International Transport Infrastructure and Regional Economic Development*

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Abstract

We evaluate how access to international transport infrastructure promotes trade and economic development. Exploiting the gradual unfolding of transcontinental rail freight connections between China and Europe, our empirical findings indicate increasing exports from connected cities, with positive spillovers to other transport modes, neighboring cities, and indicators of economic activity. Not all products and cities are equally responsive to new rail export opportunities. We set up a multi-sector heterogeneous firms model with a rich specification of trade costs, in which firms optimize trade costs by choosing alternative transportation modes and routes. Leveraging a unique data set on trade flows between Chinese cities, we calibrate our model to discuss local welfare effects, relying on a sufficient statistic that quantifies changes in city-level trade costs. We also highlight significant spatial distributional effects of trade infrastructure development.

JEL-Classification: F14, F15, R11, R41

Keywords: Transport infrastructure, Trade, Regional development, China

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1 Introduction

The economic benefits of transportation infrastructure are well documented: lower shipping costs, increased trade and economic integration lead to lower prices, greater product variety, and potentially other positive externalities.[1] Yet, while the vast majority of studies focuses on domestic infrastructure development, much less attention has been paid to international transport infrastructure and the transportation mode used for (long-distance) shipments. This paper demonstrates that these features are important, both for the magnitude as well as the distribution of gains from trade.

International transport infrastructure facilitates large-scale, routinized shipments from one origin location to (several) distant destinations. Tracing the flows of goods into and out of a country reveals patterns resembling a hub-and-spoke structure (e.g. Heiland et al., 2019; Ganapati, Wong and Ziv, 2021). Hubs represent port locations that function as gateways to other markets. Spokes are surrounding locations that utilize these gateways for foreign market access.[2] International shipments are also known to use different transportation modes. Ocean shipping and airfreight capture by far the largest fractions, while rail transportation represents only a minor share of global international trade activity. This can be explained partly by the fact that most international shipments requires goods to travel across waters. Nevertheless, the modal choice for a shipment might also depend on the preferences of the buyer or seller (Hummels and Schaur, 2013), or on the physical characteristics of a good (Harrigan, 2010).

This paper shows that both the local concentration of international trade services in a country as well as the available transport modes are important determinants of the economic effects that trade infrastructure can entail. Indeed, trade infrastructure improvements do not lead to uniformly increasing economic activity and growth. To document this, we exploit the gradual rollout of scheduled rail freight connections between China and the European Union (EU) via the so-called *China-Europe Railway Express* (CRE). We show empirically that Chinese hub-cities and their spatial surroundings benefit economically from improved foreign market access relative to other locations in the country.[3] We further show that the

[1] See, for example, Faber (2014); Baum-Snow et al. (2017); Duranton, Morrow and Turner (2014); Martincus, Carballo and Cusolito (2017); Bonfatti and Poelhekke (2017); Donaldson (2018) and Banerjee, Duflo and Qian (2020).

[2] In contrast to this, most domestic infrastructures resemble a mesh, in which individual locations are connected to multiple other locations to facilitate frequent, small-scale and non-routinized flows.

[3] We refer to cities as a particular layer of the administrative division in China. Cities can comprise large non-urban areas and, depending on certain characteristics or their geographic location, they can be called prefectures, prefecture-level cities, autonomous prefectures, or leagues. We use the term city to indicate any of these administrative units that commonly reside at the second layer of China's administrative division, i.e. below provinces.

share of rail transport in bilateral shipments increases between connected locations, but that the degree of this expansion varies across products, suggesting that alternative transport modes are imperfect substitutes. We develop a micro-founded spatial equilibrium model of international trade with multiple regions and sectors to study the economic implications of these observations. In our model, firms optimize their trade routes by exporting via alternative ports and using different transport modes. The availability of new railfreight connections from specific locations significantly lowers exporting thresholds for certain firms and products, which entails positive aggregate welfare, but also significant spatial distributional effects.

Our empirical analysis takes advantage of several features that are specific the CRE rollout and convenient for identification. Unlike other infrastructure development projects, the CRE was realized within a relatively short period of time. Trains operate on already existing rail tracks that became economically relevant after administrative alignments among transit countries and some capacity building at container terminals and junction points. We interpret the CRE rollout as a trade infrastructure upgrade, which is different from the lengthy process of physically constructing rail infrastructure. Another feature is that the market access facilitated by CRE services is destination and transport-mode specific. Terminal cities become gateways only for shipments to European markets by rail. Leveraging detailed information from the China Customs Database, we analyze city-level export activity along these dimensions to identify the impact of the first CRE schedules (adopted between 2011 and 2016) on regional export growth and economic development.

The empirical baseline results indicate a relative increase in exports to Europe by about 10% in cities that become CRE gateways. Exports to other destinations do not change significantly. Each additional year of being connected is related to a 5.0% relative increase in exports. The statistical and economic significance of our estimates remains evident in a number of robustness checks. We find further that almost the entire relative increase in trade activity is driven by rail freight shipments, while alternative modes of transportation do not reveal any systematic changes, besides some potential positive spillovers for ocean shipping. Overall, the lack of evident substitution effects between export destinations or transport modes suggests that the CRE rollout has been locally trade-creating.

We document heterogeneous effects across products and cities. To distinguish between products, we follow Harrigan (2010) and test whether heavier goods (as measured by their weight-value ratio) respond differently than light products, and we follow Hummels and Schaur (2013) in considering the time sensitivity of goods.[4] In both cases, we find that

[4]Time sensitivity refers to product-specific characteristics that result in a higher willingness to pay by customers for an earlier delivery. In Hummels and Schaur (2013), goods that are more frequently imported

products ranging at intermediate ranks of the respective distributions are significantly more responsive, which is in line with the reasoning that rail-freight services range between air-freight and ocean shipping in terms of their delivery times and average shipping costs. Regarding differential effects across cities, we exploit their geographic location within China to measure their distance to sea ports as well as their centrality in domestic transportation networks. Our results suggest that cities located in more geographically and economically remote regions of China experience higher export growth, which can be explained partly by a smaller initial export base as well as fewer alternative market access opportunities.

To investigate potential spatial spillover and local development effects, we test whether neighboring and nearby cities also reveal changes in their exporting behavior. Using a concentric ring approach, we find that neighboring cities within 200 km of a connected city also benefit from increased exporting activity, while the magnitude of this effect decreases with distance. We also find that exports in connected cities are increasingly facilitated by co-locating trade intermediaries, which indicates the creation of new business opportunities related to exporting in these locations. Moreover, exports by state-owned enterprises do not appear to respond to the CRE, while foreign invested firms and private domestic enterprises reveal significant export growth. Relying on auxiliary information from the China Tax Survey, spanning the years 2010-2016, we identify further margins of adjustment at the firm level. Specifically, we observe that firms in connected cities increasingly enter into exporting, earn higher profits, pay higher wages and have higher R&D spending after CRE integration. Also sales and employment increase over time, which suggests that firms overall start to grow (faster) after getting access to European markets.

Building on our empirical findings, we develop a spatial equilibrium model of international trade with multiple sectors and regions to evaluate the welfare consequences of a destination- and transport-mode specific infrastructure. Our model builds on the port-choice framework of Bonadio (2022), which we extend to incorporate sector and firm heterogeneity, as well as a more flexible choice of shipping decisions for exporters. Our model features a rich specification of trade costs to accommodate our empirical observation that export responses to the CRE differ across products and cities. The welfare effects of the CRE consequently depend on the effective reduction in trade costs, which is governed by the trade-cost elasticity of transport mode and port choices.

