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

Barthélémy Bonadio
NYU Abu Dhabi

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**Abstract**

What determines the relative gains from improving different parts of a transportation network? Ports and roads are key components of a country's infrastructure to access international markets. I provide a framework to jointly estimate the quality of different ports and trade costs on normal roads and expressways. 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, and estimate it using a novel transaction-level export dataset for India. A key elasticity of route switching governs the relative gains from port vs road improvements. I find that returns of improving ports are higher than those for roads under the existing Indian infrastructure network, but improvements in ports and roads have different distributional implications.

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# 1 Introduction

Access to international markets relies on a multifaceted infrastructure network. Poor national infrastructure can prevent this access and hinder economic development (see e.g. WTO, 2004; Atkin et al., 2022). Accordingly, significant investments are targeted at improving infrastructure needed to access global markets to foster growth.[1] Internal road infrastructure is key to foreign market access (Limao and Venables, 2001; Coşar and Demir, 2016), but ports are also crucial, as around 80% of the world's cross-border trade in goods transits through the sea (UNCTAD, 2018). Which part of the infrastructure network is the bottleneck to global integration remains an open question.

Answering this question requires a framework encompassing several types of infrastructure and sufficiently disaggregated data on export routes. This paper starts by building a novel transaction-level export dataset of Indian exporters well suited for this issue. A key feature of the dataset is that it contains information on firms' location, export destinations, and port of exit, which I use to document new stylized facts about exporters' port usage. Furthermore, India is a large country with a long coastline, many ports, a rich internal geography, and where roads account for most of internal transportation. Significant investments in ports and their connectivity are being undertaken, making it an ideal setting to study this question.[2]

Focusing on containerized exports, I document that, first, firms don't always use the port closest to their location, nor the one closest to their destination. Second, 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. Motivated by these facts, I build a quantitative model of internal and international trade with a rich specification of trade costs. There are many locations in India and many foreign markets. Firms in each location export to foreign destinations. In order to reach the foreign consumers, a firm in an Indian district must ship its goods by road to a port, from which the goods depart for abroad. There are multiple ports. The firm chooses the port through which to export its good to each foreign market, and by extension which road segments to use to get to that port. This choice is subject to an idiosyncratic firm-port-specific shock, which induces firms in the same origin-destination pair to choose different ports, thus rationalizing the heterogeneity in the data.

The choice of port depends on the transshipment cost at the port, on the road quality

[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. 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.

[2]See for example "Global Trade Needs a China Alternative. India Needs Better Ports.", The New York Times, 20 August 2024.

to the port, and on a key elasticity that governs how firms adapt their route depending on the costs. I call this elasticity a "port elasticity". The elasticity not only governs how port usage varies with port transshipment costs, but also how changes in some segments of the infrastructure affect the export cost. Using simple counterfactuals to underline key mechanisms, I show that this elasticity governs optimal port targeting, the relative gains from port and road improvements, and complementarities between road and port improvements.

I develop a novel approach to estimate the key parameters based on equations implied by the theory. The origin-port-destination dimensions in the data allow me to non-parametrically recover the impact of origin-port and port-destination costs on port usage shares using fixed effects. A model-implied equation further combines these costs into origin-destination specific export costs, up to the port elasticity. Those export costs in turn determine export prices. When prices react less than port shares to a given change in cost, this implies a large port elasticity. My estimation strategy uses this fact to identify the elasticity. To estimate road shipping costs and port transshipment costs, I regress port shares within an origin-destination pair on origin-port road distances on different road categories and on port fixed effects, controlling for the port-destination cost. The coefficients on the different road categories provides an estimate of the cost of distance on a normal road versus an expressway. The structural interpretation of the port fixed effects is that they reflect port quality: high port shares conditional on origin-port and port-destination costs imply an otherwise low transshipment cost at the port.

I estimate a port elasticity of around 15. This means that when the transshipment cost at a port decreases by 1%, its share of use increases by around 15%. My estimates imply significant variation across Indian ports: the standard deviation of port transshipment costs is equivalent to an ad-valorem trade cost of around 15%. My port transshipment costs 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 to find that an additional 100 kilometers (60 miles) on an expressway is equivalent to an ad-valorem trade cost of around 1.5%, while it is 18% higher on a normal road. I also explore the potential sectoral heterogeneity in port transshipment costs, but don't find large differences across sectors, consistent with the fact that containerized trade is fairly standardized.

I calibrate the model to over 630 Indian districts and 56 countries, using data on GDP, trade flows and my trade costs estimates. I first conduct simple counterfactuals that underline key mechanisms. First, a large elasticity increases gains from improving a port, all else equal, because more exporters switch to the improved port. As a consequence, a large elasticity implies that it is more effective to target a single port for improvement. Second, gains from road improvements are less dependent on the port elasticity because a given road segment might be used to reach many different ports. Hence, a larger port elasticity increases the gains from improving ports relative to roads. Third, the elasticity also governs complementarities between road and port improvements. Given a targeted port, gains from coordinating port and road improvements are larger when the elasticity is high, because improving roads leading to other ports diverts port usage away from the targeted port.

To illustrate the aggregate and regional impacts of road and port improvements, I then perform several counterfactuals individually bringing each part of the infrastructure to its best potential level. One counterfactual simulates what would happen if all ports had the same transshipment cost as the best Indian port. In that case, real wages in India would increase by around 1% on average and exports as a share of GDP would increase by 3.1 percentage points. Another counterfactual improves all roads to expressways and reduces district-to-district internal trade costs as well as the road costs to the port. In that scenario, average wages would increase by 0.6%. I then decompose this 0.6% into a component coming from increased international market access, and from gains from better connection within the internal market. Overall, the counterfactuals' results show that port improvements are an order of magnitude more important than road improvements for international market access. The two infrastructure improvement scenarios have different regional implications. Port improvement tends to favor coastal, export oriented, regions because they lower export costs the most. On the other hand, road improvements favor domestically oriented regions because roads determine district-to-district trade costs, and inland regions whose connectivity to ports improves.

I show that while improving ports has larger welfare benefits, it doesn't have a larger costs. I use data on investment in ports completed between 2015 and 2019 to estimate the marginal impact of spending on port transshipment costs. I also estimate the cost of improving all roads by using data on cost per kilometer of highway improvement. Using these estimates, I find that the costs of these broad investments are of similar magnitude, despite their different aggregate welfare implications. I also use these estimates to simulate marginal improvements to specific road segments and ports. I find that the marginal returns on investment for port are also higher than those for road.

Improving specific ports can also provide a tool to address distributional concerns. For each district, I find the port whose improvement results in the highest district-level welfare gain. The largest port of Nava Sheva (in Mumbai) is the bottleneck for the most regions. However, smaller ports are the bottlenecks for a non-negligible number of regions. For example, the port of Kolkata is the bottleneck port for many of Indian's poorest regions located in the North-East. Finally, I explore the consequences of planned port investments under the Maritime India Vision 2030, and show the importance of the port elasticity in determining optimal port targeting.

I provide a sensitivity analysis that addresses the potential presence of congestions or economies of scales at the port. I introduce port economies of scale in the model and solve it under a range of potential coefficients to show that in all cases, the main results of the paper remain qualitatively unchanged.

This paper contributes to three strands of the literature. First, the literature on infrastructures. While previous literature has typically 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., 2022; Fan et al., 2023; Jaworski et al., 2020; Xu and Yang, 2021) or rail network (Donaldson, 2018). Recently, a limited number of papers have focused on sea shipping networks (Ganapati et al., 2021; Heiland et al., 2023) and ports (Ducruet et al., 2024; Brancaccio et al., 2024).[3] In this paper, I explicitly model both 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 mostly focused on a single type of infrastructure (Fajgelbaum and Schaal, 2020; Santamaria, 2020).[4]

Second, a branch of the literature also studies how internal trade costs affect international trade and regional distributional impacts of trade liberalization (e.g. Atkin and Donaldson, 2015; Sotelo, 2020). I contribute to this literature by emphasizing the role of 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.

Third, I contribute to the fast-growing literature on infrastructure networks that uses heterogeneous shipping costs for analytical convenience following Allen and Arkolakis (2022). In these papers, agents are assumed to face heterogenous export costs. When the heterogenous component of costs is Fréchet distributed, the model typically allows 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 support the assumption of heterogenous shipping costs and provide a novel estimate of the route elasticity for the case of ports. More generally, my results highlight the importance of this elasticity in governing gains from improving particular segments of an infrastructure network.

The most closely related papers are Ducruet et al. (2024) and Brancaccio et al. (2024). The first investigates the local impact of port development, focusing on land use required to handle containerized trade. I focus on the heterogenous impact of port development across different regions of a country and directly compare the impact of port infrastructure

[3] Blonigen and Wilson (2008) uses data on import charges to estimate port productivities. My framework only requires data on port of exit, which is nowadays more commonly accessible through customs dataset.

[4] Fuchs and Wong (2023) also study multimodal transportation networks in the US setting.

and road infrastructure. Brancaccio et al. (2024) focuses on ports productivity specialized in bulk shipping in a partial equilibrium setting, while I focus on container shipping and compare ports with roads in a general equilibrium setting.

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 internal and external trade with port choices, Section 4 shows how to estimate the key parameters and port quality, Section 5 shows the estimation results, Section 6 presents the results of the counterfactuals.

# 2 Data and facts

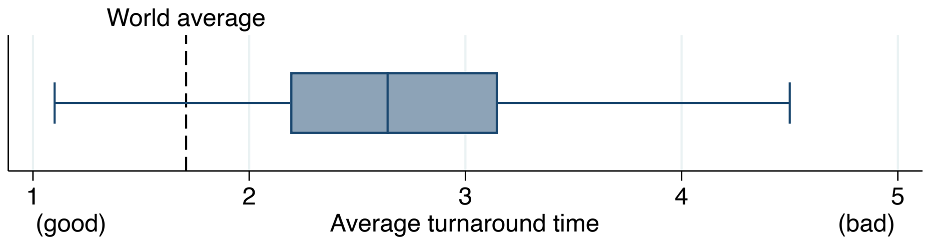
## 2.1 Data

The main data I use is a novel dataset of firm-level export transactions ("Shipping Bills") from India. The dataset construction involves several data sources, web-scraping, and name-matching techniques. I start by 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 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 and quantity of the transaction, the port of exit, the destination country, and whether the export was containerized or not. I also observe the list of the 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 in value.[5] 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 87% of sea exports in value and over 95% in numbers of firms in my sample. I keep all transactions going through ports used by at least 10 firms in my sample. The resulting sample covers around 11,400 firms, 400 Indian districts, 16 ports, and close to two hundred destinations. The 16 ports cover over 99% of Indian sea container exports. Appendix A shows that the sample is representative of the official aggregate figures for key statistics such as port and destination

[5] 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.

shares.

## 2.2 Stylized facts

In this section, I briefly describe the characteristics of ports in India, and show two stylized facts about port usage that are useful ingredients for modeling 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. 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, 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. 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.[6] 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.[7] The chosen

[6]My data doesn't explicitly say which of the firm's branches shipped the goods. I assume that the branch closest to the observed port of exit is the origin branch. Appendix B provides additional results using single-plant firms only.

[7]The closest available port is defined as the closest port for which I observe some containerized transaction.

Table 1: Observed and shortest port distances

| | origin-port distance | | | port-destination distance | | |
|---|---|---|---|---|---|---|
| | observed | closest | $\frac{close-obs}{obs}$ | observed | closest | $\frac{close-obs}{obs}$ |
| 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.

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.

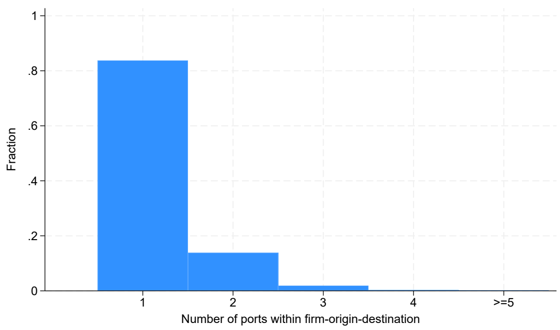
**Fact 3: firms use a single port per destination in a given period** The left panel of Figure 2 shows the histogram of the number of port used within a firm-destination pair in a year. More than 80% of firms use a unique port to reach a destination in the same year. Appendix B also looks at different time periods. The share of firm-destination pairs with more than one port increases when pooling years 2015-2019 together, and decreases when looking at individual months. This indicates that firms do switch through time, potentially reacting to changes in port quality.

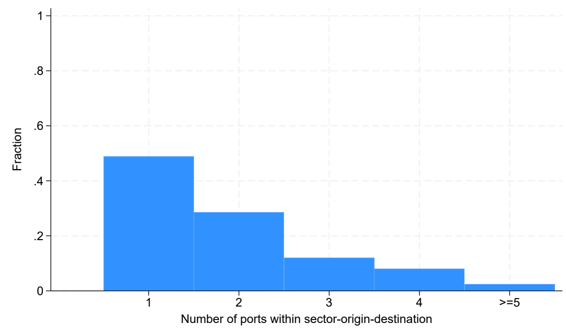
**Fact 4: observably similar firms use different ports** I next look at how homogeneous port usage is among comparable firms. To that end, I compute the number of different ports used by firms in the same sector and same origin region, to export to a same destination within a year. I define a sector as an International Standard Industrial Classification (ISIC) 5-digit group, an origin region as an Indian district, and a destination as a country.[8] 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.[9]

[8] An example of ISIC5 category is 17111 which corresponds to "Preparation and spinning of cotton fiber including blended cotton".

[9] The emerging literature incorporating ports in international shipping has built on the heterogeneous trade cost model of Allen and Arkolakis (2022). In that framework, agents (firms or traders) don't all incur

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 5 firms are kept to avoid triplets where the number of ports is 1 simply due to small sample.

Appendix B explores narrower geographical (port of discharge) or time classifications (by month). I also check that the results are not driven by small ports used only marginally. The same patterns holds overall: a least 60% of exports (measured in share of transactions or share of value) go through ports that represent less than 90% of the triplet.

# 3 Quantitative framework

The quantitative model I develop here augments the Krugman (1980) model with a richer specification of trade costs that accommodates the facts presented above. There are $N$ regions, which can be either Indian districts or foreign countries.

## 3.1 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, $\alpha_d$ is the share of goods in consumption, and $G_d$ is a CES aggregate of a continuum of goods, with elasticity of substitution $\sigma$:

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

where $c_{id}$ is the amount of good $i$ consumed in region $d$.

the same cost when using a specific route. The facts shown here support that hypothesis.

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

$$\int_i p_{id} c_{id} di + P_d^S S_s = w_d L_d,$$

where $p_{id}$ is the price of good $i$ in region $d$, $P_d^S$ is the price of services in region $d$, and $w_d$ 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 the standard CES demand function:

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

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.

## 3.2 Production

### 3.2.1 Services

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

$$y_d^S = A_d^S L_d^S, \tag{2}$$

where $A_d^S$ is labor productivity in the production of services and $L_d^S$ is total labor used for service production in region $d$. There is perfect competition, so the price of services in region $d$ is $w_d / A_d^S$, profits are zero and total sales are equal to labor costs and given by $Y_d^S = w_d L_d^S$.

### 3.2.2 Goods

**Production technology** The production of manufacturing goods is similar to Krugman (1980). Each good $i$ is produced by a corresponding differentiated firm, also denoted by $i$. Firms compete in a monopolistically competitive fashion, and the production features a fixed cost of entry and a constant marginal cost. More precisely, a firm $i$ in region $o$ is required to pay a fixed cost $f_o$ in units of labor to enter the market, and requires $1/A_o$ units of labor to produce each marginal unit of good.

