho \left(\exp\left(\sum_c \beta^c dist^c_{o\rho}\right) \tilde{\tau}_\rho \left(seadist_{\rho d}\right)^\gamma\right)^{-\theta}\right]^{-\frac{1}{\theta}}}_{\tilde{\tau}_{od}} & \text{if } o \in IN, d \notin IN \\ a^{imp}_o \left[\sum_\rho \left(\exp\left(\sum_c \beta^c dist^c_{o\rho}\right) \tilde{\tau}_\rho \left(seadist_{\rho d}\right)^\gamma\right)^{-\theta}\right]^{-\frac{1}{\theta}} & \text{if } o \notin IN, d \in IN \\ \tau_{od} & \text{if } o, d \notin IN \end{cases} \tag{35}$$

The normalization constants a^{exp}_d and a^{imp}_o allow me to match the aggregate Indian shares $\pi^{DATA}_{IND,d}$ and $\pi^{DATA}_{o,IND}$ 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:

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

   (b) India to foreign flows:

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

   (c) Foreign to India flows:

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

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

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

E Counterfactuals appendix

E.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:

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

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

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

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

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

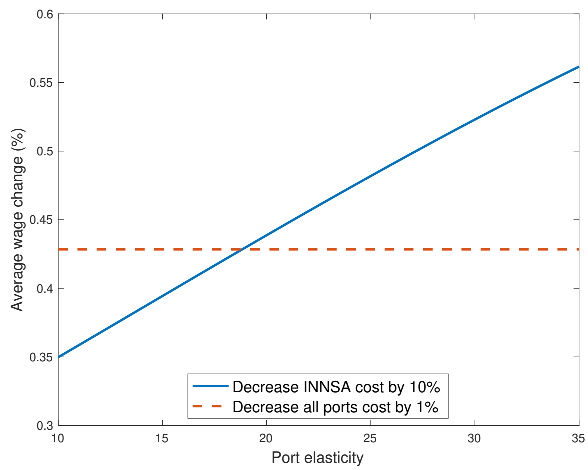
and $\hat{\tau}_{o\rho}$ and $\hat{\tau}_\rho$ are as specified in section 7.2.

E.2 Additional results

E.2.1 Varying the port elasticity for a given port cost change

Figure 14 displays the average gains under different port elasticities for two scenarios. First, from reducing the cost of the largest port (Nava Sheva) by 10%. Second, from reducing the costs of all ports by 5%. In the first case, the gains unambiguously increase with the port elasticity, as the second-order terms become larger and more firms switch to the improved port. In the second case, the port elasticity doesn't matter since all ports are improved by the same amount.

Figure 14: Impact of port elasticity on heterogenous and homogenous port improvements



Notes: The figure plots the average real wage change across districts under different port elasticities, when reducing the cost of using the port of Nava Sheva by 10%, and when reducing the cost of all ports by 5%.