Putting the model to work, we follow Dekle, Eaton and Kortum (2008) and derive sufficient statistics for changes in cities' bilateral trade costs that are reminiscent of the canonical formulas for the gains from trade derived by Feenstra (1994) and Arkolakis, Costinot and Rodríguez-Clare (2012). Specifically, we demonstrate that the sector-specific share of ex-

via air-freight instead of ocean shipping (all other things equal) are considered as more time sensitive.

ports transported via non-rail modes and the corresponding modal elasticity of substitution describe the effective change in trade costs. The advantage of this approach is that it only requires the estimated elasticity of substitution across transportation modes as well as data on exports by transport mode, while avoiding the need to estimate the elasticity of trade costs with respect to distance and other variables, which would entail complex and daunting parametrization procedures.

For our welfare analysis, we construct a novel and unique dataset of sector-specific "domestic" trade flows between China's 100 largest cities, leveraging detailed transaction records from the *Taobao Platform* (a large Chinese online B2C and C2C retailer). We quantify the aggregate welfare gain of the CRE as amounting to about 0.016% of GDP. This number ranges an order of magnitude below the welfare gains inferred in studies where trade costs reductions are not specific to a particular transport mode or export destination.[5] Since rail freight exports to the EU represents only a small fraction of China's total exports, we consider this estimate as a reasonable approximation. Further analyses suggest that the estimated aggregate welfare gains are large enough to compensate for the amount of initial start-up (i.e. subsidy) costs of the CRE.

Focusing on local economic outcomes across China, we highlight in our simulations that firm entry into exporting differs substantially across sectors and regions, reconciling the uneven effective reduction in trade costs. Consequently, also the welfare effects of the CRE are not evenly distributed across cities and we find winners and losers. Cities whose industrial base is prone to utilizing rail freight for their exports benefit directly from enhanced market access. Moreover, they benefit indirectly from general equilibrium effects, as their emerging comparative advantage attracts resources from other regions. This finding highlights an important nuance of international transport infrastructure which, next to being locally concentrated, can also entail distributional consequences across industries and regions.

Related Literature. Our paper contributes to the literature on international trade infrastructure, where early research emphasizes the role of transportation costs (Hummels, 1999; Limao and Venables, 2001; Glaeser and Kohlhase, 2004; Clark, Dollar and Micco, 2004). More recent studies document how global trade flows operate mainly via entrepôt hubs and specific routes, which create spatial network relationships through which local shocks can propagate (Heiland et al., 2019; Ganapati, Wong and Ziv, 2021). Our empirical results are in line with these features, as we observe increases in rail-freight exports to Europe in both directly and indirectly connected cities, while larger increases are found in places with less

[5] Tombe and Zhu (2019) estimate the welfare gains of 3.4% from decreasing external trade costs for China during 2000-2005. Fajgelbaum and Redding (2022) obtain larger gains for Argentina, amounting to 7.1%, following reductions in transatlantic freight rates during 1869-1914.

access to alternative routes. Our welfare estimates plausibly range an order of magnitude below those of sea port development, studied by Ducruet et al. (2020). As discussed in our paper, we suspect the main reason for these smaller effects to be found in the limited capacity of rail freight relative to ocean shipping, as well as the destination-specificity of the CRE. Indeed, estimates by De Soyres, Mulabdic and Ruta (2020) suggest that the development of a multi-destination international railway infrastructure can lead to considerably higher (though heterogeneous) welfare effects across countries. To the best of our knowledge, our paper is one of the first to the examine and quantify the local concentration, spatial spillovers and the distributional effects of trade infrastructure improvements inside a country.

We distinguish our paper from the abundant literature that focuses on domestic infrastructure development (e.g. Faber, 2014; Alder, 2016; Asturias, García-Santana and Ramos, 2019; Baldomero-Quintana, 2020; Jaworski, Kitchens and Nigai, 2020; Fan, Lu and Luo, 2021; Michaels, 2008; Xu and Yang, 2021; Donaldson, 2018; Banerjee, Duflo and Qian, 2020; Allen and Arkolakis, 2022). Although their promotion of economic integration and market access can have similar implications for economic development outcomes, as we document empirically in our paper, the underlying mechanisms can differ substantially. A paper at the intersection of domestic and international trade infrastructure, and therefore most closely related to ours, is Bonadio (2022), which compares the trade and development effects of improvements in port vs. road infrastructure in India. Expanding on his framework and applying it to the case of the CRE in China, we make a novel contribution by highlighting that imperfect substitution between transportation modes can be an obstacle to benefiting from trade infrastructure improvements. In a scenario where these obstacles result in a comparative disadvantage in foreign market access, they can even have locally adverse welfare consequences that are reminiscent of the challenges highlighted in the context of place-based policies (e.g. Moretti, 2024).

Besides this, we contribute to the recent literature that focuses on the economic consequences of China's recent international trade infrastructure development activities, more broadly summarized under the *Belt and Road Initiative* (BRI). Quantitative studies by De Soyres, Mulabdic and Ruta (2020) and Baniya, Rocha and Ruta (2020) document noticeable aggregate trade creation effects among participating countries and stress that benefits concentrate especially among time-sensitive and supply-chain trade flows. These cross-country findings — which exclude the CRE we study in our paper — are complemented by empirical evidence for export growth among Chinese firms since the launch of the BRI (Görg and Mao, 2022). In addition to this, Li, Bolton and Westphal (2018), Mau and Seuren (2023), and Kleimann and Schmerer (2024) provide country-level evidence of export growth and other outcomes focusing exclusively on the CRE. In contrast to these studies, our re-

search is based on significantly more granular data, which enables us to employ a much finer identification strategy and to assess impacts along several other dimensions than what could be done in previous studies.

The remainder of our paper is organized as follows. Section 2 describes the context of China-Europe Railway Express and the data used in our analysis. Section 3 investigates the effects of CRE using reduced-form estimations. Motivated by the empirical facts, section 4 sets up a multi-sector heterogeneous-firms model with a rich specification of trade cost, which we use to estimates the cross-transportation and cross-route elasticities for each sector in Section 5. Section 6 computes the welfare effects of the CRE, based on the estimated elasticities and discusses their implications. Section 7 concludes.

2 Background and Mechanisms

Early railfreight from China to Europe. The first commercial railfreight schedule between China and Europe was adopted in 2011 with the Yu-Xin-Ou (渝新欧) railway connection from Chongqing to Duisburg (Germany). Its launch is tightly linked to the Chongqing municipal government's promotion of consumer electronics industries, which attracted large-scale investments by multinational enterprises in laptop production facilities. Being located in a mountainous area of Southwest China, far a way from sea ports, the successful distribution of the goods produced in Chongqing relied critically on its integration into global transport and logistics networks. While traditional export routes were either slow (ocean shipping) or expensive (air freight), facilitating direct access to European markets could significantly boost its exporting potential. Indeed, EU countries were the destination of one third of China's laptop exports in the years 2007-2010 and accounted for slightly more than 50 percent of global laptop imports at that time.[6]

Chongqing's municipal government pioneered the use of the New Eurasia Land Bridge corridor for its exports, which relied on existing rail tracks, spanning from Lianyungang in East China to Rotterdam in the Netherlands, and passing through six countries: China, Kazakhstan, Russia, Belarus, Poland, Germany.[7] The first train running from Chongqing to Duisburg arrived on March 19, 2011, after travelling more than 11,000 kilometers in 16 days and carrying mainly electronic products and mechanical parts among other goods.[8] Regular shipments required administrative and logistic alignment between all transit countries, which

[6]Calculations are based on data from CEPII Baci (v202301) and reflect nominal value shares of EU27 imports in the respective years. Laptops are identified as corresponding to HS6 product code 847130.