**India-foreign trade costs through ports** Trade of goods between regions is costly. To export to a foreign country, a firm located in an origin region $o$ in India must first bring its good to a port, pay a transshipment cost at the port, and then incur the cost of going from the port to the destination. I assume that an iceberg trade cost occurs at each part of the journey. A fraction $1/\tau_{o\rho}$ "melts" on the way from the origin to the port, so that the firm must ship $\tau_{o\rho}q$ units for $q$ units to reach the port. Similarly, there is an iceberg physical transshipment cost $\tau_\rho$ when the good is loaded on the ship, and an iceberg cost $\tau_{\rho d}$ from the port to the destination. As a result, the total aggregate iceberg trade cost is given by:

$$\tau_{o\rho d} = \tau_{o\rho}\tau_\rho\tau_{\rho d} \tag{3}$$

To match the heterogeneity of port choice documented above, I further assume that each firm $i$ is subject to an idiosyncratic shock such that the firm-specific iceberg trade cost is given by

$$\tau_{io\rho d} = \frac{\tau_{o\rho}\tau_\rho\tau_{\rho d}}{\varepsilon_{io\rho d}}, \tag{4}$$

where $\tau_{o\rho}\tau_\rho\tau_{\rho d}$ captures the costs of using port $\rho$ to reach destination $d$ from origin $o$ common to all firms, and $\varepsilon_{io\rho d}$ is a firm-route-specific ($io\rho d$) productivity shifter that rationalizes the fact that different firms within the same sector-origin-destination use different ports. The firms only learn their idiosyncratic port-route productivities $\varepsilon_{io\rho d}$ after paying the fixed entry cost.

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

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

where $\theta$ is a shape parameter that governs the dispersion of $\varepsilon$. High values of $\theta$ imply a low dispersion of the idiosyncratic shock, implying that all firms face the same trade cost.

The firm chooses the port $\rho^*$ 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 $\rho$ is given by (see Appendix C for proofs):

$$\pi^{port}_{o\rho d} = \frac{\left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}}{\sum_k \left(\tau_{okd}\right)^{-\theta}}, \tag{5}$$

so that $\theta$ can also be interpreted as the port elasticity. For large values of $\theta$ (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 $\varepsilon$ is more concentrated and a larger mass of firms see their optimal choice changing.

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

$$d_{od} = E\left[\min_{\rho} \frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}}\right] = \kappa\left[\sum_{\rho}\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}\right]^{-\frac{1}{\theta}}, \tag{6}$$

where $\kappa$ is a constant involving the Gamma function and $\theta$. Notice that the expected trade cost depends on the same term $\Phi_{od} = \sum_{\rho}\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}$ as the denominator of the port probability equation (5), and the probability of choosing port $\rho$ can be rewritten in term of expected export cost:

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

and $\theta$ is the elasticity of port share with respect to both the cost of using the port $(\tau_{o\rho}\tau_{\rho}\tau_{\rho d})$ and the expected average trade cost $(d_{od})$. In addition to being the elasticity of port shares with respect to port costs, the parameter $\theta$ governs how changes in individual port costs aggregate up to changes in the average cost. To see this, consider the second order approximation of the (log) change in $d_{od}$ following a change in $\tau_{\rho}$:

$$d\ln d_{od} \approx \underbrace{\pi_{o\rho d}^{port} d\ln\tau_{\rho}}_{\text{F.O.}} - \underbrace{\theta\pi_{o\rho d}^{port}\left(1-\pi_{o\rho d}^{port}\right)\left(d\ln\tau_{\rho}\right)^{2}}_{\text{firm choice adjustment}}. \tag{7}$$

The first term of equation 7 captures the first order effect, which depends on the share of firms using a particular port. Because firms are already choosing their optimal port, the envelope theorem implies that the first order effect of the decrease in a particular port is equal to the share of firms that use this particular port. The second term captures the reallocation of firms towards the newly lower cost port. When the port elasticity $\theta$ is large, more firms adjust their port choice which results in a reduction in the trade cost. Note that the second-order term is always negative regardless of whether the port cost increases or decreases, because it capture the reoptimisation of firms following any type of change. As a results, the parameter $\theta$ is central in governing how individual port cost changes aggregate up to the average trade cost.

Foreign firms shipping to an Indian district through Indian port $\rho$ also faces an idiosyncratic cost that depends on the port, in a symmetric fashion as Indian exporters. This specification of trade costs is related to an earlier working paper version of Allen and Arkolakis (2022), with the following departure.[10] That paper introduces an intermediary trader

[10]The earlier working paper version distinguishes between the route choice elasticity and the trade elasticity. In the final version (Allen and Arkolakis, 2022) and in most follow up papers in the subfield (e.g. Ganapati et al., 2021) 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,

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.

**Exports aggregation** Conditional on firm entering the market, profit maximization combined with the CES demand function in (1) implies that exports of firm $i$ in district $o$ to foreign destination $d$ are given by:

$$X_{iod} = \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o}\tau_{iod}\right)^{1-\sigma}\frac{X_d^G}{\left(P_d^G\right)^{1-\sigma}}.$$

Integrating over all firms and their Fréchet draws that enter $\tau_{iod}$, expected exports of goods of a firm in region $o$ to destination $d$ are given by:

$$E[X_{iod}^G] = \kappa\left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o}d_{od}\right)^{1-\sigma}\frac{X_d^G}{\left(P_d^G\right)^{1-\sigma}}, \tag{8}$$

where $\kappa$ is a constant involving the Gamma function and parameters $\sigma$ and $\theta$. Multiplying by the number of firms in region $o$ gives the following expression for aggregate exports from $o$ to $d$:

$$X_{od}^G = N_o^f\kappa\left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o}d_{od}\right)^{1-\sigma}\frac{X_d^G}{\left(P_d^G\right)^{1-\sigma}}, \tag{9}$$

where $N_o^f$ is the number of firms in region $o$. For India-foreign pairs, $d_{od}$ is given by equation (6) and depends on all the port specific costs $\tau_o$, $\tau_\rho$ and $\tau_d$. When $o$ and $d$ are both foreign countries or both Indian districts, the same formula holds but where $d_{od}$ is the exogenous trade cost.

**India internal cost and foreign-foreign costs** Other trade costs are constant and common to all firms. A firm in a foreign country $o$ shipping to another foreign country $d$ faces an iceberg trade cost $d_{od}$. A firm located in an Indian district $o$ shipping to an other Indian district $d$ faces a trade cost $d_{od}$ common to all firms.

### 3.3 Equilibrium

**Aggregate goods output and variable profits** Total sales of goods in region $o$ are given by:

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

the dispersion parameter $\theta$ has the interpretation of a trade elasticity. In the present paper, the dispersion parameter in trade costs draws $\theta$ is allowed to differ from the trade elasticity.

and the aggregate variable profits associated with these sales are given by:

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

**Labor demand aggregation** Labor demand from firm $i$ is isoelastic and given by:

$$l_{io} = \frac{1}{w_o} \left( \frac{\sigma}{\sigma - 1} \right)^{-\sigma} \sum_d \left( \frac{w_o}{A_o} \tau_{iod} \right)^{1-\sigma} \frac{X_d^G}{\left(P_d^G\right)^{1-\sigma}} + f_o,$$

and aggregate labor demand for goods production in region $o$ is given by:

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

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 the aggregate variable profits are equal to the fixed entry cost $w_o f_o$ multiplied by the number of firms $N_o^f$. Plugging that in the total labor demand from the goods sector gives the following demand for labor in the goods sector $L_o^G$:

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

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

$$w_d L_d^S = \underbrace{(1 - \alpha_d) w_d L_d}_{\text{demand for services}},$$

and market clearing together with balanced trade in the goods sector implies that:

$$\underbrace{\sum_o X_{od}^G}_{\text{goods exports}} = \underbrace{\alpha_d w_d L_d}_{\text{goods consumption}}$$

**Labor market clearing** Labor payments in the two sectors add up to the total labor income:

$$w_o L_o^G + w_o L_o^S = w_o L_o$$
$$w_o \sigma N_o^f f_o + (1 - \alpha_o) w_o L_o = w_o L_o,$$

so that firm entry depends only on exogenous parameters and is given by $N_o^f = \frac{\alpha_o L_o}{\sigma f_o}$, and the sectoral labor quantities are given by:

$$L_o^S = (1 - \alpha_o) L_o, \qquad L_o^G = \alpha_o L_o. \tag{10}$$

**Equilibrium system** In the end, the equilibrium can be reduced to a set of trade flows $X_{od}^G$, port costs $\tau_\rho$, wages $w_o$, and goods sector price indices $P_o^G$ that satisfies the following system of equations, given exogenous parameters $\alpha_o$, $L_o$, $f_o$, $A_o$, $d_{od} \forall o, d \in IN$ and $\forall o, d \notin IN$, and $\tau_{o\rho} \forall o \in IN$, $\tau_{\rho d} \forall d \notin IN$ as well as elasticities $\sigma$ and $\theta$:

$$X_{od}^G = \frac{\alpha_o L_o}{\sigma f_o} \left( \frac{\sigma}{\sigma - 1} \frac{w_o}{A_o} d_{od} \right)^{1-\sigma} \frac{\alpha_d w_d L_d}{\left(P_d^G\right)^{1-\sigma}}, \tag{11}$$

$$\left(P_d^G\right)^{1-\sigma} = \sum_o \frac{\alpha_o L_o}{\sigma f_o} \left( \frac{\sigma}{\sigma - 1} \frac{w_o}{A_o} d_{od} \right)^{1-\sigma} \tag{12}$$

$$\alpha_o w_o L_o = \sum_d X_{od}^G \tag{13}$$

where

$$d_{od} = \begin{cases} 1 & \text{if } o = d \\ d_{od} & \text{if } o, d \in IN \text{ or } o, d \notin IN \\ \kappa \left[ \sum_\rho \left( \tau_{o\rho} \tau_\rho \tau_{\rho d} \right)^{-\theta} \right]^{-\frac{1}{\theta}} & \text{if } o \in IN \text{ \& } d \notin IN, \text{ or } d \in IN \text{ \& } o \notin IN. \end{cases} \tag{14}$$

# 4 Estimation of the port elasticity $\theta$ and costs $\tau_{o\rho d}$

In this section, I show how to identify the elasticities $\theta$ and $\sigma$, as well as the port costs $\tau_\rho$ (up to a normalization), and infrastructure costs $\tau_{o\rho}$, $\tau_{\rho d}$.

## 4.1 Port elasticity

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 $\rho$ is equal to the probability that it choses port $\rho$. This gives rise to the following estimation equation:

$$E\left[1_{io\rho d}\right] = \frac{\left(\tau_{o\rho} \tau_\rho \tau_{\rho d}\right)^{-\theta}}{\left(d_{od}\right)^{-\theta}}, \tag{15}$$

where $1_{io\rho d}$ is a dummy variable equal to 1 if firm $i$ located in region $o$ uses port $\rho$ to export to destination $d$. I estimate equation 15 using a Poisson PMLE procedure and use $o\rho$, $\rho d$

and $od$ fixed effects to capture the unobservable $\tau$ terms:

$$E\left[1_{io\rho d}\right]=\exp\left(\underbrace{-\theta\ln\tau_{o\rho}-\theta\ln\tau_{\rho}}_{f_{o\rho}\text{ FE}}-\underbrace{\theta\ln\tau_{\rho d}}_{f_{\rho d}\text{ FE}}+\underbrace{\theta\ln d_{od}}_{od\text{ FE}}\right). \tag{16}$$

The estimated $f_{o\rho}$ and $f_{\rho d}$ fixed effects are estimated up to the port cost $\tau_{\rho}$, 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.[11] Armed with a consistent estimate of $-\theta\ln\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)$, I construct the following generated regressor:

$$z_{od}=\sum_{\rho}\exp\left(f_{o\rho}+f_{\rho d}\right). \tag{17}$$

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 $-\theta\ln\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)$.[12]

Substituting $d_{od}$ with $\left(z_{od}\right)^{-1/\theta}$ in the firm's optimal price (constant markup over marginal price) gives:

$$\begin{aligned} E\left[p_{iod}\right] &= E\left[\frac{\sigma}{\sigma-1}c_i\min_{\rho}\frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{o\rho d}}\right]=\gamma\frac{\sigma}{\sigma-1}c_i d_{od} \\ &= \alpha_i\left(z_{od}\right)^{-\frac{1}{\theta}}\nu_{od}, \end{aligned} \tag{18}$$

where $\gamma$ is a constant involving the Gamma function, $\nu_{od}$ is an error term that vanishes as the sample grows and $\alpha_i$ captures the marginal cost of firm $i$.[13] Equation 18 provides a way to consistently estimate $\theta$ from the coefficient on $z_{od}$, by using data on unit prices of the export transactions. Appendix E.3 discusses the potential small sample bias of the consistent estimation procedure.

[11] Intuitively, for each $o\rho$ pair, there is a large number of destinations, and for each $\rho d$, there is a large number of origins. However, the $od$ fixed effect isn't consistently estimated because its dimensionality grows with $OD$. 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 $D$. See Weidner and Zylkin (2021) on the consistency of the PPMLE estimator with three-way fixed effects.

[12] Remember that the expected trade cost $d_{od}$ is given by $d_{od}=\left[\sum_{\rho}\left(\tau_{o\rho d}\right)^{-\theta}\right]^{-\frac{1}{\theta}}$. Note that a specificity of the PPML estimator is that it satisfies adding-up of the observable (see Fally, 2015). Hence under PPML, the generated $z_{od}$ is actually exactly equal to the $od$ fixed effect because the left-hand side sums to 1 because it is a probability. This is not generally true if an other estimator was used.

[13] In the quantitative model in Section 3, all firms in a region have the same marginal cost $c_i=w_o/A_o$. In the estimation, I allow for firm heterogeneity in marginal cost to avoid contaminating the estimation with heterogeneity from the well documented firm heterogeneity in productivity.

Further, substituting $d_{od}$ with $(z_{od})^{-1/\theta}$ in the firm export value equation (8) gives:

$$\begin{aligned} E\left[X_{iod}\right] &= \gamma\left(\frac{\sigma}{\sigma-1}c_i\right)^{1-\sigma}\frac{X_d}{P_d^{1-\sigma}}\left(d_{od}\right)^{1-\sigma} \\ &= \alpha_i\beta_d\left(z_{od}\right)^{\frac{\sigma-1}{\theta}}\nu_{od}, \end{aligned} \tag{19}$$

which 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 *free-on-board* value of exports, so that the cost of going from the port to the destination is not included in the observed value while it should be in the model equivalent price. To account for this, I assume that I observe $X^*_{iod} = (X_{iod}/\tau_{\rho d})\,\mu_{iod}$, where $\mu_{iod}$ is an iid error term. In that case, adding a port-destination ($\rho d$) fixed effect to the second stage regression controls for $\tau_{\rho d}$ and the fact that I observe only FOB value.[14]

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 triplet level instead of origin-destination pair level, and explore sector-specific elasticities as well.

## 4.2 Infrastructure quality

This section shows how to estimate the trade costs on the key parts of the infrastructure network: different types of roads, and ports. As mentioned above, the share of firms within an origin-destination pair using a given port is informative on the underlying trade cost to the port and port quality. As a reminder, the equation of port shares (5) with the three-part trade cost assumption gives:

$$\pi_{o\rho d} = \exp\left(-\theta\ln\tau_{o\rho} - \theta\ln\tau_\rho - \theta\ln\tau_{\rho d} + \theta\ln d_{od}\right).$$

While the previous section focused on estimating $\theta$ and didn't need to identify $\tau_\rho$, I now show how to recover estimates of $\tau_\rho$ given an estimate of $\theta$. The strategy is to express $\tau_{o\rho}$ as a function of the distance on different types of roads on the route between $o$ and $\rho$, parametrize $\tau_{\rho d}$, and estimate $\ln\tau_\rho$ using a port fixed effect.

Intuitively, if a large share of firms uses port $\rho$ after controlling for the cost of going from the origin to the port and from the port to the destination, the cost of transhipment at port $\rho$ ($\tau_\rho$) is likely to be low. Hence regressing the port use share on a port fixed

[14] In more details:

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

effect after controlling for $\tau_{o\rho}$ and $\tau_{\rho d}$ will provide a measure of $\tau_{\rho}$. How much the observed share differential translate into an underlying change in cost also depends on the port elasticity $\theta$. With a large port elasticity, a given port share differential implies a small port cost differential, while a small port elasticity means that even small port usage differential capture large underlying port costs differentials.

I assume that firms ship their good to the ports using roads.[15] The cost of shipment between $o$ and $\rho$ is the product of the cost over each segment of road $k$ used to get from $o$ to $\rho$ on least-cost path on the road network, as well as a term capturing if the origin is in a different state as the port:

$$\tau_{o\rho} = \prod_{k} t_{k(o\rho)} \left(sameState_{o\rho}\right)^{\beta_{ss}}. \tag{20}$$

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

$$t_k = \exp\left(\tilde{\beta}^{c(k)} dist_k\right). \tag{21}$$

where $c(k)$ is the road category of segment $k$ and $dist_k$ is the distance travelled on the segment. Using the product of segment-level costs and an exponential form for the segment-level costs has two advantages. First, when the distance on the segment tends to 0, the iceberg trade cost naturally tends to 1. Second, taking the product of the exponential implies that only the total distance over all segments matters for the route cost. This means that the costs under this parametrization are not dependent on arbitrary segmentation of the road network. 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 total, two per direction). The parameter $\tilde{\beta}^{c}$ captures the trade cost semi-elasticity with respect to distance on a particular type of road.

I also parametrize the cost between the port and the destination as a function of the sea distance between the port and destination, and the existence of a direct container shipping route between the port and the destination:

$$\ln \tau_{\rho d} = \lambda_1 \ln seadist_{\rho d} + \lambda_2 liner_{\rho d}, \tag{22}$$

where $liner_{\rho d}$ equals one if there exists a regular container liner service between the port and the destination country.

[15] See below in section 5.3 for a discussion on other modes of transportation in India.

Combining the parametrizations leads to the following estimating equation:

$$\pi_{o\rho d} = \exp\Bigg(\sum_c \underbrace{\beta^c}_{-\theta\tilde{\beta}^c} dist^c_{o\rho}(\{\beta^c\}) + \beta^{ss} sameState_{o\rho}$$

$$+\beta^{sea}\ln seadist_{\rho d} + \beta^{liner} liner_{\rho d} + \underbrace{\alpha_\rho}_{-\theta\ln\tau_\rho} + \Phi_{od}\Bigg),$$

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

$$\min_{\{\beta_c\},\beta^{sea},\{\alpha_\rho\},\{\Phi_{od}\}} \Bigg[\pi_{o\rho d} - \exp\Bigg(\min_{r\in R_{o\rho}}\left\{\textstyle\sum_c \beta^c dist^c_{o\rho}(r,\{\beta^c\})\right\} - \beta^{ss} sameState_{o\rho}$$

$$-\beta^{sea}\ln seadist_{\rho d} - \beta^{liner} liner_{\rho d} - \alpha_\rho - \Phi_{od}\Bigg)\Bigg]^2, \tag{23}$$

where $R_{o\rho}$ is the set of routes on the road network that go from origin $o$ to port $\rho$. Appendix E.1 shows that this problem can be solved as a fixed point, where the $\beta^c$ are used to compute the least-cost route and updated using a traditional regression until convergence.

This estimation procedure provides a joint estimate of port quality ($\tau_\rho$) and of the effect of different road types on trade costs ($\beta^c$). Estimating the $\beta^c$s directly ensures that the parameters are identified using the same framework as the measure of port quality, and that they are rooted in the context of India.

# 5 Estimation Results

## 5.1 Port elasticity

I run the estimation defining an origin as an Indian district and a destination as a foreign country. Table 2 displays the results. The standard errors are computed using a bootstrap procedure, clustered at the firm level. I estimate both $1/\theta$ from equation (18) and $\frac{\sigma-1}{\theta}$ from equation (19). In both cases, I also estimate $\theta$ allowing for heterogenous demand fixed effects by sector. I use years 2015-2019, compute the port shares at the sector-origin-destination-year level, and add a sector-year dimension to all fixed effects mentioned in the estimation strategy, so that the estimation should be thought of as using only cross-sectional variation. The column "by sector" flexibly allows for sectoral heterogeneity in origin-port,

port and port-destination costs, while restricting $\theta$ to be the same for all sectors.

Table 2: Elasticity estimation results

| | Export value (eq. 19) | | | Export unit price (eq. 18) | |
|---|---|---|---|---|---|
| | Pooled | By sector | | Pooled | By sector |
| $\frac{\sigma-1}{\theta}$ | 0.234*** | 0.225*** | $\frac{1}{\theta}$ | 0.0797* | 0.0656* |
| | (0.036) | (0.025) | | (0.046) | (0.037) |
| N. clusters | 34,063 | 32,666 | | 34,063 | 32,666 |
| Firm FE | ✓ | ✓ | | ✓ | ✓ |
| Port-dest. FE | ✓ | ✓ | | ✓ | ✓ |
| Implied $\sigma - 1$ | 2.94 | 3.42 | Implied $\theta$ | 12.5 | 15.2 |

**Notes:** This table shows the results of estimating the elasticity parameter using the strategy outlined in section 4. Sectors refer to slight aggregates of ISIC 2-digit and are listed in table A.1. The regressions "by sectors" compute generated regressors by computing port shares at the sector-origin-destination level, and adding a sector subscript to all fixed effects. Standard errors are based on 1000 cluster-bootstrap samples, with replacements at the firm level.

The first two columns provide similar estimates of the ratio between the trade elasticity and the port elasticity. They imply that the port elasticity is around 4 times larger than the trade elasticity. The standard error of the regression by sector is slightly lower, consistent with the fact that sectoral heterogeneity acts as noise in the pooled regression.

The last two columns indicate a port elasticity of 12.5 and 15.[16] The port elasticity estimated removing the sectoral noise is slightly higher. When different sectors are pooled, the sectoral heterogeneity inflates the heterogeneity of the route idiosyncratic shock required to match the data, resulting in a lower $\theta$.

Finally, combining the estimates of $1/\theta$ and $(\sigma - 1)/\theta$ provides with an estimate of the trade elasticity. The pooled estimate imply a trade elasticity of around 2.9, and the estimates by sectors give an estimate of around 3.4, on the lower side but well within the range of existing estimates.[17] This is reassuring as it implies that the estimation procedure provides meaningful estimates consistent with existing literature. It also means that while the estimates of $1/\theta$ are relatively noisy, using the more precise estimates of $(\sigma - 1)/\theta$ and conventional estimates of the trade elasticity from the literature would yield similar results.

Appendix E.4 investigates sectoral heterogeneity in $\theta$ and $\sigma$. Overall, the data at the sectoral level is too noisy to reliably reveal heterogeneity. Nevertheless, Figure E.2 in the

[16] I compute these by taking the inverse of the estimated $1/\theta$. This might be a biased estimate of $\theta$, but looking directly at the median of the inverse of the individual $1/\theta$ bootstrap results yields very close results of 12 and 14.

[17] Using the median of the ratio of each bootstrap draws gives similar estimates of 2.8 and 3.4.

appendix shows that estimated sectoral level trade elasticities using my estimation method correlate well with existing sectoral estimates from Caliendo and Parro (2015), again lending confidence to the estimation procedure.

Few papers estimate a port elasticity. Fan et al. (2023) estimate a value of around 6.7 in a setting that only has a composite rest-of-the-world destination region rather than many destinations.[18] Asturias (2020) finds a value around 13 for elasticity of substitution across US ports in a different estimation setting. Finally Wong (2022) estimates a composite trade and port elasticity that is also higher than typical trade elasticities, consistent with my estimate of a $(\sigma - 1)/\theta < 1$.

Other papers that explicitly incorporate different destinations either calibrate the port elasticity from other route elasticity estimates (Ducruet et al., 2024) 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 $\theta$ parameter (e.g. Ganapati et al., 2021).

### 5.2 Infrastructure quality

I use India's national highway network extracted from Open Street Map (OSM).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. 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 (23) 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.

Table 3 displays the results of the estimation. The first column shows the result when computing the port shares pooling across sectors, the second column computes sector-specific share but imposes single coefficient for all sectors, while the third column reports the weighted average coefficient of sector-level coefficients.

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

**Ports** Table 4 shows the estimates of the estimated port fixed effects $-\ln \tau_\rho$ relative to the best port for the 10 largest Indian container ports and some summary statistics over the 16 ports in my sample. The variation across ports is large: the standard deviation across

[18] The destination dimension that my paper explicitly incorporates is included in the idiosyncratic shock $\varepsilon$ in their framework, which increases the importance of the idiosyncratic component of port choice. As a result, the port elasticity is lower, because a lower $\theta$ is needed to accommodate the higher volatility in the idiosyncratic shock.

Table 3: Road parameters and port quality estimation

| | Pooled | by sector (single coef) | by sector (sectoral coef) |
|---|---|---|---|
| Normal road (100km) | -0.392 | -0.360 | -0.370 |
| ($\theta\tilde{\beta}^{normal}$) | (.01) | (.01) | (.01) |
| Expressway (100km) | -0.339 | -0.344 | -0.340 |
| ($\theta\tilde{\beta}^{expressway}$) | (.01) | (.01) | (.01) |
| $\ln seadist_{\rho d}$ | -0.592 | -0.530 | -0.532 |
| | (.078) | (.058) | (.058) |
| $liner_{\rho d}$ | 0.088 | 0.085 | 0.085 |
| | (.032) | (.022) | (.022) |
| Same state port | 0.529 | 0.613 | 0.613 |
| | (.029) | (.019) | (.019) |
| Port FE | ✓ | ✓ | sector-port |
| *odsy* FE | ✓ | ✓ | ✓ |
| *odsy* Cluster | ✓ | ✓ | ✓ |
| N | 217,494 | 683,262 | - |

**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. The first column pools all sectors together and the second column separates at the ISIC section level, but forcing the coefficients on different types of roads to be the same across sectors. The third column displays the (observation weighted) average of the sector-specific coefficients.

ports is between 21% and 11% depending on the port elasticity value, with a value of 14% 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 14%.

The left panel of Figure 3 displays the ports on the Indian map, where the size of each port is proportional to its estimated quality (a larger circle represents a lower cost). It is apparent that while the geographical distribution of port location is fairly balanced, the geographical distribution of port quality isn't and regions in the North-East are further away from ports with low costs.

To ensure that the estimated fixed effect really captures differences in costs, Figure 4 displays the scatterplot of the estimated port fixed effect estimates against three types of measures of port quality, for ports 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 relative $\ln \tau_\rho$ | | |
|---|---|---|---|---|
| | $(-\theta\ ln\hat{\tau}_\rho)$ | $(\theta = 10)$ | $(\theta = 15)$ | $(\theta = 20)$ |
| Mumbai (NSA) | 0 | 0 | 0 | 0 |
| Mundra | -0.81 | -0.08 | -0.05 | -0.04 |
| Tuticorin | -1.13 | -0.11 | -0.08 | -0.06 |
| Chennai | -1.20 | -0.12 | -0.08 | -0.06 |
| Kochi | -1.64 | -0.16 | -0.11 | -0.08 |
| Kattupalli | -2.25 | -0.22 | -0.15 | -0.11 |
| Vizac | -2.68 | -0.27 | -0.18 | -0.13 |
| Kolkata | -2.89 | -0.29 | -0.19 | -0.14 |
| Mangalore | -2.92 | -0.29 | -0.19 | -0.15 |
| | | | | |
| Average | -3.09 | -0.31 | -0.21 | -0.15 |
| Median | -2.91 | -0.29 | -0.19 | -0.15 |
| Std deviation | 2.11 | 0.21 | 0.14 | 0.11 |

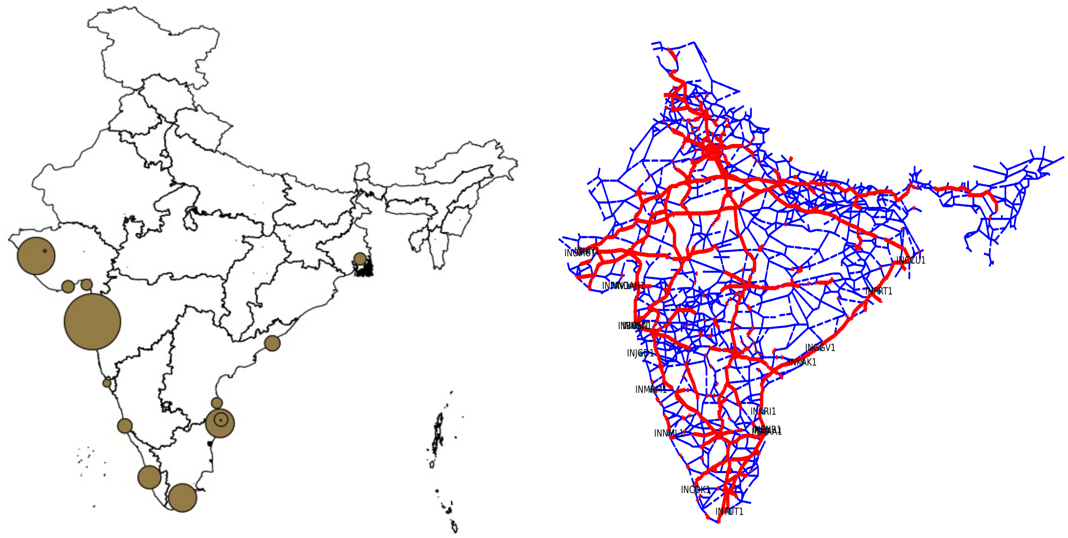
**Notes:** This table displays the estimated port qualities, defined as the negative of $\ln \tau_\rho$. The largest 10 ports in my dataset are displayed, and they account for around 90% of total shipment value through sea. The Kolkata port includes both the Haldia dock complex and Kolkata dock system.

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

Finally, the left panel of Figure 5 plots the estimated sector-specific port fixed effects (relative to the Mumbai port) against the port fixed effect from the pooled estimate. Sector-specific port fixed effects are estimated while also letting all the coefficients on distances (so also potentially the optimal routes from the origin to the port) to vary by sector. All sectors are virtually indistinguishable, and observations lie close to the 45 degree line except for the low-quality ports. This implies that there is little heterogeneity across sectors in the ranking of the port. This is consistent with the fact that all these transactions are containerized, hence very much standardized. The right panel of Figure 5 also displays the results of estimating the port fixed effects while controlling for the road and sea costs more flexibly by including distance bins rather than continuous measures.

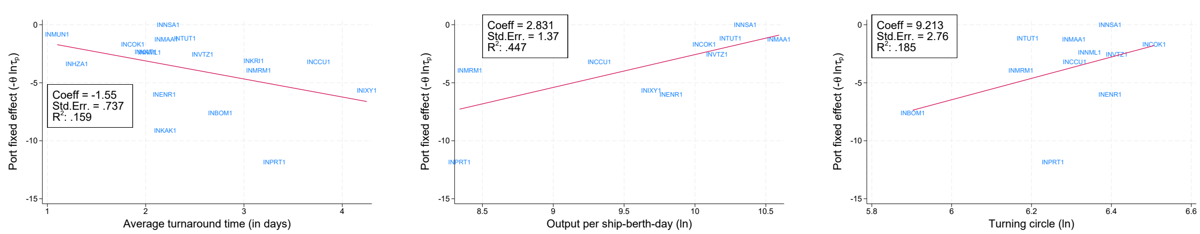
**Roads** As one would expect, distance on the expressway has a smaller negative impact on the probability of choosing a port than distance on normal roads. The first row of Table 3 shows that an additional 100km on normal road distance to a port decreases the probability of using that port by 0.392, while the same distance on an expressway decreases it by 0.339. The difference between $\beta^{expressway}$ and $\beta^{road}$ is both statistically and economically significant: the cost associated with traveling on a normal road is about 18% higher than

Figure 3: Estimated port 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.

Figure 4: Port quality estimates and observables



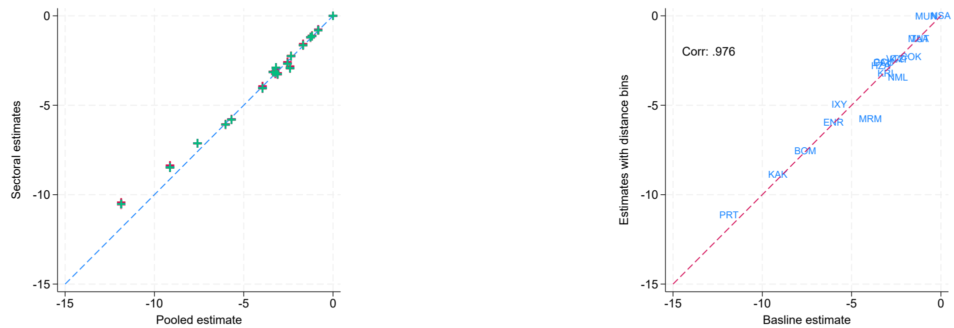

Turnaround time | Output per ship-berth-day | Turning circle diameter

**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.

that of traveling on an expressway. My estimate is consistent with existing literature: Fan et al. (2023) find a difference of around 20% for the difference between expressways and regular roads in China.