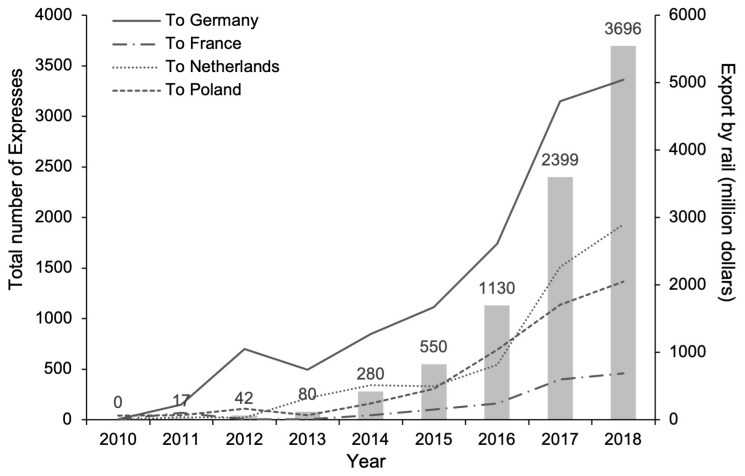
[7]Figure B.1 displays how the Yu-Xin-Ou connects Chongqing to Western Europe via the New Eurasia Landbridge, referred to as the "Western route".

[8]See www.ecns.cn (2021), accessed March 19, 2024.

involved expedited customs procedures and facilitating switches to different rail gauges at the borders. In subsequent years, the railfreight share in Germany's laptop imports from China increased from zero to about 25 percent within one decade. The share of other transport modes decreased from 80-90 percent to 60-70 percent (airfreight) and from about 20 to less than 10 percent (ocean shipping), respectively.[9]

Development of the China-Europe Railway Express. Following Chongqing's example, other cities from across China adopted regular freight schedules for the transport of goods to Europe by rail, which are administered by the *China State Railway Group Cooperation* as the China-Europe Railway Express (CRE).[10] By the end of 2016, 12 Chinese cities had direct railfreight connections to Europe on a regular schedule. Many more followed in subsequent years, counting 62 in 2018 and 86 by the end of 2023 (including a few non-EU destinations in Eastern Europe or Central Asia).[11]

Figure 1: China Railway Expresses and export



Sources: Belt and Road Portal and China Custom Database. The graph displays the number of China Railway Expresses departing from China (bar) and export from China to Germany, France, Netherlands and Poland (line) in 2010-2018.

Figure 1 presents aggregate statistics on the number of West-bound trains under the CRE and rail exports to selected EU destinations since 2010. While initial shipments are

[9]Calculations based on data from Eurostat (ds-058213) for the years 2005-2020.

[10]The CRE is part of China's Belt and Road Initiative, which was officially launched in 2013 to promote trade infrastructure development for better economic integration of China with the rest of the world.

[11]Recent statistics on the number of trains and containers shipped to and from Europe are documented on the CRE websites `https://www.crexpress.cn/en/#/allTraffic` (last accessed: 20 March 2024). While initial years saw a strong imbalance in the number of departures (exports) and arrivals (imports), they are almost equal today. In this paper, we focus only on the exports of goods from China to Europe via rail or other transport modes. During our investigation period (2010-2018), China's export to Europe by rail increases by over 500% while China's import from Europe by rail increases by less than 10%.

negligible, the number of train departures doubled almost every year. The differential growth in rail export volumes across destinations can be explained partly by the different terminal stations of the CRE schedules and the year in which their operations started (Mau and Seuren, 2023). Germany, the first connected and most centrally located country within Europe's railfreight network, saw a five-fold increase of their rail import from China between 2013 and 2018.

The CRE introduces a new modal choice for international trade between China and Europe, even for cities with direct access to sea ports. Railway shipping times and costs from Shanghai/China to Hamburg/Germany decreased from 47 to only 16 days between 2006 and 2017, while the cost for a forty foot equivalent unit decreased by almost 25 percent (Table B.1). No other transport mode experienced comparable cost reductions during this period. Most of the reductions in travel time and costs can be attributed to administrative alignments and logistical collaboration between the sending, transit and receiving countries (Pomfret, 2021). Nevertheless, the capacity and importance of rail exports remains relatively constrained compared to other modes of transport and total trade volumes. For both the EU27 and Germany in its center, the rail share in total imports from China peaked at about 2.5 and 4.5 percent, respectively, in the years 2017-2019.[12] Given these numbers, it is unlikely that large gains materialize in terms of aggregate welfare. Nevertheless, it might entail meaningful local trade creation and welfare effects.

Economic mechanisms. Our descriptions of the CRE places our analysis close to recent research on the effects of international trade infrastructure on local economic development (e.g. Ducruet et al., 2020). An important distinctive feature of our setting is that the facilitation of transcontinental rail freight did not follow from the construction of physical transport infrastructure, which would take years or decades to be realized. Instead, the dismantlement of non-tariff barriers to existing trade routes could take place almost instantaneously and constitutes the main driver behind improved foreign market access for connected Chinese cities. We therefore interpret the gradual adoption of CRE schedules by Chinese cities as "port upgrades", along the lines of Bonadio (2022), which entails that firms can (re-)optimize their shipping routes, if (i) they are close enough to CRE terminal cities and (ii) their goods are suitable for rail transportation.

The first condition follows from the nature of international trade logistics, which operate via entrepôt hubs in spatial networks (Heiland et al., 2019; Ganapati, Wong and Ziv, 2021)

[12] Years since 2020 might be exceptional, due to expedited imports of personal protective equipment (PPE) from China during the COVID-19 pandemic on the one hand (increasing rail shares in 2020-2021), and the sanctions and potential other disruptions to rail transport via Russia and Belarus on the other hand (depressing the rail share in EU imports from China since 2022).

and imply potential regional spillover effects. In this respect, the fact that CRE trains do not stop on their journey between origin and destination becomes an important feature that works in favor of formulating testable hypotheses. Only cities that are starting points of CRE trains, as well as those located relatively nearby, will benefit from improved market access. Cities located along the railway route, but far away from CRE terminals, are likely to benefit less or not at all. For example, the Yu-Xin-Ou (渝新欧), which we introduced above, loads containerized goods only at the Chongqing train terminal and discharges them in Germany. Likewise, the Han-Xin-Ou loads containers at the Wuhan train terminal and discharges them in Poland and Germany. Logistics firms, such as H&T, provide trucking services to pick up containers from other cities and carrying them to the respective terminal stations.[13]

The second condition emphasizes a feature that distinguishes CRE connections from conventional thinking on ports or export hubs. Indeed, the trade infrastructure considered in our paper is *destination specific*, which is different from the "global" market access facilitated by sea ports. Moreover, long-distance shipments by rail face significant capacity constraints in comparison to ocean transport. Statistics published on CRE shipments count a maximum of 100 containers per train, which is considerably less than the several thousands of containers that can be carried on a container ship.[14] The probability that CRE schedules lead to increased exports and other forms of economic activity will consequently depend on the cost (and time) elasticity of transport mode choices for exports, which is reminiscent of earlier work by Harrigan (2010) and Hummels and Schaur (2013).

Overall, the gradual roll-out of CRE schedules across China constitute a convenient setting for the identification of trade elasticities and the economic effects of foreign market access, by exploiting variation along different margins. In the following, we describe our data and empirical strategy to evaluate how much and where international trade and other economic activity appears to change in response to the introduction of the railfreight express.

[13] See https://www.chinaeuroperailwayexpress.com (last accessed 21 Aug 2024). The China Customs database allows us to observe how railfreight exports to Europe are spread across different exit ports (or cities). For 2018, we observe that exports from cities we identify as CRE terminals cover 67% of these shipments. This implies that about one third of railfreight exports take place on an irregular (non-scheduled) and customized basis from other cities (also see RailFreight.com, last accessed 29 Aug 2024). Considering railfreight departing from CRE cities, we further observe that 55% of these shipments originate from these cities, while the remainder comes from other cities but is shipped via CRE terminals, implying potential regional spillover effects.