The coefficients on the road distances have the structural interpretation of $\theta * \tilde{\beta}^c$. Using $\theta = 15$ as estimated above, this implies that an additional 100km on an expressway is equivalent to an ad-valorem trade cost of around 2.2%.

Figure 5: Port quality robustness




Sectoral heterogeneity | Flexible road and sea costs

**Notes:** Each + sign on the left panel represents a different sectoral port fixed effect when the estimation procedure (E.1) is implemented at the sector level. The dashed-line is the 45 degree line. The right panel displays the estimates of the port fixed effects when including bins of road distance by 50km and sea distance by 100km, instead of using the continuous measures.

To illustrate the heterogenous road quality across Indian regions, the right panel of Figure 3 shows the road network, with expressways displayed as bold red solid lines and normal roads displayed as dashed blue lines. Historically, the first large scale expressway build in India was the Golden Quadrilateral, connecting Delhi, Mumbai, Chennai and Kolkata. 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.

## 5.3 Discussion of assumptions

**Ports as piece of infrastructure** Decomposing the trade cost into the product of underlying segment costs (equation 3) is ubiquitous in the literature.

An important assumption is that all firms face the same port specific cost $\tau_\rho$ up to the iid shock $\varepsilon$. 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. In Appendix E.2, I show that there is no clear pattern in how transactions are handled according to observables - transactions broadly satisfy a *first-in-first-out* pattern.[19]

A potential deviation from assumption 3 might lead to an inconsistent estimate using

[19] Specifically, while there is some evidence that large exporter face lower transhipment time on average, that differential is orthogonal to my estimate of port quality. Note that for the port elasticity estimation, price discrimination by ports is not an issue as long as all ports discriminate a given firm by the same amount, in which case the firm fixed effect in the second stage controls for the common discrimination part.

my strategy. If the cost $\tau_{o\rho d}$ is not given by $\tau_{o\rho}\tau_{\rho}\tau_{\rho d}$, but instead 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 be a second-order approximation of a CES form of trade costs.[20] 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 generated regressor would not converge to $d_{od}^{-\theta}$, so that the second stage estimate wouldn't be consistent.[21] However, the residuals in the first stage would be more volatile than if assumption 3 didn't hold. In Appendix E.2, I show that the distribution of residuals is close to what one would expect from random Fréchet draws given my sample size. I conclude that a violation of assumption 3 is unlikely to drive my results.

I treat ports as a piece of infrastructure similar to roads, rather than as price-setting actors. In Appendix D, I also extend the model to allow ports to set $\tau_{\rho}$ by maximizing profits in an oligopolistic setting. I show that equation 3 still holds as long as ports set a unique price of transshipment and don't price discriminate across origin and destinations. Such price discrimination is unlikely to hold given the exercise described above.

**Road quality heterogeneity** If road quality within my two broad categories is different close to some ports, or if there is congestion on the roads close to certain ports, my measure of road cost might be systematically biased near certain ports. For example, if the expressways close to the port of Kolkata are not as good as those in the rest of India, port usage will be lower. The model will interpret this as a low port quality, while high road costs are the problem. In Appendix E.5, I compare my road cost estimates around each port with Google map travel times, and show that differentials in average speed around the ports are not correlated with my measure of port quality.

**Endogeneous roads** A potential worry is that the government targets segments that are the most used, so that we would mechanically observe more usage of ports connected by an expressway precisely because road improvements are more likely when traffic is high. This would bias my estimates of $\beta^c$ and inflate the estimated differential between costs on expressways versus normal roads. However, this potential bias would actually work against the finding in the next section that improving ports would yield higher returns than improving normal roads to expressways.

[20] If $\tau_{o\rho d} = \left[a\left(\tilde{\tau}_{o\rho}\right)^{\eta} + b\left(\tilde{\tau}_{\rho}\right)^{\eta} + c\left(\tilde{\tau}_{\rho d}\right)^{\eta}\right]^{1/\eta}$ instead of the multiplicative assumption 3, a second order approximation around $\eta = 1$ (Cobb-Douglas) gives a similar expression, where $\eta_{o\rho d} = \exp\left(\kappa\left[\ln\tau_{o\rho} - \ln\tau_{\rho d}\right]^2\right)$ (see Kmenta, 1967).

[21] The generated regressor would still converge to $\sum_{\rho}\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}$, but $d_{od}^{-\theta}$ would be equal to $\sum_{\rho}\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}\eta_{o\rho d}$, not to $\sum_{\rho}\left(\tau_{o\rho}\tau_{\rho}\tau_{\rho d}\right)^{-\theta}$ in this context.

**Other transportation modes** I assume that transportation only take place through road (domestic shipments and internal part of international shipments) or sea (international shipments). This is in line with data. Sea represents around 80% of international trade shipments in India. The remainder is mostly air shipments and little land shipments. For total internal movement of freight, roads represent around 71%, rail 17.5%, and pipelines and waterways the remaining (NITI and RMI, 2021).[22] Further, rail is mostly used for bulk rather than container shipping. EXIM containers represent less than 4% of total tonnage in 2018-19 of the total inland rail freight movement (7% of tonne-kilometer and 6% of revenues, Indian Railway Statistics). Figure E.3 in the Appendix plots my estimated port quality against the share of containers that enter the ports by rail and displays no significant relationship. Hence, ignoring rail should not affect my estimation.

# 6 Counterfactuals

To investigate how the heterogeneity in transportation costs due to road or to ports translates into regional output and welfare disparities, I now use the full quantitative model to conduct counterfactuals. Specifically, I use the model to solve for changes in district-level real wags following changes in either port costs ($\tau_\rho$) or costs on the road to the port ($\tau_{o\rho}$).

## 6.1 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 G.1. For that purpose, the only data requirements are data on goods trade shares $\pi_{od}^{trade} = X_{od}^G / \sum_k X_{kd}^G$ and port shares $\pi_{o\rho d}^{port}$, as well as parameter values for $\sigma$ and $\theta$. Following my estimates, I use a trade elasticity of $\sigma - 1 = 3.4$, and a value for $\theta = 15$. Since my sample of firms doesn't cover all Indian districts, and data on trade at the district level is unavailable, I also need to impute some of the 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:

$$\pi_{o\rho d}^{port} = \frac{\left(\tau_{o\rho}\tau_\rho\tau_{\rho d}\right)^{-\theta}}{\sum_k \left(\tau_{ok}\tau_k\tau_{kd}\right)^{-\theta}}, \tag{24}$$

[22] While rail has historically been an important mode of transport for moving goods within India (Donaldson, 2018), its share has decreased significantly from 89% in the 1950s, to 30% in 2007-08 (NTDPC, 2014), and 17.5% in 2020 (NITI and RMI, 2021).

where $\tau_{o\rho}$ depend on the road costs estimates, $\tau_\rho$ come from the port productivity estimates, and $\tau_{\rho d}$ depend on the sea estimate. For consistency purposes, I also calibrate port share of the districts that appear in my dataset in the same way. 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 implied by the coefficients in Table 5.

**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 (11) and (12), the following equation holds:

$$\underbrace{\alpha_o X_o}_{\text{data}} = \sum_d \frac{\lambda_o \left(d_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(d_{kd}\right)^{1-\sigma}} \underbrace{\alpha_d X_d}_{\text{data}}, \tag{25}$$

where $\lambda_o = N_o^f \left(\frac{\sigma}{\sigma-1}\frac{w_o}{A_o^G}\right)^{1-\sigma}$ and $X_o = w_o L_o$ is the region's GDP. In this equation, the $\alpha_o X_o$ terms can be taken directly from 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 $\lambda_o$'s are the only unknowns.

Equation (25) is useful to calibrate the model, because there is a unique vector of $\lambda_o$ consistent with data on $X_o$ and trade frictions $d_{od}$ (see Lemma 1 in Appendix F). Since data on trade across Indian districts and between districts and foreign countries is not readily available, I use equation (25) to recover the $\lambda_o$ 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 $d_{od}$.

The last hurdle to solve is that the port-level productivities $\tau_\rho$ 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 resolve these issues, I add a set of origin- and destination-specific free parameters scaling the district-foreign trade costs. These allow me to match the aggregate India-foreign trade shares exactly, and use the road and ports relative costs to calibrate the relative shares of Indian districts in the aggregate. Appendix F describes the procedure in detail.

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

**Data sources** I use the OECD Inter-Country Input-Output (ICIO) Tables to get data on country-level trade shares ($\pi_{od}^{trade}$) in the goods sector, and the share of goods in consumption ($\alpha_d$).[23] 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 and I use additional data on the share of literacy by district from the Census and on night lights from Asher et al. (2021) to predict GDP in missing districts.[24]

**Model calibration fit** The calibrated model consists of 44 countries, 636 districts, a composite rest of the world, and 16 ports. The left panel of Figure 6 shows how the calibrated within-India trade shares perform against untargeted data. It compares the model with data on aggregated inter-state trade shares within India. The interstate trade flows data from the 2016-2017 Indian Economic Survey. The correlation is around 0.7. The right panel of Figure 6 plots the demeaned (log) total value at the port in the model, against the demeaned log value in the data. Again, the correlation is high and dots lie close to the 45 degree line.

## 6.2 Simple counterfactual scenarios

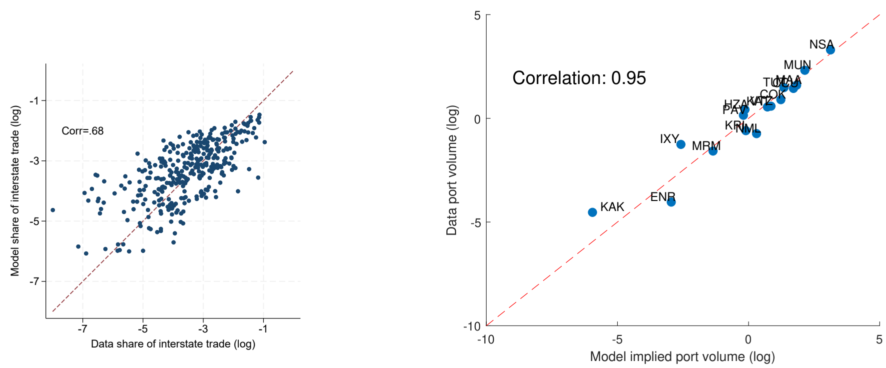
I now present first simulation results designed to understand the mechanisms in the model and the importance of the port elasticity, and then more policy relevant counterfactuals in the next section.

**Optimal port targeting** I simulate two scenarios: one where I reduce the transshipment cost of the Mumbai (Nhava Sheva, code NSA) port by 10% ($\hat{\tau}_{NSA} = 0.9$, the largest container port), versus one where I improve all ports by 4% ($\hat{\tau}_\rho = 0.96\ \forall \rho$). The first scenario captures the gain from a concentrated investment in a single node of the infrastructure network, while the second scenario captures the gains from an extremely diffuse investment. When the port elasticity is very high, the gains from a concentrated investment will be higher as more shipments would be rerouted through the improved port.

[23] I define goods as Agriculture, Mining, and Manufacturing. The average share of goods in final consumption is around 0.38 across countries. For Indian districts, I use Census data on employment by sector and use equation 10 to calibrate $\alpha_o$. The country-level trade shares together with balanced trade imply a level of goods expenditure for each country.

[24] I first regress GDP per capita on population, literacy and maximum observed night lights using data on 535 available districts. I then use the coefficients to predict GDP per capita in other districts and multiply it by population to construct GDP for missing districts. The correlation between the predicted and observed GDP for districts with existing data is high at 0.903.

Figure 6: Calibration fit




Interstate trade　　　　Port volume

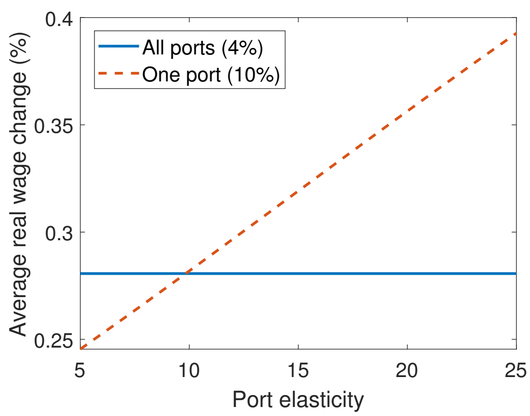
**Notes:** The left panel of the figure displays the share of interstate imports in the model against the data. Each dot is the share of bilateral flows in the exporting state's total interstate exports. The dashed line is the 45 degree line. The right panel displays the fit of the (relative) port volume in the model and in the data.

The left panel of Figure 7 illustrates this point. The solid blue line displays the results when improving all ports by a small amount, and the dashed red line when improving only one port by a large amount for different values of the port elasticity. The blue line is flat, since the port elasticity doesn't matter when all port transshipment costs decrease by the same percentage. On the other hand, the dashed line is increasing, as the benefits of improving a single port are higher when the port elasticity is large and more shipments are rerouted.

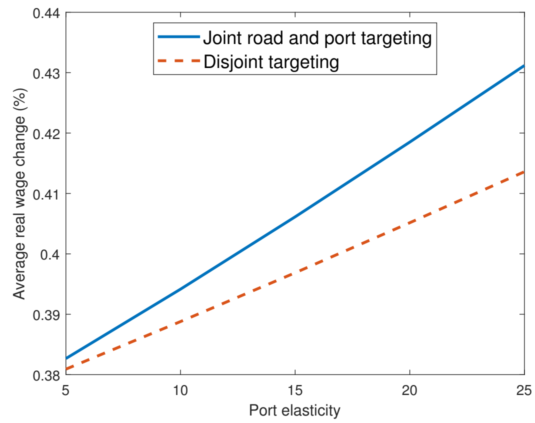
Appendix G.2.1 extends the model to allow for economies of scale or congestion at the port. Figure G.1 displays the results. In the uniform improvement case, the gains are uniformly higher (lower) when there are economies of scale (congestion). When targeting a single port, however, the presence of scale economies magnifies the gains and the dashed red line becomes convex. Congestion has an opposite effect: a larger port elasticity leads to more switching to the improved port, which leads to more congestion. Nevertheless, the curve remains increasing under this calibration.

**Road and port complementarity** When shipments are rerouted through a particular improved node of the network, it can become counterproductive to improve segments linking an other node. In the case of ports and roads, improving a port while improving roads that lead to an other port would be counterproductive, especially when the port elasticity is high. To illustrate this point, I improve the port of Mumbai (NSA) by 5% ($\hat{\tau}_{NSA} = 0.95$), and either all the road segments that are ever used to reach that port by at least one district, or all the other road segments never used to ship through the Mumbai port. More

Figure 7: Simple counterfactuals




Port targeting




Road and port complementarity

**Notes:** The left panel shows the average real wage change across Indian districts when reducing $\tau_\rho$ by 4% for all ports (solid blue line) or reducing $\tau_{NSA}$ by 10%, for different values of the port elasticity. The right panel shows the average change in real wage when reducing $\tau_{NSA}$ by 5% and improving road segments used to connect NSA (blue line) or segments never used to connect to NSA (dashed red line).

precisely, I proceed as follows. First, I simulate what would happen if the transportation cost on road segments that are used by any district to reach the port of Mumbai decrease by 10% ($\hat{t}_k = 0.9\ \forall k \in o\rho$ in equation 21). Then, I compute a welfare-quivalent uniform improvement of all other road segments ($\hat{t}_k = c < 1\ \forall k \notin o\rho$ in equation 21). I then add an improvement of the port of Mumbai to both scenario, and compute the average change in real wages. I repeat the exercise for various port elasticities.

The right panel of Figure 7 displays the results. The solid blue line shows the results when road and port improvements are coordinated, while the dashed red line shows the results when road and port improvement are not coordinated. In both cases, the GDP gains increase with the port elasticity, since only one port is improved - consistent with the counterfactual presented above. However, the increase is greater when road segments that lead to the port of Mumbai are improved.

The reason is twofold. First, improving the roads to the targeted port compounds the route reoptimization even further when the port elasticity is high. Second, there is a mechanical complementarity due to the fact that the trade costs are multiplicative in specification 3, and that is also amplified when the port elasticity increases. While the multiplicative assumption seems appropriate as discussed above, the first mechanism is meaningful by itself: Appendix G.2.2 repeats the simulation with additive trade costs to shut down the mechanic complementary between road and port costs in the multiplicative baseline specification.

**Broad road or port improvements** I perform three counterfactuals that harmonize the quality of infrastructures for all region and bring them to the best level, to illustrate the different regional impact of port and road improvements. 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 across-district 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:

$$\hat{\tau}_\rho = \frac{\min_p \tau_p}{\tau_\rho}, \tag{26}$$

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:

$$\hat{\tau}_{o\rho}^{CF} = \hat{\tau}_{\rho o}^{CF} = \exp\left(\left[\beta^{expressway} - \beta^{normal}\right] dist_{o\rho}^{normal}\right), \tag{27}$$

where $dist^{normal}$ is the distance on normal roads one the route between $o$ and port $\rho$. In the counterfactual that also decreases within-India costs, I decrease trade costs across districts in the same way.

Table 5 shows 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, for the three broad counterfactuals. The first column displays the port counterfactual. The middle column displays the results of bringing all costs to the ports to the level they would have if all roads where expressways, and the last column shows the full road improvement counterfactual.

Improvements in ports increase the export share of GDP by around 3.1%, from a baseline average of 7.1%. This change is an order of magnitude smaller when the road component of export/import costs is improved.[25] 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 indicates 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 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.

[25] By construction, the change in import share is similar because of balanced trade.

Table 5: Broad improvement counterfactuals results

| | Change in export share of GDP (%) | | |
|---|---|---|---|
| | Equal ports ($\tau_\rho$) | 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 ($\tau_\rho$) | 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 |

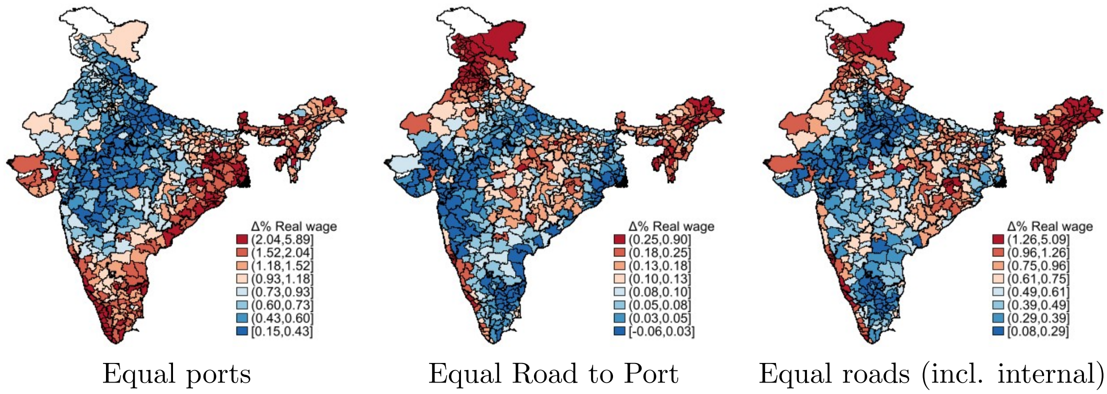
**Notes:** This table shows summaries of the percentage change in export share and real wages across Indian districts in the counterfactuals. "Equal ports" refers to the counterfactual where all ports costs are put to the same level as the minimum port cost. "Equal road to ports ($\tau_{o\rho}$)" refers 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.

The distributional impact of these counterfactual is also large: the standard deviation across districts is almost half of the average effect. Figure 8 displays the real wage changes across Indian districts in the infrastructure improvement counterfactuals. Dark red implies a larger increase in real wage and blue implies a lower increase.

The left panel of Figure 8 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. This is consistent with the fact that coastal regions are more export oriented, because they face lower baseline trade costs. The left panel of Figure 9 illustrates this fact by ploting the change in real wage against baseline export exposure, showing a positive relationship. 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 3. Districts on the central West coast, close to the most productive port of Nava Sheva (Mumbai), are lighter than districts near lower quality ports on the East.

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 8, to

Figure 8: District-level counterfactual real wage changes




**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.

compare with the road network displayed in Figure 3). Regions located close to the existing expressways that connect to the ports don't benefit as much from the road improvements. Overall, roads improvement benefits regions with a high domestic exposure, as they are the regions most exposed to domestic trade costs. The right panel of Figure 9 illustrates this fact by plotting the change in real wage against baseline domestic exposure, showing a positive relationship.

Overall, the counterfactual results show that port improvements are an order of magnitude more important than road improvements in terms of international market access. Even taking into account the internal trade cost impact on internal trade, port improvement still produces higher aggregate welfare gains. Port improvement tends to favor coastal regions, while road improvements favor inland regions.

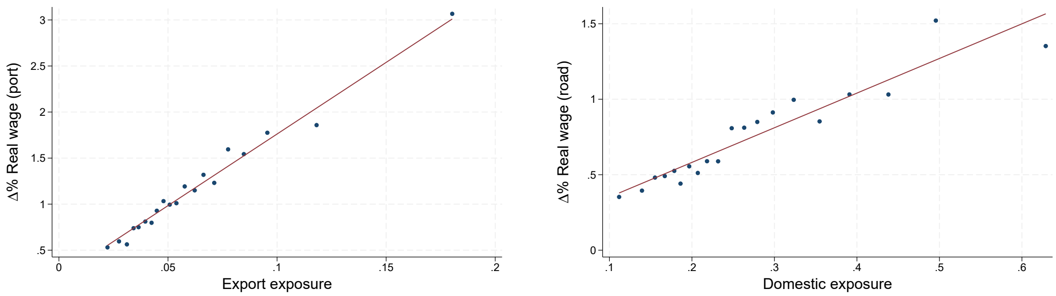
### 6.3 Policy relevant counterfactuals

Having illustrated the main mechanisms at play in the model, I now turn to more policy-relevant counterfactuals.

#### 6.3.1 Marginal returns on investment

I start by computing which infrastructure has the highest returns on investment. To do so, I first estimate the cost of improving roads and ports.

Figure 9: Real wage changes, export and domestic exposure




Ports | Roads (incl. internal)

**Notes:** The figure displays the bin-scatter plot of real wage changes against export exposure (left panel) in the ports improvement scenario, and against domestic exposure in the road improvement scenario (right panel). Export exposure is defined as the district total exports to foreign countries as a share of GDP and domestic exposure is defined as total sales to other Indian districts as a share of GDP.

**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.[26]

Taking log-differences of the port share equation (5) between 2015 and 2019 gives:

$$\ln \frac{\pi_{o\rho d,2019}}{\pi_{o\rho d,2015}} = \theta \Delta \ln \tau_\rho + \theta \Delta \ln \tau_{o\rho} + \theta \Delta \ln \tau_{\rho d} + \alpha_{od}. \tag{28}$$

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

$$\ln \frac{\pi_{o\rho d,2019}}{\pi_{o\rho d,2015}} = \theta \beta^{invest} invest_\rho^{port} + \alpha_{od} + u_{o\rho d}. \tag{29}$$

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, or if they target both the port and the roads to the port at the same time.[27] To assess

[26]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.

[27]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 $\rho$ won't be correlated with the error term because of the

the relevance of the identification 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 (28), using *completed* investments, *partially completed* investments, and *planned but not started* investments. If projects targeted ports with anticipated growth in the $u_{opd}$ 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 | 0.441** | | | 0.806*** |
| | (.177) | | | (.218) |
| Under completion | | 0.150 | | -0.047 |
| | | (.204) | | (.179) |
| Planned | | | 0.049 | -0.349*** |
| | | | (.112) | (.085) |
| Origin-dest FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 22,628 | 22,628 | 22,628 | 22,628 |

**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 29). 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 transshipment cost by around 2.2% (0.44/15), using my estimate of $\theta = 15$.

**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 per kilometer.

**Marginal benefits** I simulate the gains from improving each 50km normal road segment into an expressway. Taking the average cost per kilometer of improvement, this would cost

$\alpha_{od}$ fixed effect. 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.

Table 7: Cost-benefit analysis

| | Marginal improvement | | Bring to frontier | |
|---|---|---|---|---|
| | Ports | Roads | Ports | Roads |
| $\Delta$ Annual GDP | $206 mil | $87 mil | $27.7 bil | $11.2 bil |
| Estimated cost | $75 mil | $75 mil | $150 bil | $250 bil |

**Notes:** The table shows the estimated costs and benefits of the broad port and road improvements, as well as the marginal improvement scenario .

around $75 million. I then simulate what would happen if $75 million were instead spent on the port of Mumbai (Nhava Sheva), converting this amount of money into a decrease of 0.165% in transshipment cost using the estimates above.

Table 7 summarizes the results of these marginal improvement, as well as the results of the broad improvement counterfactual presented above. The highway segment with the highest gains yields an increase in aggregate GDP of around $87 million. As a comparison, the increase in GDP would be close to $200 million when spending that money on the port of Nhava Sheva. Hence the marginal returns of improving ports is higher than that of roads. Appendix Figure G.3 repeats the exercise under a range of port economies of scale or congestion with similar qualitative findings.

#### 6.3.2 Mega ports projects

The cost estimates presented above are suggestive and might not be accurate to estimate the cost of large projects, since they are based on marginal improvements. The Maritime India Vision 2030 proposed the development of several mega ports (MOP et al., 2021). Focusing on container ports, the report suggests three ports to be developed as "mega ports": Mumbai (NSA), Kandla and Enore.[28] Given data on existing berth, potential draft depth, and cost of land, the report suggests investments needed to improve the ports to the level of "world-class mega ports". Given differences in the ports current endowment and specificities, the estimated costs are different even if the stated goal is the same "world class" level.

In this counterfactual, I take the cost estimates as given, and improve the ports in the model. I make the assumption that all three ports will end up at the same level (they will share the same $\tau_\rho$ after the investments), and that for the port of NSA, the decrease in $\tau_{NSA}$ will be given by the amount invested, multiplied by the factor of 2.2% estimated

[28] The report uses alternative names for those port (Kandla's other name is Deendayal, and Enore's other name is Kamarajar). For simplicity, I keep the same names as above.

Table 8: Assumed investments and iceberg port cost changes

| | Three ports | | | INNSA only | |
|---|---|---|---|---|---|
| | Cost (USD bil.) | $\ln \hat{\tau}_\rho$ | cost per % | Cost | $\ln \hat{\tau}_\rho$ |
| NSA (Mumbai) | 0.521 | -0.015 | 34.7 | 2.099 | -0.062 |
| Kandla | 1.0205 | -0.394 | 2.59 | 0 | 0 |
| Enore | 0.5567 | -0.416 | 1.34 | 0 | 0 |

**Notes:** The numbers are based on exhibit 1.44 of the Maritime India Vision 2030 (MOP et al., 2021), converted to USD. The iceberg cost changes for INNSA is computed as $0.5214 * 0.44/15$ following the estimates from Table 6. The changes for the other two port is such that $\hat{\tau}_\rho \tau_\rho = \hat{\tau}_{NSA} \tau_{NSA}$, so that all three ports become as efficient.

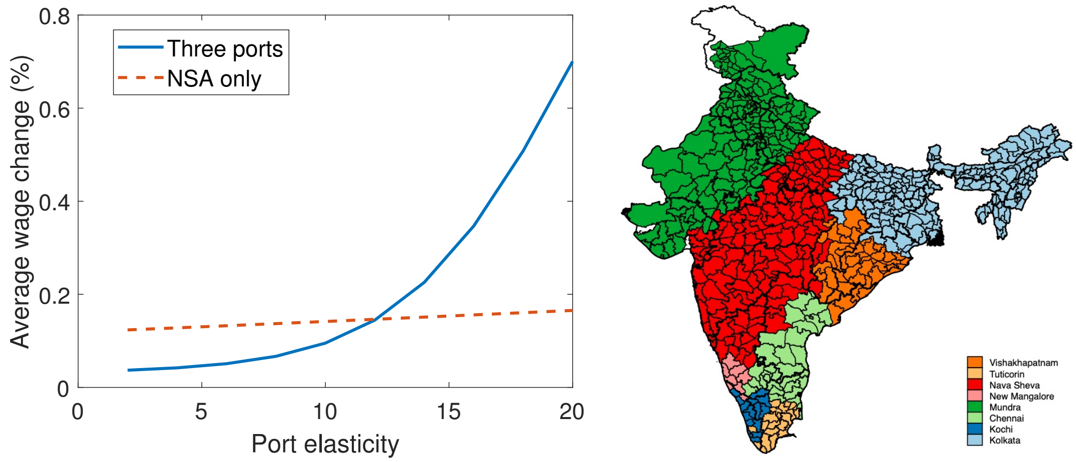
above. Table 8 summarizes the assumed cost of investment, and resulting changes in port cost fed into the model. Both the absolute iceberg cost decrease and the decrease per USD are much larger for Enore than for the other two, especially NSA. This implies that money spent on Enore has better returns in terms of transshipment cost decreases. On the other hand, the first order gains are much higher for NSA for a given cost decrease, since it is the largest port. Hence, it might be better to decrease NSA's cost a little bit, than to improve Enore and Kandla a lot. The strength of the port elasticity will play a key role in determining which approach is the best. A large $\theta$ implies that many firms could switch to Enore or Kandla and result in large welfare gains. A small $\theta$ would instead prevent firms from switching away from NSA and benefit from the lower costs in the other ports.

The left panel of Figure 10 displays the results of two scenarios under different values of the port elasticity. The first improves all ports according to the numbers in Table 8. The second instead focuses on NSA and invests all the money there, so that the total cost of both scenarios is the same. The solid blue line shows the average real wage gains across Indian districts in the first case. The dashed red line shows the results of the second case. For my preferred estimate of $\theta = 15$, improving the low-cost ports has higher returns. However, for smaller values of $\theta$, improving the single bottleneck port would remain better even. For example, under the assumption that the port elasticity is equal to the trade elasticity (3.4 in my simulation), the results would be flipped. This result indicates that under a fairly realistic calibration of the model, the port elasticity matters.

### 6.3.3 Regional bottleneck ports

Policymakers might be interested in which port matters to which region. I reduce each port's iceberg cost by 10% and compute the counterfactual real wage change for all regions. The right panel of Figure 10 plots the port with the highest returns for each region. It

Figure 10: Mega ports and district-specific bottlenecks




**Notes:** The left panel displays the average real wage change across Indian districts in the two counterfactuals described in the text. The right panel displays the port that has the largest effect on the district's real wage when improved.

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. For example, the poorest regions in the north-east would benefit more from an improvement at the port of Kolkata.

# 7 Conclusion

Port and road infrastructure connect regions to the world market. In this paper, I build a framework to jointly 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. Of course, these results are specific to the existing infrastructure network, but the framework could be used in an other context. I also show that the regional distributional implication are different: port improvements benefit coastal regions relatively more, while road improvements benefit inland regions. My results highlight the importance of the elasticity of route switching when improving parts of the transportation infrastructure.

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# ONLINE APPENDIX

# (NOT FOR PUBLICATION)

# 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.[29] 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*).[30] 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.[31] The list includes the shipping bill number, the date of the transaction and the port of exit. I then obtain additional details

[29] The directory was accessible online at the DGCIS website: `http://dgciskol.gov.in/` under the menu "Trade Directory" up until at least early 2020. See the archived version of the webpage here.

[30] 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.

[31] 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.[32]

**Sectoral classification** I merge the list of exporter/importer firms 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 A.1 lists the sectors by ISIC section. 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 A.2 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 A.1 plots the share of each port in my sample against the share in the full dataset. The dots are located along a 45 degree line, indicating that my sample is representative in this key dimension.

[32] 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.