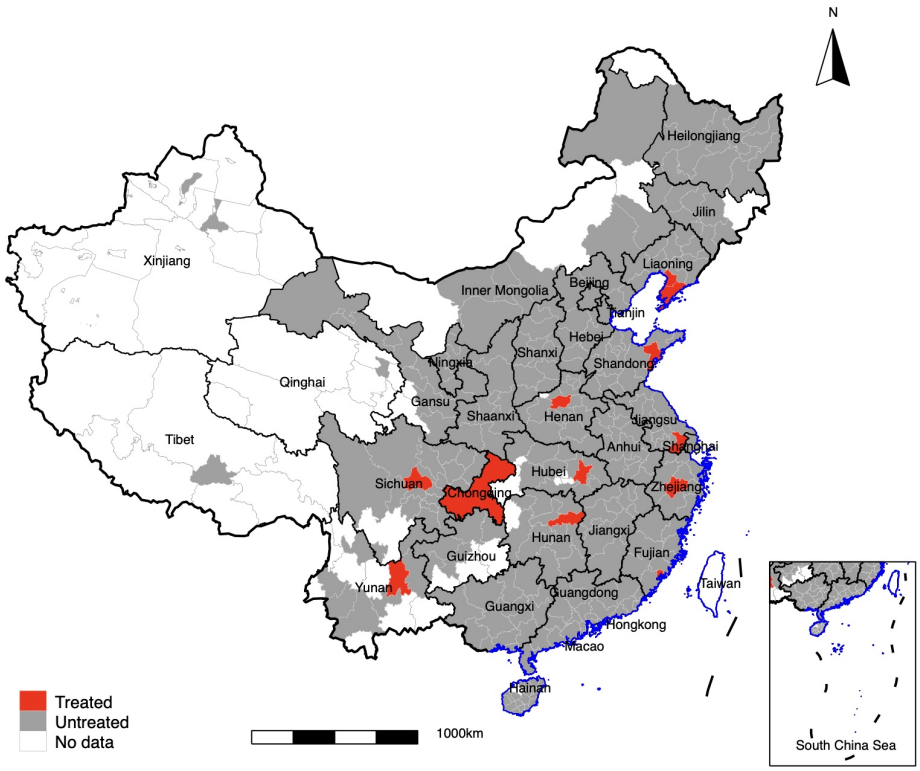
[14] Air shipments faces additional constraints associated with the weight of the freight (Harrigan, 2010).

3 Empirical Analysis

3.1 Data

Our empirical analysis relies on Chinese city-level information on the adoption of a regular CRE connection to Europe between 2011 and 2016 (Table B.2). While the starting point of a CRE connection typically refers to a prefecture-level city, there are three exceptions: Yiwu and Jiaozhou are county-level cities and we convert their starting points to their respective superseding prefecture-level cities, Jinhua and Qingdao. Chongqing, the origin of the first CRE connection, has the status of a province-level city.[15] Figure 2 illustrates our sample and indicates how the differential geographic location of CRE terminal cities my give rise to different treatment intensities, depending on their distance to seaports and effective travel time reductions.

Figure 2: The geographic distribution of the origins of regular CRE



Notes: Red areas represent the CRE terminal cities considered in our paper. Coastlines are colored in blue. The area in light color serves as control cities in our baseline analysis.

[15] China's administrative division has five hierarchical levels of governance: (1) the central government at the national level; (2) provinces; (3) prefectures; (4) counties; and (5) townships. In this paper we generally refer to the second level, prefecture-level cities, which also include the four province-level cities Beijing, Tianjin, Shanghai and Chongqing.

To evaluate the relationship between the adoption of regular CRE schedules and the international trade activity of a city, we look at the universe of China's export transactions that are documented in the Chinese Customs database for the years 2001-2018.[16] Each observation provides information on the city-level export values and quantities, reported at the 8-digit product level, by destination country and mode of transportation.[17] We also observe the (city) location of the producing and the exporting firm which enables us to distinguish direct or transit trade of a city.[18] For our analysis, we aggregate the product-level information to the 2-digit level of the *Harmonized System* (HS) nomenclature, which supersedes the 8-digit product codes in the raw data.

Finally, to evaluate outcomes related to general economic activity, we use a firm-level dataset from the China Tax Survey which covers about 600,000 firms per year. The survey includes different types of firms, including exporters, manufacturing enterprises, as well as small-scale service sector firms and individual businesses. Variables included in this survey concern the balance sheet of the firms, including their foreign and domestic sales, R&D expenditures, operating profits, payrolls, and employment. Based on the reported tax ID of a firm and its city-level location, we are able to construct a firm-level panel dataset for the years from 2010 to 2016 that matches our information on CRE connectivity. Appendix A provides further details on the data sources used in this paper. Table B.3 reports summary statistics for our main variables of interest.

3.2 Baseline estimation

Econometric specification. To assess the impact of CRE operations on city level export performance, we employ a Poisson Pseudo Maximum Likelihood (PPML) estimator, which enables us to employ high-dimensional fixed effects while taking into account the information contained in export zeros, i.e. observations without documented trade activity, (Santos Silva and Tenreyro, 2006, 2011). Our baseline specification takes the following form:

$$Export_{ikt} = \exp(\beta CRE_{it} + \gamma' \mathbf{X}_{ikt} + \mu_{ik} + \mu_{kt}) \times \epsilon_{ikt} \tag{1}$$

The dependent variable, $Export_{ikt}$, measures the value of exports to Europe shipped from city i in (2-digit HS) industry k and year t. Since all CRE routes during this period enter

[16] The dataset used here corresponds to the data that was purchased and harmonized by Feenstra et al. (2018), and generously provided by the Center for International Data at the University of California, Davis.

[17] Quantity information in provided in kilograms (kg) for all products, as well as an additional quantity unit that depends on product characteristics. Main transport modes are sea, air, and rail freight.

[18] While we observe whether an exported good was also produced in the same city from where it is exported, we cannot distinguish whether the producer is also the exporter.

European destinations via the same railway corridor (Mau and Seuren, 2023), we do not distinguish between destinations inside Europe. On the right-hand side of the equation, the main variable of interest is CRE_{it}. It is a city-year specific binary indicator that equals one, once the city becomes an official starting point of a CRE connection. In our baseline specification, we consider only the directly connected cities as treated and consider all other cities in our sample as control units. Potential caveats of this approach and our strategies to mitigate them will be discussed alongside with our empirical results. To minimize omitted variable bias, we include a vector of control variables, $\mathbf{X}_{ikt}$. These include cities' global exports in industry k, as well as their respective GDP and employment, overall and in the secondary sector. We also include city-industry (μ_{ik}) and industry-year (μ_{kt}) fixed effects to control for cities' sector-specific supply capacities and comparative advantages, as well as aggregate industry dynamics, respectively. Standard errors are adjusted for clustering at the city level.

Main findings. Table 1 reports our main findings for city-level exports, obtained from estimating alternative versions of equation (1). Column (1) constitutes our benchmark estimate, which suggests that CRE connections result in a 10 percent relative increase in city-industry-level exports to Europe. Column (2) suggests that exports to the rest of the world (RoW) increase at a lower and statistically insignificant rate, which is in line with our expectations that market access via the CRE is destination specific. Columns (3)-(4) indicate that these results also hold in a more carefully composed control group, which we identify with Propensity Score Matching (PSM).[19] Columns (1)-(4) in Panel B confirms our results and suggests that the differential export growth of connected cities amounts to about 5% on average per year.