[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 A.1: Main sectoral composition

| Sector code | Description | Share of firms | Share of value |
|---|---|---|---|
| 15t16 | Food and tobacco | 0.045 | 0.071 |
| 17t19 | Textile, apparel, leather | 0.141 | 0.132 |
| 20t23 | Wood, paper, publishing | 0.019 | 0.013 |
| 23t24 | Coke, Chemicals | 0.109 | 0.147 |
| 25t26 | Rubber, non-metallic | 0.048 | 0.037 |
| 27t28 | Metals | 0.075 | 0.072 |
| 29 | Machinery and equipment, NEC | 0.057 | 0.052 |
| 30t33 | Office, electrical, radio, medical equipment | 0.037 | 0.026 |
| 34t35 | Transport equipment | 0.017 | 0.029 |
| 36t37 | Furniture, recycling | 0.014 | 0.008 |
| 72t74 | Business activities | 0.133 | 0.097 |
| AtB | Agriculture, Fishing | 0.032 | 0.049 |
| C | Minning and Quarrying | 0.016 | 0.019 |
| E_F | Utilities, construction | 0.021 | 0.027 |
| G | Wholesale and retail | 0.165 | 0.145 |
| H_I | Hotel, restaurants, transport | 0.011 | 0.009 |
| JtQ | Other services | 0.061 | 0.066 |

**Notes:** The sectoral codes refer to the Indian National Industry Classification, which correspond to the general International Standard Industry Classification (ISIC).

Table A.2: Firm level summary statistics

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

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

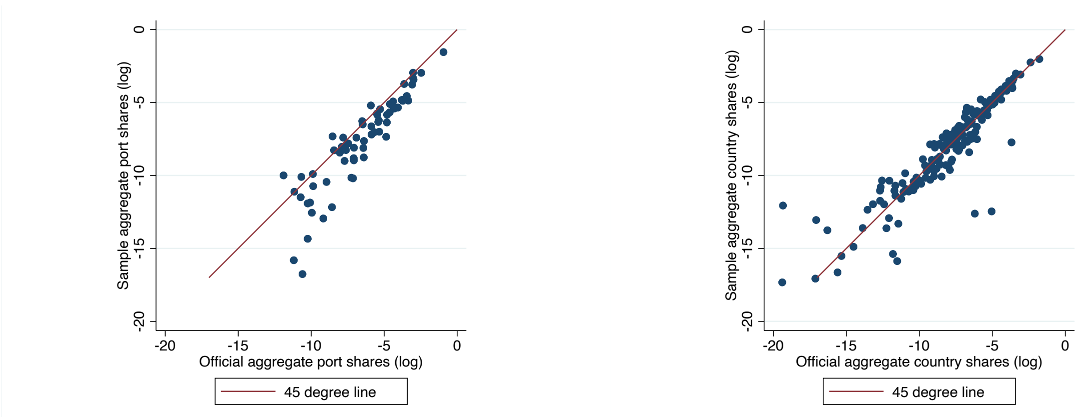
The right panel of Figure A.1 repeats the same exercise at the country level. Again, all dots are close to the 45 degree line.

## A.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.

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

Figure A.1: Port and country shares representativity




Port shares | Country shares

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

**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 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 Tsunghao Huang's Ports Distance Calculator.[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

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

[38] The package is available at https://github.com/tsunghao-huang/Python-Ports-Distance-Calculator and allows to compute the sea distance between two points by specifying their coordinates, based on a raster image of the world.

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

I extract all large roads from OSM using the following rule. I first extract any road segment from OSM that are either tagged as "NHXX", where NH stands for "National Highway" and XX for the relevant number. Then, because some states also have high quality state highways, I also keep any segment that matches the tag "motorway", "trunk", or "motorroad=yes".[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 A.2 shows the scatter plot of the length by category at the state level in my final data and against the official 2017 statistics. The right panel shows the share of "expressway" against the share of national highways with 4 or more lanes (in total for both directions) in the state. The dots lie along the 45 degree line, and the correlation is large and highly significant. In the aggregate, the road network in my data contains around 54,900 km of "expressway" and 164,500 km of "normal road".

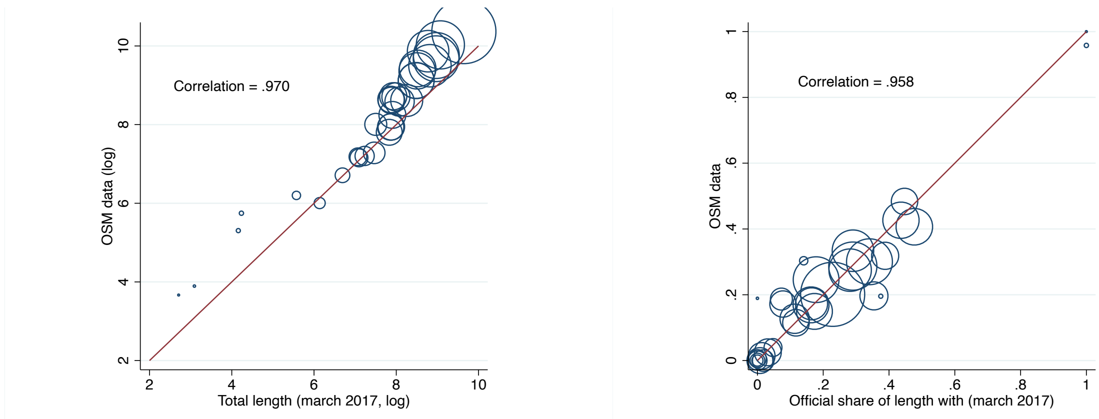
**Least-cost distance** To compute the least-cost route between an origin district and a port, I first compute the centroid of the district based on the map files provided by the Data{Meet} Community Maps Project.[40] I then find the closest point of the centroid on the highway network, and use that 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 (21) and (**??**), by fist weighting the edges of the highway network using their distance multiplied by the cost parameters $\beta^c$, and then using the Dijkstra algorithm. I compute the district-district road distances in the same way.

[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.

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

Figure A.2: Match between OSM and aggregate data




Length | Quality composition

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

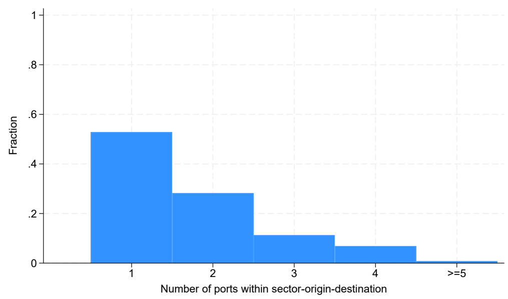
# B Stylized facts robustness

Figure B.1 displays the number of ports per sector-origin-destination triplet for different aggregation of origin and destination, and for different firm subsamples. In no case the share of triplets with a unique port goes above 0.6. Figure B.2 shows the histogram of the port share in transactions (top panel) or value (bottom panel) within each triplet. If there was a single main port, and alternative ports were used only marginally, the CDF should be close to 0 until 1. The left figures display the CDF for origin-destination-sector triplets, while the right figures show the CDF for firm-destination. The different lines display different robustness checks.

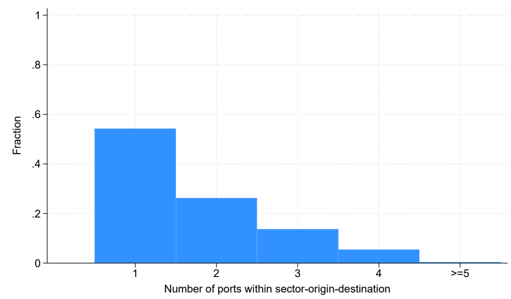
In the left figures, 60% or more of exports go through port whose share is less than 95% in all cases. Hence, the fact that similar firms use different firms is robust.

In the right figures, only at most 30% of exports go through ports with a share of less than 95%. When reducing the time frequency, that share decreases further. The share of transactions where the firm doesn't always use the same port of exit for a given discharge port is of around 30% (dashed blue line) when computed over 2015-19, and reduces to 20% when looking at transactions within the same month.

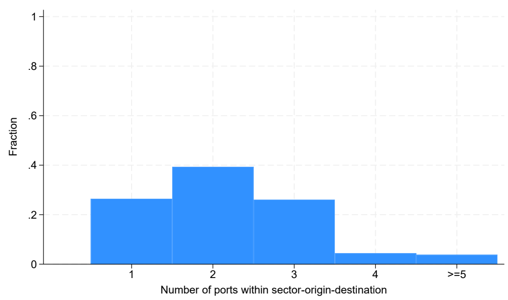
Figure B.1: Number of ports per sector-origin-destination



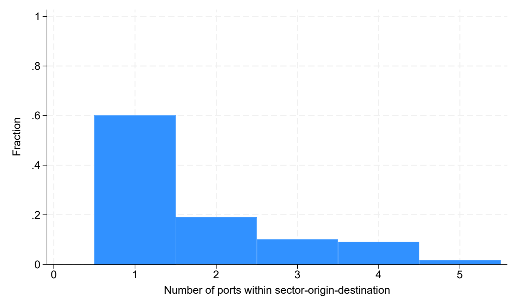

Destination as discharge port




Transactions in the same month



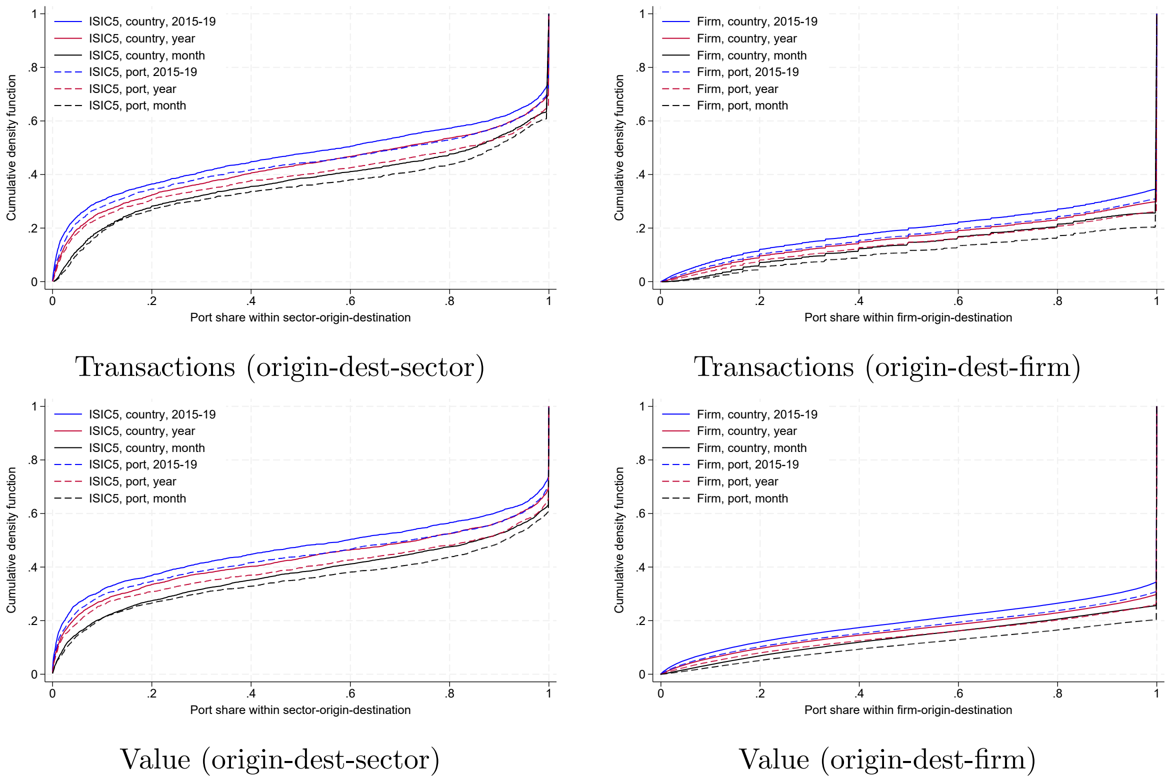

Firms with unique branch




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 five or more firms are kept to avoid artificial ones.

Figure B.2: Port shares in value or transactions




**Notes:** The top left panel displays the CDF of the share of transactions within an origin-destination-sector triplet. The top right panel the CDF of the share of transactions within an origin-destination-firm. The bottom figures compute the share of value. In each figue, the solid line use a country as the destination, and the dashed lines use a discharge port as a destination. The blue line pools all observations between 2015 and 2019. The red line computes the shares within a year, and the black line compute the shares within a month.

# C Model derivation proofs

**Port choice probability** The probability that port $\rho$ is the lowest cost port is given by:

$$\pi_{o\rho d} = P\left(\frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}} \leq \frac{\tau_{ok}\tau_{k}\tau_{kd}}{\varepsilon_{iokd}}, \forall k \neq \rho\right).$$

Conditioning on $\varepsilon_{io\rho d}$, that probability is given by:

$$\begin{aligned}
P\left(\varepsilon_{iokd} < \frac{\tau_{okd}}{\tau_{o\rho d}}\varepsilon_{io\rho d}, \forall k\right) &= \prod_{k} \exp\left(-\left(\frac{\tau_{okd}}{\tau_{o\rho d}}\varepsilon_{io\rho d}\right)^{-\theta}\right) \\
&= \exp\left(-\sum_{k \neq \rho}\left(\frac{\tau_{okd}}{\tau_{o\rho d}}\right)^{-\theta}\left(\varepsilon_{io\rho d}\right)^{-\theta}\right)
\end{aligned}$$

Remembering that the pdf of $\varepsilon_{io\rho d}$ is given by $f(\varepsilon) = \theta\varepsilon^{-\theta-1}\exp\left(-\varepsilon^{-\theta}\right)$, the unconditional probability is:

$$\begin{aligned}
P\left(\frac{\tau_{o\rho}\tau_{\rho}\tau_{\rho d}}{\varepsilon_{io\rho d}} < \frac{\tau_{okd}}{\varepsilon_{iokd}}, \forall k\right) &= \int_0^{\infty} \exp\left(-\sum_{k \neq \rho}\left(\frac{\tau_{okd}}{\tau_{o\rho d}}\right)^{-\theta}(x)^{-\theta}\right)\theta x^{-\theta-1}\exp\left(-x^{-\theta}\right)dx \\
&= \int_0^{\infty} \exp\left(-\sum_{k}\left(\frac{\tau_{okd}}{\tau_{o\rho d}}\right)^{-\theta}(x)^{-\theta}\right)\theta x^{-\theta-1}dx \\
&= \left[\exp\left(-\sum_{k}\left(\frac{\tau_{okd}}{\tau_{o\rho d}}\right)^{-\theta}(x)^{-\theta}\right)\frac{1}{\sum_k\left(\frac{\tau_{okd}}{\tau_{o\rho d}}\right)^{-\theta}}\right]_0^{\infty} \\
&= \frac{\left(\tau_{o\rho d}\right)^{-\theta}}{\sum_k\left(\tau_{okd}\right)^{-\theta}}
\end{aligned}$$

**Aggregation** The following result is useful to derive all the aggregation results in the model: 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 $\lambda$, is given by:

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

where $\Gamma$ 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:

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

**Expected trade costs** To get equation (6), simply plug-in $\lambda=1$ in equation (C.1).

**Export aggregation** To get equation (9), start by using equation (C.1) with $\lambda=1-\sigma$ to obtain the expected export value of an individual firm. Multiplying by the number of firms $N_o^f$ gives equation (9). Deriving the aggregate labor demand follows a similar proof.

# D Model with oligopolistic ports

In this section, I present the details of the extension where ports charge a price. Denote by $t_\rho$ the physical iceberg trade cost of transhipment at port $\rho$, but assume that a port may charge a cost for the use of its facilities.

**Monopolistic competition** If ports don't internalize their impact on the $d_{od}$ average trade cost, their optimal pricing will simply be a constant markup over the real iceberg cost, and the cost to the firms will be $\tau_\rho = \frac{\theta+1}{\theta} t_\rho$. Every derivations in the main model will go through in terms of firms' deicision on port and export pricing descisions, so that the estimation strategy also remains valid.

Of course, the the assumption of atomistic ports is unrealistic, so I also present a model where ports act like an oligopoply.