Columns (5)-(7) of Table 1 distinguish exports to Europe by three different modes of transport: rail, sea and air freight. The coefficients reported in Panels A and B seem to confirm that CRE connections entail significant growth in rail-freight exports. However, also sea-borne exports appears to grow in connected cities. In the final column, we observe a negative but statistically insignificant coefficient for exports via airfreight, which implies that systematic modal substitution effects cannot be observed and that the launch of CRE operations may have entailed local trade creation. The positive relationship with sea exports in column (6) may be due to several reasons, such as economies of scale at the firm level or agglomeration effects. However, these would imply systematic increases in exports also to other destinations (e.g. Mau, 2017; Fajgelbaum et al., 2024), which is not evident in

[19] We describe our PSM procedure in Appendix B.3. It reveals that connected cities are typically larger and more specialized in manufacturing sector activities compared to an average city of the control group. The matched city sample shares those characteristics with the treated cities.

Table 1: CRE connections and city-level exports

Dep. var.: $Export_{ikt}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	By destination				By transport mode (to Europe)		
	Full sample		PSM sample		Full sample		
	Europe	RoW	Europe	RoW	Rail	Sea	Air
Panel A							
CRE_{it}	0.102***	0.081	0.095**	0.065	0.998***	0.084***	-0.092
	(0.032)	(0.068)	(0.037)	(0.062)	(0.208)	(0.031)	(0.104)
Panel B							
Years since $CRE_{it} = 1$	0.050***	0.028	0.062**	0.036	0.336**	0.018	-0.007
	(0.019)	(0.025)	(0.025)	(0.026)	(0.084)	(0.020)	(0.053)
Observations	192,565	192,565	57,190	57,190	192,565	192,565	192,565

Notes: Table reports PPML estimation results for alternative subsamples and specifications. Panel A uses our baseline measure for CRE connectivity by city and year. Panel B employs an alternative measure, which indicates the yearly change in exports after a CRE connection was launched. All specifications employ control variables and fixed effects, as described in equation (1). Standard errors, displayed in parantheses, have been adjusted for clustering at the city level. Statistical significance: *** = 0.01; ** = 0.05, * = 0.10.

this table.[20] Alternative explanations could be business-network effects (e.g. Chaney, 2018) or temporary congestion that arises from initial capacity constraints of railfreight trains. Although we cannot formally test these alternative channels, we find the latter explanation most plausible due to the smaller and insignificant coefficient in column (6) of Panel B, which is suggestive of a temporary spillover effect.

Robustness checks. To scrutinize our findings, we perform a number of robustness checks. We first test for potentially different pre-trends across cities. Indeed, if connected cities already had growing exports to Europe before CRE services were launched, our estimates would be upward biased. We therefore adopt an event study design to reveal how exports behaved in individual years before and after CRE were launched:

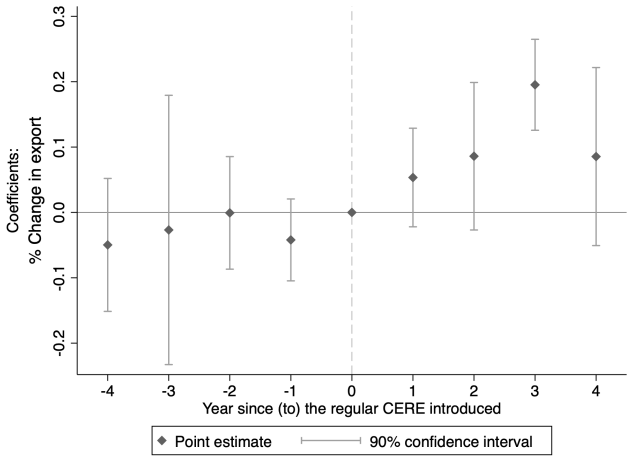
$$Export_{ikt} = \exp\{\sum_{\tau} \delta_{\tau} CRE_{it+\tau} + \gamma' \mathbf{X}_{ikt} + \mu_{ik} + \mu_{kt}\} \times \epsilon_{ikt} \tag{2}$$

The main variables of interest are represented by a vector of dummy variables $CRE_{it+\tau}$ that take a value equal to one whenever t is τ year(s) after the city becomes connected to the CRE. We set the first connected year as the base year, so that δ_{τ} indicates the average difference in time trends between our treated group and control cities. The results are reported in Figure 3

[20] Further unreported results suggest that the increases in exports using rail and sea transport are specific to European destinations and cannot be observed for exports to other destinations.

and suggest that no significant pre-trends can be identified. Exports seem to take some time to pick up after a CRE connection is launched. The lower coefficient and precision at $\tau = 4$ might be attributed to the small number of cities that have several years of operational CRE connections in our sample, but also to the existence of potential regional spillover effects onto cities in our control group.

Figure 3: CRE connections and exports in an event study design



Notes: Figure displays τ-specific coefficients of differential exports to Europe between connected and not-connected cities, before and after the launch of the CRE. Vertical lines indicate the 90% confidence interval of point estimates where standard errors are clustered at the city level.

As an additional robustness check we employ a Synthetic Control Methods (SCM) approach (e.g. Abadie and Gardeazabal, 2003; Abadie, Diamond and Hainmueller, 2010; Cavallo et al., 2013). SCM requires us to look at each connected city individually to exploit the time series variation before CRE operations are taken up. Figure B.3 displays the paths of actual and synthetic exports of each connected city, where at least 9 out of our 12 cities reveal positive deviations after the start of CRE operations. The most noticeable deviation can be observed for Chongqing, where the first connection was established, but we find no evidence that a single city drives our baseline results.[21] Figure B.4 and Table B.5 report the corresponding average treatment effects, which indicate a significant increase in shipments to Europe relative to their synthetic control group.

3.3 Heterogeneous Effects

Next to our baseline estimates, we acknowledge that our sample consists of a heterogeneous set of cities and industries that make further exploration interesting and relevant. Doing so,

[21] Re-estimating our baseline model, but excluding Chongqing from the sample, we obtain quantitatively somewhat smaller point estimates, while their precision is not materially affected. Compared the results in Column (1) of Table 1 they amount to 0.080 (0.027) in Panel A and 0.046 (0.020) in Panel B.

we shed light on the potentially underlying mechanisms, which will help us to rationalize our findings.

Distance to seaports and road-network centrality. As highlighted in Figure 2 at the beginning of this section, CRE terminal cities are spread across mainland China. Their spatial distribution and corresponding differential access to alternative transport modes or routes implies potentially different treatment effects. For example, export growth could be larger in more remote cities, if their exports start to grow from a lower base or if their effective reduction in trade barriers is comparatively larger. However, export growth could also be smaller if remote cities lack the production and logistical capacity that is needed to fully exploit their enhanced market access. We employ alternative metrics to differentiate between cities along these margins.

Column (1) of Table 2 shows that the generally observable post-CRE increase in rail exports is larger for cities that are further way from sea ports. Indeed, for every additional 100 kilometers between a city and a seaport, the estimated response in relative export growth increases by 10 percent. For the cities in our sample this implies that they experience quite different market access shocks, as their distances to sea ports range from less than 10km to up to 1,000km (see Table B.2). Column (2) employs a different measure that distinguishes classifies cities as inland cities if they are located more than 200km away from a sea port. While the coefficient for inland cities is positive, it is not statistically significant.

In columns (3) and (4), we control for differential effects based on cities' centrality in the domestic transportation network, assuming that this can reflect both their starting conditions as well as their exporting capacity. To measure this, we calculate a city's eigenvector centrality in the 2010 expressway network, which reveals that cities in East China as well as adjacent inland cities are most centrally located (see Appendix D). Column (3) suggests that a higher eigenvector centrality is associated with a lower, yet statistically not significantly different, export response. Column (4) suggests that cities with above-median centrality are significantly less responsive. This implies that cities in South, Central or Northern China, which are less centrally located in the national expressway network, benefit relatively more from export opportunities via the CRE.