**Oligopolistic competition** The port may charge additional costs for the use of the infrastructure. Specifically, I assume that the port charges a share $s_\rho$ of the total shipment value, where $s_\rho$ is to be determined later. As a result, the effective cost of using the port is given by $\tau_{o\rho d} = \tau_{o\rho}\tau_\rho\tau_{\rho d}$, where $\tau_\rho = t_\rho/(1-s_\rho)$ acts as an iceberg cost from the point of view of the firm.[41]

The total profits of the port are given by $s_\rho X$, where $X$ is the total export value transiting through the port.[42] Of course, $X$ is itself a function of the port's charges. As above, I redefine a port iceberg cost as $\tau_\rho = t_\rho/(1-s_\rho)$ and rewrite the port's problem of chosing its port charge as:

$$\max_{\tau_\rho} \left(1 - \frac{t_\rho}{\tau_\rho}\right) \sum_{o \in IND, d \in ROW} \pi_{o\rho d} X_{od}$$

where the port takes into account the impact of its charge $\tau_\rho$ on the port share (equation 5) and exports $X_{od}$ (equation 9, through $d_{od}$ and equation 6). The solution to this problem

[41] To see this, consider that the firm is chosing its price to maximize profits:

$$\max_p (1-s_\rho) p \times q(p) - c\tau_{o\rho}t_\rho\tau_{\rho d} q(p) \iff \max_p p \times q(p) - c\frac{\tau_{o\rho}t_\rho\tau_{\rho d}}{(1-s_\rho)} q(p)$$

so the port's charge can be modeled in the same way as a tariff and as an iceberg cost from the point of view of the firm. One might wonder why the port is not charging a cost per unit instead of this ad valorem trade cost tariff equivalent. The option I choose here is appealing because it preserves tractability and embeds the port's problem in the canonical models that use iceberg trade costs since Samuelson (1954).

[42] I assume that the port can set different prices for export and import transactions.

is a varying markup that depends on the port share in all origin-destination pairs:

$$\tau_\rho = t_\rho \frac{(\theta+1)\sum_{od}\pi_{o\rho d}X_{od} - [\theta-(\sigma-1)]\sum_{od}X_{od}(\pi_{o\rho d})^2}{\theta\sum_{od}\pi_{o\rho d}X_{od} - [\theta-(\sigma-1)]\sum_{od}X_{od}(\pi_{o\rho d})^2}. \tag{D.1}$$

Equation D.1 shows that as the port share goes closer to 1, the port will start charging a constant monopoly markup $\sigma/(\sigma-1)$ similar to that of the firm, similar to the issue of double marginalization in imperfect competition. On the contrary, as $\pi_{o\rho d} \to 0$, the markup become $(\theta+1)/\theta$ as the firm only takes into account the direct impact of its price on the port share. In that case, a large port elasticy $\theta$ induces a smaller markup. To get additional intuition, consider as well the case where there is a single origin-destination pair, so that the summation term disapears, and terms simplify. In that case, the port cost would be given by

$$\tau_\rho = t_\rho\left(1 + \frac{1}{\theta - [\theta-(\sigma-1)]\,\pi_{o\rho d}}\right)$$

and the markup is increasing in the port share, as long as the port elasticity is higher than the demand elasticity ($\theta > \sigma - 1$). This implies that investment in ports or roads will also impact the ports' markups, which introduces complementarity between the two types of infrastructure.

Importantly, Equation D.1 tells us that the port fixed effect in regression 23 can still be interpreted as the cost to the firm of using the port ($\tau_\rho$). It also provides a link between the real port's iceberg trade cost $t_\rho$ and the estimated fixed effect $\tau_\rho$, where the only required data are the total values of transactions and port shares at each port. Figure D.1 displays the estimated $\tau_\rho$ against the "cleaned" marginal cost $t_\rho$ based on $\theta = 15$, $\sigma - 1 = 3.4$ and equation D.1. The ranking of ports is largely preserved.

# E Estimation appendix

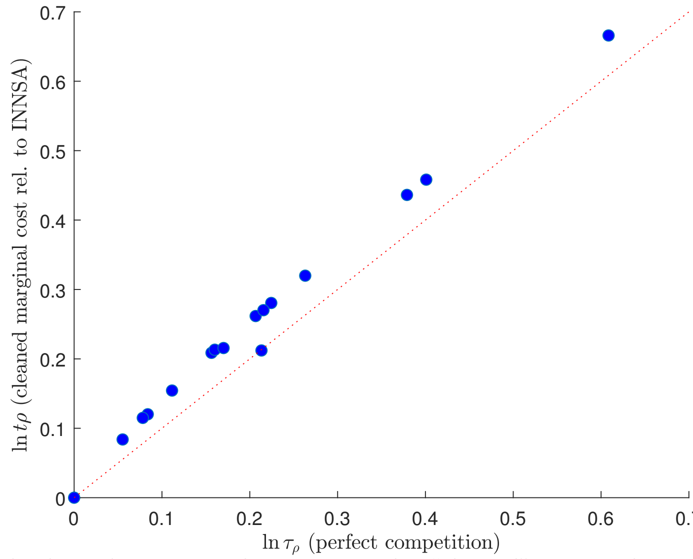
In this section, I provide additional robustness checks for the assumptions underlying the estimation framework.

## E.1 Fixed point estimation algorithm

A necessary condition for the vector $\beta^* = \{\beta^{*c}\}$ to be a solution to the minimization problem 23 is that:

$$\begin{aligned}\beta^* \quad = \quad & arg\min_{\{\beta^c\}}\Bigg\{\pi_{o\rho d} - \exp\Bigg(\sum_c \beta^c dist^c_{o\rho}(\beta^*) - \beta^{ss} sameState_{o\rho} \\ & -\beta^{sea}\ln seadist_{\rho d} - \beta^{liner} liner_{\rho d} - \alpha_\rho - \Phi_{od}\Bigg)\Bigg\}^2,\end{aligned} \tag{E.1}$$

Table D.1: Estimated port marginal cost with oligopolies




**Notes:** The figure displays the estimated $\tau_\rho$ against the "cleaned" marginal cost $t_\rho$ based on $\theta = 15$, $\sigma - 1 = 3.4$ and equation D.1.

where $dist^c_{o\rho}(\beta^*)$ is the total length on category $c$ in the solution of the least cost route given $\beta^*$. In other words, regressing the port shares on the distances computed conditional on $\beta^*$ and other covariates needs to result in the same vector $\beta^*$, so that $\beta^*$ is a fixed point to the mapping defined by the $arg\min$ function in (E.1). Note that given $\beta^c$, the least-cost route problem is well defined and easily solved using standard routing algorithms.

One can solve the fixed-point problem in (E.1) using the following steps:

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

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

3. Solve for $\{\beta^c\}, \beta^{sea}, \beta^{liner}, \{\alpha_\rho\}, \{\Phi_{od}\}$ given $dist^c_{o\rho}$ by Poisson pseudo-maximum likelihood estimation,[43]

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. Given initial values for $\beta^c$ based on the maximal speeds on each type of road, the algorithm only takes few iterations to converge because the optimal route using my initial guess is very close to the one using the final $\beta^c$.

[43] Strictly speaking, problem E.1 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.

Being a solution to the fixed point problem (E.1) is only a necessary condition to being a solution to the minimization problem (23), 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.[44]

## E.2 Trade costs assumptions robustness

**First-in-first out** In the data, I can observe two dates that informs me on how long the port handling process can take for each transaction. The first is the date at which the customs office at the port allows the shipment to leave the territory after inspection, called the "Let Export Order" (LEO) date. The second is the date at which the "Export General Manifest" (EGM) was emitted. The EGM is emitted when the goods actually leave the territory. Hence the difference between the EGM and LEO date if informative on the time taken at the port to handle the shipment, between customs approval and the cargo leaving the port. If transactions are handled without discrimination (first-in-first-out), the difference between the two dates should not be correlated with observables such as size or origin of exporter. To test this, I regress the difference between the two dates on the total exports of the firms and a dummy for wether the firm is located in a different state as the port, after controlling for port-destination fixed effects that capture any port-destination systematic variation in the date difference.[45] I also add origin-destination fixed effects, since my assumption is that the idiosyncratic shock is iid within the origin-destination pair. I also interact it with my measure of port quality, to check that any potential departure from my iid assumption is uncorrelated with port quality. Table E.1 shows the results of this regression. The first row shows that large exporter seem to face lower transit time. However, the second row of the second column shows that this effect is uncorrelated with port quality. Hence, the lower cost faces by large exporters is independent of the port quality, so that it doesn't affect my estimates. Furthermore, the point estimate is very low. A one standard deviation increase in the firm size (around 1.8) would lead to a decrease of around $-1.8 * 0.008 \approx -0.014$ in the log waiting time, while the standard deviation of the log waiting time is 2.5, several order of magnitude higher.[46]

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

[45] For example, if the frequency of ships going from the port to the destination is low, the time delay might be higher independently of the port quality.

[46] At the sample mean, the 1.4% increase in waiting time would translate into around 0.2 days. Hummels and Schaur (2013) estimate that an additional day in transit is equivalent to an ad-valorem trade cost between 0.6 and 2.1. Even using the upper end of this range, the 0.2 days would translate into an ad-valorem trade cost of 0.4%, which is an order of magnitude lower than the standard deviation of my estimated trade cost at the ports (around 15%).

Table E.1: Correlates of firm-level transhipment time

| | $\ln(datediff_{io\rho d})$ | |
|---|---|---|
| $\ln(totexp_i)$ | -0.008** | -0.007*** |
| | (.003) | (.002) |
| $\ln(totexp_i)$ | | -0.001 |
| x $\ln \tau_\rho$ | | (.001) |
| $\ln(dist_{o\rho})$ | -0.029 | 0.017 |
| | (.041) | (.019) |
| $\ln(dist_{o\rho})$ | | -0.003 |
| x $\ln \tau_\rho$ | | (.006) |
| Same state | 0.012 | -0.009 |
| | (.014) | (.059) |
| Same state | | 0.020 |
| x $\ln \tau_\rho$ | | (.026) |
| *od* and $\rho d$ FE | yes | yes |
| N | 141,011 | 141,009 |

**Notes:** This table shows the results of regressing (log) difference between the EGM date and LEO date on some firms characteristics. Standard errors are clustered at the port level.

**Fit of first stage** As explained in section 5.3, Assumption 3 is crucial for the identification of the port elasticity. 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 $\theta$ 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

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

instead of

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

In that case, regressing the port shares on a set of $o\rho$, $\rho d$ and $od$ 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 $od$ pair. Given values for $\tau_{o\rho}$, $\tau_\rho$ and $\tau_{\rho d}$ (or composites up to $\tau_\rho$), and a value of $\theta$, I can simulate Fréchet draws

Table E.2: First stage fit and residual volatility

| | Data residuals | Simulation residuals (no $\eta$) | Simulation residuals (with $\eta$) |
|---|---|---|---|
| Average | 0 | 0 | 0 |
| Median | -.003 | -.003 | -.062 |
| SD | 0.20 | 0.21 | 0.31 |
| p25 | -.018 | -.020 | -.132 |
| p75 | -.0005 | -.0004 | -.021 |

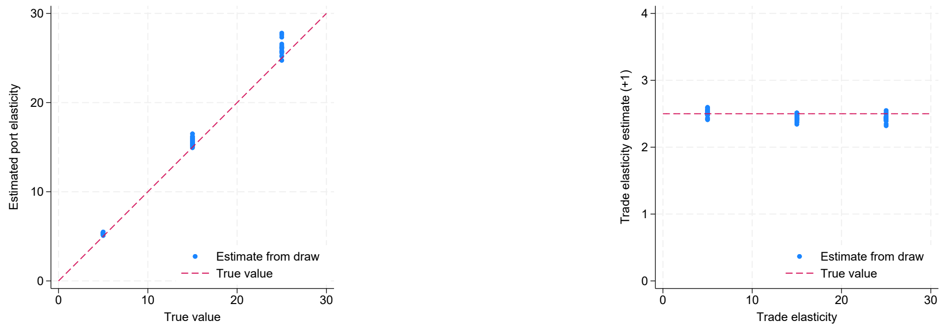
**Notes:** The table reports summary statistics of the residuals from the first-stage regression (16). The first column is the data regression. The second column is a regression on simulated data with $\theta = 15$ and no $\eta_{o\rho d}$. The third column adds a log-normally distributed $\eta_{o\rho d}$ term with a variance of 1.

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 $\eta$ term might be. The first two columns of Table E.2 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. In the third column, I report summary statistics of the residual in a simulated dataset where I further add an $\eta_{o\rho d}$ shock that is normally distributed with variance 1. In that case, the volatility of the residuals is much higher than what is in the data. As a consequence, I conclude that the presence of an extra $\eta_{o\rho d}$ term is unlikely, and that Assumption 3 fits the data well.

### E.3 Small sample bias

As argued in the main text, the estimate for $\frac{\sigma-1}{\theta}$ is consistent, but not necessarily unbiased. The asymptotic consistency of the elasticity estimates relies on the number of origin and destination growing to infinity given a fixed number of firms. In my sample, I have an average of 140 destinations per origin district, and 220 origin district per destination. Here, I provide an assessment of the small sample bias that might arise. Given values the first-stage estimated values for $\tau_{o\rho}$, $\tau_{\rho}$ and $\tau_{\rho d}$ (or composites up to $\tau_{\rho}$), and a value of $\theta$, I can simulate Fréchet draws and the resulting port choices for the same number of origins, destinations, and firms as in my data. I can then use this simulated dataset to run the estimation strategy and check that the estimation recovers the assumed value of $\theta$. Figure E.3 displays the results of the estimation procedure on a simulated dataset where $\sigma - 1 = 3.5$ and different values of $\theta$. The left panel shows the estimates of different draws compared to the true value for $\theta$ equals to 5, 15 and 25. The procedure seems to perform well, as there is only a small upward bias. The right panel shows that the estimation of the trade

Table E.3: Small sample bias of the port elasticity estimation procedure




**Notes:** The figure displays estimates of $\theta$ and $\sigma$ in the monte carlo simulation. Each dot is an estimate from 20 simulations.

elasticity is unbiased.

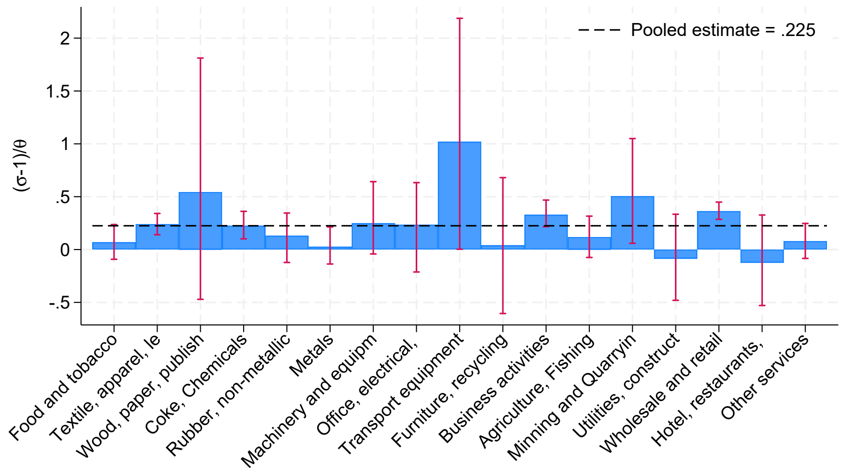
## E.4 Sectoral estimates of $\theta$ and $(\sigma - 1)$

I run the same estimation strategy separatedly by sector, each sector being defined as a ISIC section (see Table A.1). Figure E.1 presents the sectoral-level estimate of $1/\theta$ and $(\sigma - 1)/\theta$, with the horizontal line representing the pooled estimate. In all cases, the pooled estimate lies within the sectoral estimate, although the confidence intervals are quite wide because cutting the data to the sectoral level reduces the statistical power. That being said, runing the regression at the sectoral level stills allows me to recover a sector-level trade elasticity. To ensure that my results are consistent with the existing literature, I compare it to estimates from Caliendo and Parro (2015) in Figure E.2.