Product characteristics. Besides the spatial distribution of cities across China and their differential effective reduction in trade and transport costs, also product characteristics are likely to matter. Indeed, most international trade flows are realized via sea shipments, which have large capacity, relatively low per-unit shipping costs and long transportation times. The most popular alternative to sea transport is airfreight, which is considerably faster but also

Table 2: Distance to seaports and centrality in domestic transportation networks

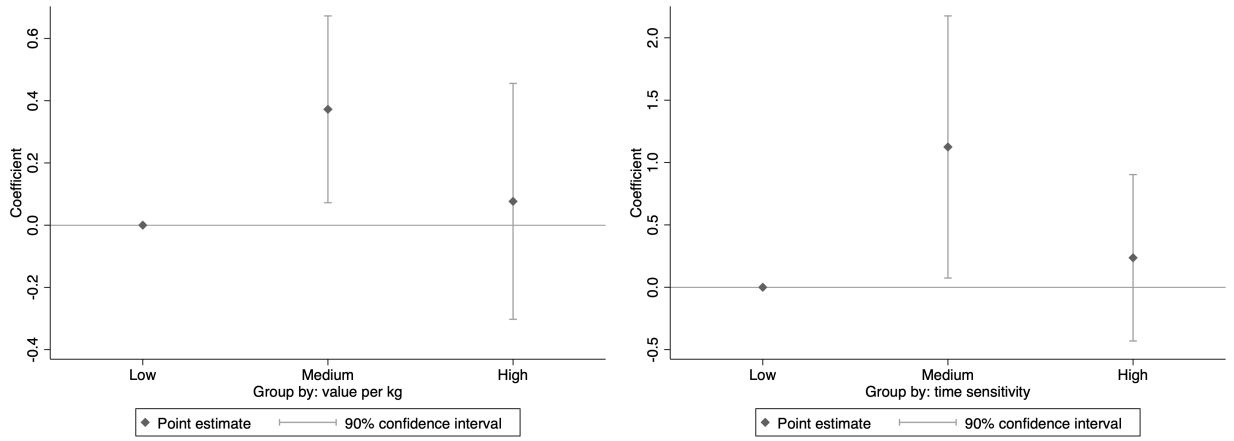
	Distance to ports		Road network centrality	
Dep. Var.: $Export_{ikt}^{\text{EUR, rail}}$	(1)	(2)	(3)	(4)
$CRE_{it} = 1$	0.667***	0.811***	1.312***	1.615***
	(0.251)	(0.208)	(0.280)	(0.265)
× minimum distance (in km)	0.001**			
	(0.000)			
× distance > 200km		0.444		
		(0.392)		
× centrality			-0.546	
			(0.355)	
× centrality > median				-0.896**
				(0.365)
Observations	192,565	192,565	185,060	185,060

Notes: Table shows PPML estimates of city-industry level rail exports to Europe, conditional on having a CRE connection and on their geographic location in China, measured either by their minimum distance to a coastal seaport, based on whether they are more than 200km away from a coastal seaport, measured by their centrality within the expressway network in 2010, or based on whether they have centrality higher centrality than the median. Standard errors in parentheses are adjusted for clustering at the city level. Statistical significance: *** = 0.01; ** = 0.05, * = 0.10.

more expensive and capacity-constrained. As discussed in Harrigan (2010), the additional cost of airfreight can become prohibitive if goods are very heavy compared to their value. Similarly, for some goods, there is a lower willingness to pay for an earlier delivery (Hummels and Schaur, 2013), meaning that they are less time-sensitive. If such attributes can explain the choice between ocean and airfreight, they should also matter for rail transport. Rail freight is less capacity-constrained and less sensitive to weight than airfreight. At the same time, it is considerably faster than ocean shipments. Hence, products with intermediate value-to-weight ratios and time sensitivity should show a stronger increase in rail exports.

To test this hypothesis, we turn to the most disaggregated version of our export data, observing 8-digit product lines, and split these goods into three equally-sized groups that indicate low, medium, or high value-to-weight ratios or time-sensitivity, respectively. Average value-to-weight ratios are calculated for the entire sample period, but the sample is limited to those goods where shipping quantities are reported in kilograms. For a classification of time-sensitivity, we rely on the estimates of Mau and Seuren (2023) and Ciani and Mau (2023) who replicate Hummels and Schaur (2013) to obtain estimates at the 2-digit HS Chapter level. Subsequently, we augment our baseline model by including interaction terms of our main variable of interest to identify differential effects among products classified as low, medium or high in terms of their value-to-weight ratio or time sensitivity.

Figure 4: Heterogeneity of products



(a) Unit value (b) Time sensitivity

Notes: Figures display PPML coefficient estimates of interaction terms in our augmented baseline specification. Products are divided into three groups. The grouping is according to value-to-weight ratio in figure (a) and time sensitivity in figure (b). The horizontal axis shows that corresponding characteristic in each group is low, medium or high. Low indicates the benchmark in the estimation and coefficients for the other groups display their differential effect from that benchmark. The lines with caps indicate the 90% confidence intervals where standard errors are clustered at the city level.

Figure 4 displays the results which broadly support our hypotheses. In both panels, products classified at mid-ranging weight-value ratios or time-sensitivity show a significantly higher responsiveness compared to low-ranging products. In turn, products classified as high-ranging do not reveal any statistically distinguishable effects relative to low weight-value ratios or time-sensitivity. While the discrepancies between groups appears to be quantitatively larger along the time-sensitivity dimension, we conclude that CRE services do not equally facilitate access to European markets in all product categories. Export growth can be expected to materialize primarily for products that are also suitable for for long-distance rail transport, an observation that will have important repercussions in our welfare analysis.

3.4 Further results

Regional spillover effects. While our estimates have shown that CRE connections to Europe have led to increased exports from directly connected cities, it is reasonable to assume that these are not confined to cities' administrative boundaries. Also other cities are able to benefit, depending on how well they are connected to CRE terminal cities. Since the trains departing from a specific location do not stop in other Chinese cities along the way, we assume that cities located along the route do not necessarily benefit from CRE operations. However, cities that are located geographically close to a CRE terminal might

show increased exporting activity.

Table 3: Regional spillovers of railfreight exports to Europe

	(1)	(2)	(3)	(4)	(5)
	Distance from CRE terminal city				
Dep. Var.: $Export_{ikt}^{\text{EUR, rail}}$	0 km	0<dist.≤100	100<dist.≤200	200<dist.≤300	300<dist.≤400
Panel A:					
CRE_{it}	0.925***	0.447***	0.289*	0.084	-0.041
	(0.233)	(0.160)	(0.174)	(0.171)	(0.150)
Panel B:					
Years since $CRE_{it} = 1$	0.362**	0.168**	0.253***	0.159**	-0.031
	(0.183)	(0.078)	(0.076)	(0.079)	(0.075)
Observations	63,650	74,860	97,280	95,000	84,645

Notes: Table reports PPML panel estimates for city-industry level rail exports to Europe. Industries are classified by HS 2 digit level. CRE_{it} is a dummy variable that equals one if city i is treated and year t is larger than the first operating year, and zero otherwise. Years since $CRE_{it} = 1$ is the number of years since operation for treated cities. It equals to zero if it is before the operation or if it is untreated. In all columns, we define cities with distance to nearest origins of regular CRE larger than 400 km to be untreated, i.e, controls. In all columns, we control for city-year level variables, GDP, GDP of secondary industry, employment, employment of secondary industry. Additionally, we control for city-industry-year level global export, city-industry fixed effects and year-industry fixed effects. Statistical significance: *** = 0.01; ** = 0.05, * = 0.10.

To evaluate such patterns, we employ a concentric ring approach and allocate cities in bins that correspond to distances within 100, 200, 300 and 400 kilometers from a terminal city. All other cities are relegated to the control group. Column (1) of Table 3 reproduces our baseline result for rail exports to Europe from terminal cities. In subsequent columns, we observe, in Panel A, that also cities within a range of 100 and up to 200 kilometers from a terminal reveal increased exports after CRE services were launched. The size and statistical significance of the coefficients decreases with distance. Panel B provides similar evidence, but a less monotonous relationship. Altogether, these findings suggest that the local trade-creation effects inferred in our baseline analyses can be interpreted as a lower bound, as they appear extend also into neighboring cities.

Direct vs. indirect exports and firm ownership. To investigate further margins of export growth, we exploit unique information in our data that is suggestive of whether exports rely on trade intermediation or whether it is shipped directly from the location where goods are produced. More specifically, observing whether the producer and the exporter of a good operate in the same city, we can identify local (i.e. direct) exports and distinguish them from non-local (i.e. indirect) exports. Indirect exports imply that that firms have to rely on specialized trade intermediaries to take advantage of the new market potential that

is created by the CRE. Direct exports would imply that firms can either export directly or they create new business opportunities for companies who act as local trade intermediaries. Our results in Appendix Table B.6 suggest that local exports drive our overall results, while we observe a negative though statistically insignificant correlation coefficient for exports via non-local intermediaries. The findings point towards increased direct exports from connected cities and, hence, lower dependence on non-local intermediaries.

Our customs data also provides information on the ownership of the exports producing firms, where we can broadly distinguish state-owned enterprises (SOEs), private domestic firms and foreign owned firms. The results are reported in Table B.7 and suggest that the latter two types of firms drive the entire effects on railfreight exports to Europe. Indeed, Foreign-owned enterprises reveal the largest increase in rail-exports, while the coeffcient for private domestic firms is positive and significant, but an order of magnitude smaller. State-owned enterprises reveal a negative but statistically insignificant coefficient, which suggests some potential (but not systematic) substitution effects among firms. The concentration of export growth among privately owned enterprises suggests that the launch of CRE connections to Europe might be unrelated to efforts by the Chinese government to boost the exports of state-owned enterprises, as suggested in other studies (Görg and Mao, 2022).

Firm level outcomes. We finally turn to our auxiliary data set to evaluate potential responses in non-trade economic activities at the firm level. To do so, we exploit firm-level information from the Chinese Tax Surveys, from which we construct a panel spanning the years 2010-2016. We adopt a staggered differences-in-differences (DID) estimation framework to identify whether the launch of regular CRE operations in a city is systematically associated with subsequent to firm-level performance outcomes:

$$Y_{j_it} = \beta CRE_{it} + \beta' \mathbf{X}_{it} + \mu_j + \mu_t + \epsilon_{jt}. \tag{3}$$

The dependent variable Y_{j_it} denotes an outcome that is observed for a firm j in city i at year t. As before, our main variable of interest is a binary indicator of the connection status of city i, CRE_{it}, while $\mathbf{X}_{it}$ represents a vector of control variables. Given the lower dimensionality of our data, fixed effects, μ_j and μ_t, control for unobserved variation at the firm and year level respectively.

Table 4 presents our results for a number of performance measures, including a firm's export status, sales, R&D expenditures, profits, total payroll expenses, and employment. For our baseline specification in Panel A, we find that the introduction of CRE connections to Europe is associated with a significantly higher entry rate into exporting among firms

Table 4: Firm-level estimates

Dep. Var.:	(1) $Exporter_{jt} = 1$	(2) $\ln Sales_{jt}$	(3) $\ln RD_{jt}$	(4) $\ln Profit_{jt}$	(5) $\ln Payroll_{jt}$	(6) $\ln Emp_{jt}$
Panel A:						
CRE_{it}	0.104***	0.013	0.106***	0.056***	0.086***	-0.005
	(0.003)	(0.010)	(0.035)	(0.012)	(0.008)	(0.005)
Panel B:						
Years since $CRE_{it} = 1$	0.070***	0.024***	0.100***	0.042***	0.048***	0.010***
	(0.002)	(0.007)	(0.022)	(0.007)	(0.005)	(0.003)
Observations	2,850,236	1,575,008	87,232	1,414,756	2,466,588	2,794,388

Notes: The table reports OLS estimates with observations at the firm-year level. The dependent variables include a dummy variable equal to one if a firm has a positive export value and zero otherwise, as well as the natural logarithms of domestic sales, R&D expenditure, operating profit, payroll, and employment in columns (1) through (6). The variable CRE_{it} is a dummy that equals one if city i is an origin of regular CRE and year t is greater than the first operating year; otherwise, it equals zero. The variable $Connectionyear_{it}$ represents the number of years since operation for origins of regular CRE, equaling zero if it is before operation or if it is not an origin of regular CRE. Robust standard errors, clustered by firm, are reported in parentheses. In all columns, we control for city-year level variables, including GDP, GDP of the secondary industry, employment, and employment of the secondary industry. Additionally, we control for firm-fixed effects and year-fixed effects. Statistical significance: *** = 0.01; ** = 0.05, * = 0.10.

that operate in the connected cities. Similarly, their R&D expenses, profits, and total payroll increases. Total sales and employment appear to be insensitive to CRE connectivity, initially, but increase (slowly) over time, as shown in columns (2) and (6) in Panel B. These findings indicate that cities with CRE terminals experience also broader changes in local economic activity, where the documented patterns can be interpreted as an indication of economic development and industrial upgrading. While the short-term adjustments documented here appear to take place primarily at the extensive margin (i.e., more firms start exporting), the medium-to-long term effects are beyond the scope of our empirical analysis.

In the remainder of this paper, we take our empirical findings to a model, which enables us to explore aggregate welfare of the CRE, as well as potential spatial distributional effects that may arise from the heterogeneous export responses across cities and products we have documented in this section. Indeed, while the identified relative increases in exports indicate local trade creation and promotion of industrial development, it is unclear whether other regions are worse off as resources are reallocated across the country. An evaluation of the CRE within a quantitative general equilibrium model enables us further to relate the gains from enhanced CRE exports and economic activity to its potential costs. Doing so, we obtain a more complete picture of the economic balance of setting up large scale international trade infrastructures that we can discuss in our conclusions.

4 A Model of Transportation Mode Choice

We develop a quantitative general equilibrium model which features multiple regions and sectors, where firms optimize their trade costs by choosing alternative export ports (Bonadio, 2022). Our main innovations are to incorporate heterogeneous firms (Melitz, 2003) into this framework and to introduce alternative, but not full substitutable, transportation modes. In section 5 we estimate the unknown parameters of the model and use these primitives to quantify the effective reduction in trade costs between Chinese cities and European markets. Section 6 exploits a novel and unique dataset on inter-city trade flows, which allows us to assess how the inferred trade costs reductions entail changes in city-level and aggregate welfare.

4.1 Model Environment

Our stylized model economy consists of $N + 2$ regions (indexed by either i or j, depending on whether the region in question is the origin i or the destination j of a shipment). Like in our empirical analysis, regions can be a Chinese city, Europe, or the rest of the world (ROW). Moreover, there are S sectors, indexed by s.