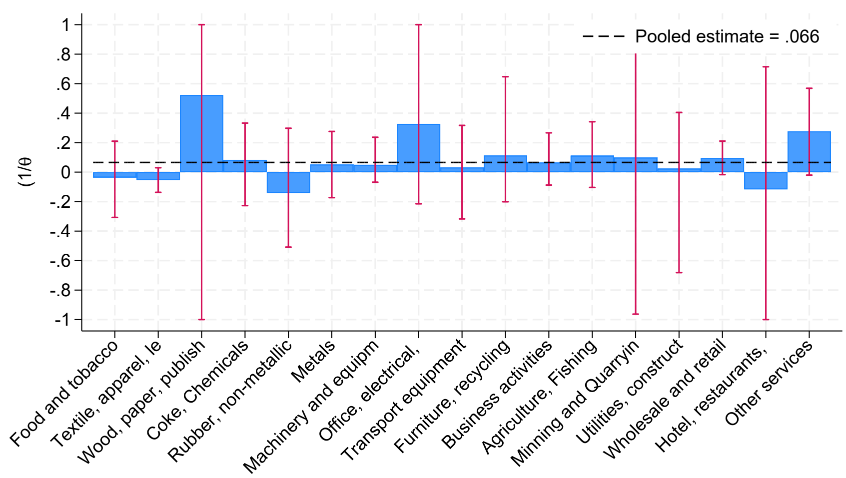
## E.5 Road infrastructure quality

My estimation controls for the cost of going to the port on the road by separating the road in two categories, normal road and expressway. If the expressways located close to a given port are for some reason of lower quality than the average, or if there is more congestion on the road around ports, the estimation will attribute the low expressway quality to the port and estimate a lower port quality. Hence, it is important to ensure that the expressway quality around all ports is similar. To check this, I use Google Map API to obtain average speed around each ports. In particular, I obtain the travel time and road distance between each port pair. I then regress the average speed between any two port pair on an origin port and a destination port fixed effect. The port fixed effects capture the deviation from average speed when making trips from and to this port. I take the average of the origin and destination fixed effect as a measure of road quality around the port. The left panel

Figure E.1: Sectoral estimates of elasticities



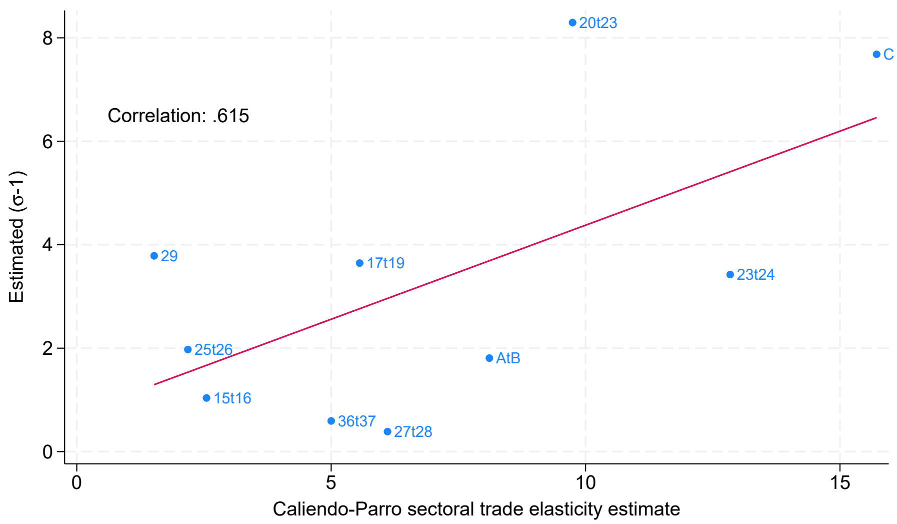

(a) Estimates of $(\sigma - 1)/\theta$




(b) Estimates of $1/\theta$

**Notes:** This figure plots the results of running regression equations 19 and 18 at the sectoral level. The horizontal line represents the pooled estimate from the main text.

Figure E.2: Sectoral estimates of $(\sigma - 1)$ compared to existing estimates

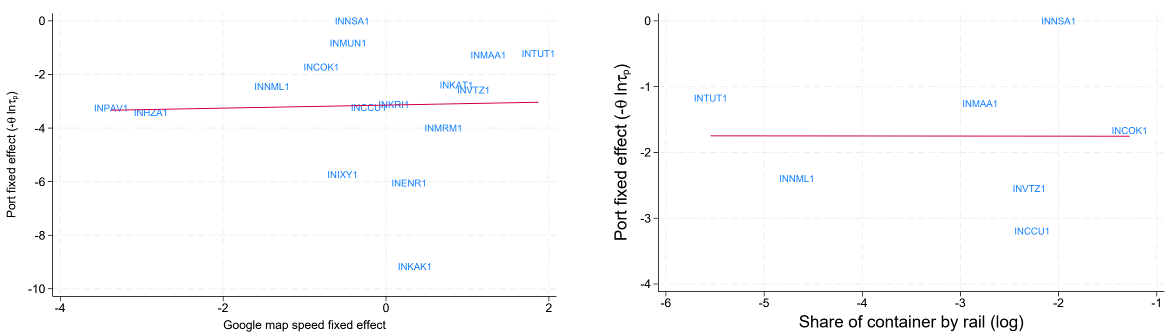



**Notes:** Sectoral trade elasticity estimates are computed as the ratio between the estimated sectoral $(\sigma - 1)/\theta$ and $1/\theta$. I aggregate the Caliendo-Parro estimates to my section aggregates.

of Figure E.3 plots this measure of road quality around the port against my port quality estimates. Reassuringly, there is no significant relationship, so I conclude that my port quality estimates are not driven by heterogeneity in road quality near the port.

An other potential issue is if some ports are differentially connected the rail network and the road network. For example, if a port is not well connected by road but very well connected by rail and receives many shipments by rail, my estimation strategy will interpret the many shipment as a sign that the port is very good, since shipments arrive despite the poor road connection. To ensure that this is not driving my results, the right panel of Figure E.3 plot my estimated port quality against the share of the port's container traffic that arrives by rail. This measure is only available for a subset of port in the Basic Port Statistics, but for those port, there is no clear relationship.

Figure E.3: Road quality around the port and port quality estimates




Speed around port

Rail usage

**Notes:** The left figure plots the estimated port quality against the average road speed at the port, defined as the fixed effect when regressing Google map speed between all port pairs on port fixed effects. The right panel plots the estimated port quality against the share of container (in TEU) arriving to the port by rail.

# F Model calibration appendix

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 $\lambda_o$ that satisfies equation (25). To further fit the observable country-level trade share exactly, I set up the following problem.

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

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

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

$$\sum_{o \in IND} \pi_{od} = \sum_{o \in IND} \frac{\lambda_o \left(d_{od}\right)^{1-\sigma}}{\sum_k \lambda_k \left(d_{kd}\right)^{1-\sigma}} = \pi_{IND,d}^{DATA}, \tag{F.2}$$

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

$$\sum_{d \notin IND} \frac{X_{d,IND}}{X_{IND}} = \frac{\sum_{d \in IND} \lambda_o \left(d_{od}\right)^{1-\sigma} \alpha_d X_d}{\sum_k \sum_{d \in IND} \lambda_k \left(d_{kd}\right)^{1-\sigma} \alpha_d X_d} = \pi_{o,IND}^{DATA}, \tag{F.3}$$

where:

$$d_{od} = \begin{cases} 1 & \text{if } o = d \\ \exp\left(\sum_c \beta^c dist_{od}^c\right) & \text{if } o, d \in IN \\ a_d^{exp} \underbrace{\left[\sum_\rho \left(\exp\left(\sum_c \beta^c dist_{o\rho}^c\right) \tilde{\tau}_\rho \left(seadist_{\rho d}\right)^\gamma\right)^{-\theta}\right]^{-\frac{1}{\theta}}}_{\tilde{\tau}_{od}} & \text{if } o \in IN, d \notin IN \\ a_o^{imp} \left[\sum_\rho \left(\exp\left(\sum_c \beta^c dist_{o\rho}^c\right) \tilde{\tau}_\rho \left(seadist_{\rho d}\right)^\gamma\right)^{-\theta}\right]^{-\frac{1}{\theta}} & \text{if } o \notin IN, d \in IN \\ d_{od} & \text{if } o, d \notin IN \end{cases} \tag{F.4}$$

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

1. Guess a vector of $\lambda$ and compute the corresponding $d_{od}$ to match the observable trade shares exactly

   (a) Foreign-foreign shares:

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

   (b) India to foreign flows:

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

   (c) Foreign to India flows:

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

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

3. Go back to 1 with the new guess for $\lambda$ until convergence.

# G Counterfactuals appendix

## G.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:

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

where $\hat{\tau}_{o\rho}$, $\hat{\tau}_\rho$ and $\hat{\tau}_{od}^{IN}$ are counterfactual-specific. $\hat{\tau}_{o\rho}$ and $\hat{\tau}_{od}^{IN}$ depend on the assumed changes in road network through equation 20.

## G.2 Additional results

### G.2.1 Scale economies with port targeting

Ports and sea shipping may be subject to congestion or economies of scale (e.g. Ganapati et al., 2021). In that case, the port cost estimates recovered in section 4.2 are inclusive of economies of scales.[47] More precisely, assume that the iceberg trade cost at the port is given by:

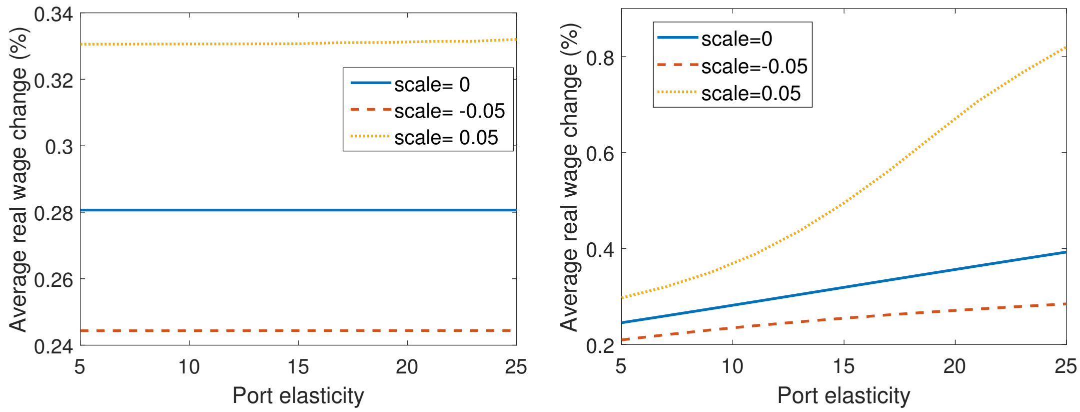
$$\underbrace{\tau_\rho}_{\text{port iceberg cost}} = \underbrace{t_\rho}_{\text{port quality}} \underbrace{(x_\rho)^{-\lambda}}_{\text{scale}},$$

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

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 $\lambda$. I first take the estimated $\tau_\rho$ and compute $t_\rho$ based on data on the aggregate volume at the port and the value of $\lambda$. Then, I exogenously decrease $t_\rho$ by 4% for all ports (uniform improvement) or $t_{MUMBAI}$ by 10% (targeted improvement).

[47] 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.

Figure G.1: Targeted improvement with scale economies




Uniform improvement  Targeted improvement

**Notes:** The left panel shows the average real wage change across Indian districts when reducing $t_\rho$ by 4% for all ports as a function of the port elasticity, for different values of scale economies or congestion. The right panel displays the same, but for the scenario where only the port of Mumbai is improved by 10%.

To pick a data-driven value for $\lambda$, I run a simple OLS regression of the estimated $\tau_\rho$ on (log) total volume at the port. I get a value of $\lambda = 0.056$. The estimate is likely upward biased, since the value at the port is negatively correlated with the unobservable $t_\rho$.[48] Figure G.1 thus displays the counterfactual results for a scale economy of 0.05 and a symmetric congestion scale $-0.05$ for illustration.

### G.2.2 Complementarity with additive trade costs

The complementarity exercise described in section 6.2 has potentially built-in complementarity between road and port improvement, given that I assume that the trade costs are multiplicative: $\tau_{o\rho d} = \tau_{o\rho}\tau_\rho\tau_{\rho d}$. Any reduction in $\tau_{o\rho}$ is amplified if $\tau_\rho$ also decrease. This source of complementarity is different from the one hlighlighted in the paper about the substitution toward a given port. To ensure that the results are not driven by the multiplicative form, I repeat the exercice but this time assuming that the trade costs are additive:

$$\tau_{o\rho d} = \tau_{o\rho} + \tau_\rho + \tau_{\rho d}.$$

[48] In detail, 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 $\theta = 15$ to recover $\lambda = 0.056$. For comparison, Ganapati et al. (2021) find an elasticity of 0.07 for economies of scale in leg-level shipping.

I then sove for the model in changes using the same algorithm as described in section G.1, changing the trade cost changes as:

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

Since I don't estimate the levels of the trade costs elements $\tau$s, I assume for simplicity that the internal, port, and external parts all account for a third of the costs ($\tau_{o\rho}/\tau_{o\rho d} = \tau_{o\rho}/\tau_{\rho d} = \tau_\rho/\tau_{o\rho d} = 1/3$).[49] Note that this calibration doesn't change the complementarity mechanism.

Figure G.2 displays the results of the simulation when improving the port of Mumbai and road segments that are used to reach the port (in blue) vs segments that are not (in dashed red).[50]

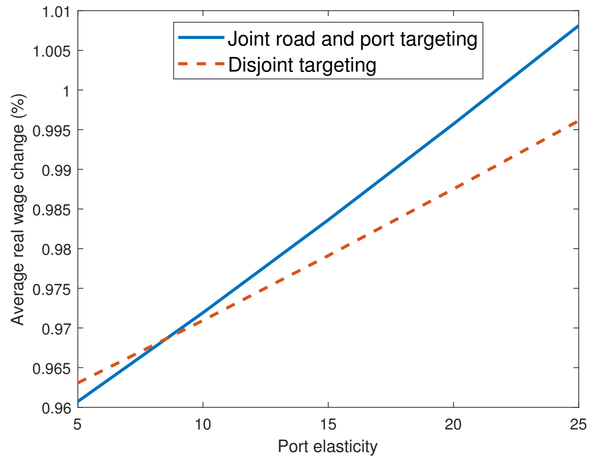
### G.2.3 Marginal returns with returns to scale

Figure G.3 repeats the marginal improvement exercise in the main text, but adds port congestion or economies of scales in the same way as in section G.2.1 above. For all values, the returns of improving ports are higher.

[49] Anderson and Van Wincoop (2004) estimates internal trade costs of around 55% and external trade costs of around 74% for a representative country. That is estimated in a multiplicative framework, but is broadly consistent with the assumption that internal cost represent a third of the total cost.

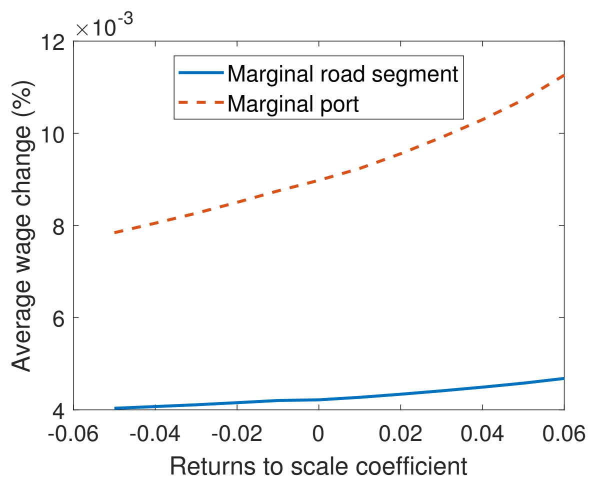
[50] In the baseline, I reduce the transhipment cost at Mumbai by 5% this corresponds to a 5% decrease in overall trade costs given the multiplicative assumption. To match this aggregate reduction, I reduce the cost by 15% in the additive case under the assumption that each account for a third of the total cost. In the baseline, I reduce the cost of traveling on each road segment by 10%. Again, I convert this to 30% in the additive case to match the aggregate. This results in slightly bigger gains in level because internal trade costs across indian districts also decreases by more than in the baseline.

Figure G.2: Targeted improvement with additive road and port costs




**Notes:** The figure displays the average change in real wage when reducing $\tau_{NSA}$ by 5% and improving road segments used to connect NSA (blue line) or segments never used to connect to NSA (dashed red line).

Figure G.3: Marginal improvements with returns to scale




**Notes:** The solid blue line displays the average change in real wage when transforming the normal road segment into an expressway under different port scale elasticities. The dashed red line shows the impact of improving the port of Nava Sheva for a similar cost.