Although our model is static, it is convenient to think of it as unfolding in four sub-periods. In the first sub-period, firms considering to start producing decide whether to pay the fixed market entry cost so as to get a quality draw in their respective sector. Following this, firms with good enough quality stay in the market and decide on the quantity they produce and whether to export or not, based on their *expected* trade costs. In the third step, exporters choose the optimal transportation mode and ports after learning about their idiosyncratic productivity (quality) that affects shipping costs via specific routes. Finally, in the fourth sub-period, the production and consumption of all goods take place. In the following, we describe these steps and the relevant features of the economic environment and refer to Appendix C for more detailed derivations.

Consumer Preferences. Each region j is home to a mass L_j of identical agents, who have Cobb-Douglass preferences over sectors s,

$$U_j = \prod_{s=1} \left(Q_j^s\right)^{\alpha^s}, \tag{4}$$

where α^s is the expenditure share of sector s so that $\sum_{s=1}^{S} \alpha^s = 1$, and Q_j^s is a constant elasticity of substitution (CES) aggregator of a continuum of goods, with the elasticity of

substitution σ^s:

$$Q_j^s = \left[\sum_i \int_{\omega \in \Omega_{ij}^s} \left(z(\omega) q_{ij}(\omega) \right)^{\frac{\sigma^s - 1}{\sigma^s}} d\omega \right]^{\frac{\sigma^s}{\sigma^s - 1}}. \tag{5}$$

Each variety is denoted by ω and $z(\omega)$ captures the quality of that variety. $q_{ij}(\omega)$ denotes how much of the variety that is supplied from region i is consumed in region j.

Each consumer inelastically supplies one unit of labor. Labor income $w_j L_j$ is the only source of revenue which consumers spend on varieties from different regions and sectors:

$$\sum_s \sum_i \int_{\omega \in \Omega_{ij}^s} p_{ij}(\omega) q_{ij}(\omega) d\omega = w_j L_j. \tag{6}$$

In the above budget constraint, $p_{ij}(\omega)$ denotes the price of variety ω of sector s, supplied from region i to region j. w_j denotes the wage rate in region j.

Production and Market Structure. Each differentiated variety can be produced by a firm (indexed k or z) using a constant returns to scale production technology in which labor is the only factor of production. Firms compete in a monopolistically competitive environment and all differentiated goods are tradable.

In each region i, firms produce a single variety of a differentiated good of sector s that has quality z. Following convention, we will use the quality of the variety z also to index each producer. Specifically, upon entry, for which firms pay a fixed cost equal to f_E units of domestic labor, a firm's quality draw z is obtained from an unbounded Pareto distribution whose c.d.f. and p.d.f. are $H_i(z) = 1 - (b_i/z)^\kappa$ and $h_i(z) = \kappa b_i^\kappa / z^{\kappa+1}$, respectively. κ and b_i are positive constants that govern the shape and the position of the distribution. In addition to fixed entry costs (f_E), the firms face fixed operating costs (f_j) in each market to which they sell. As a result of these fixed costs, less efficient producers supply to fewer markets, while some do not operate at all. Only a mass J_i^s of firms establishes and pays the fixed entry cost f_E that is measured in home labor units. Free entry drives expected operating profits to $w_i f_E$.

Firms in region i produce their goods with the same marginal cost c_i. Once a firm decides to sell to region j, it pays a fixed cost f_j in destination labor units, i.e., $w_j f_j$. Upon entering j, firms optimize their production based on the expected bilateral trade cost d_{ij}^s that differ by sector and depend on logistical infrastructure that is used to ship goods from i to j. In our setting, firms can choose from alternative transportation modes and routes, as we detail below. Substituting the inverse demand function into firm k's revenue function, we derive

its net profits from exporting to region j:

$$\pi_{kij}(z) = L_j \left[\frac{\alpha^s w_j}{\left(Q_j^s\right)^{\frac{\sigma^s-1}{\sigma^s}}} z^{\frac{\sigma^s-1}{\sigma^s}} q_{kij}(z)^{\frac{\sigma^s-1}{\sigma^s}} - c_i w_i d_{ij}^s q_{kij}(z) \right] - w_j f_j, \tag{7}$$

In the given environment, the price a firm with quality z charges in destination j is determined by a constant markup over its marginal costs of production and delivery. The revenues of exporting from region i to j can be described as follows:

$$r_{kij}(z) = \frac{L_j(\sigma^s-1)^{\sigma^s-1}(\alpha^s w_j)^{\sigma^s}}{(\sigma^s)^{\sigma^s-1}\left(Q_j^s\right)^{\sigma^s-1}} \left(c_i w_i d_{ij}^s\right)^{-(\sigma^s-1)} z^{\sigma^s-1}. \tag{8}$$

Evidently, the value of trade from i to j is affected by the expected trade costs d_{ij}^s a firm faces, which further depends on the firm's optimal choice of transportation mode and port, which we specify in the following.

Trade Costs and Optimal Transportation Mode Choice. Trade of goods between regions is costly but costs nothing within a region. The sector-specific expected bilateral trade costs d_{ij}^s $(i \neq j)$ depend on firms' choice of transportation mode and ports in shipping. For simplicity, we first focus on an exporter k from i, and assume that it faces the following iceberg trade cost when exporting to destination j, using transportation mode m and port ρ:

$$\tau_{kij,\rho m}^s = \frac{\tau_{ij,\rho m}^s}{\varepsilon_{kij,\rho m}}. \tag{9}$$

In the numerator of this expression, $\tau_{ij,\rho m}^s$ captures all the costs that are common to firms when using mode m and port ρ for shipping goods from i to j. In line with our empirical findings, the common cost component can vary across sectors, depending on product characteristics that determine their suitability for alternative transport modes. Furthermore, $\tau_{ij,\rho m}^s$ captures heterogeneity in port quality, which can result in firms' decision to export via more distant ports. The denominator is a random firm-specific productivity shifter $\varepsilon_{kij,\rho m}$, which allows for the possibility two identical firms choose different ports and transport modes, even if they sell the same (amount of the same) good from i to j. The idiosyncratic productivity shifter becomes known to a firm after it decided to produce and sell to market j.

We assume that firms draw $\varepsilon_{kij,\rho m}$ simultaneously and independently from the following

multivariate nested Fréchet joint distribution:

$$F^s(\boldsymbol{\varepsilon}_{kij}) = \exp\left[-\sum_m \left(\sum_\rho \left(\varepsilon_{kij,\rho m}^{-\vartheta^s}\right)^{\frac{1}{\theta^s}}\right)^{\theta^s}\right], \tag{10}$$

where ϑ^s denotes a dispersion parameter. A smaller value of ϑ^s implies that firms are more heterogeneous in their ε across ports. Parameters θ^s govern the degree of within-transportation mode correlation in productivities, which is decreasing in θ^s. As in Bonadio (2022), when $\theta^s = 1$, $\forall s$, these productivities are independent. After realizing the productivity shifter, firms choose the transportation mode (m^*) and port (ρ^*) to minimize their export cost $\tau_{kij}^s = \min_{\rho,m}\{\tau_{kij,\rho m}^s\}$.

Using the properties of the Fréchet distribution, we derive the probability of using transport mode m and port ρ in shipping goods to the final destination in the following equation:

$$\mu_{ij,\rho m}^s = \underbrace{\frac{\left(\tau_{ij,\rho m}^s\right)^{-\frac{\vartheta^s}{\theta^s}}}{\sum_{\rho'}\left(\tau_{ij,\rho' m}^s\right)^{-\frac{\vartheta^s}{\theta^s}}}}_{\equiv \mu_{ij,\rho|m}^s} \times \underbrace{\frac{\left(d_{ij,m}^s\right)^{-\vartheta^s}}{\sum_{m'}\left(d_{ij,m'}^s\right)^{-\vartheta^s}}}_{\equiv \mu_{ij,m}^s}. \tag{11}$$

The unconditional probability of shipping goods with mode m via port ρ equals the probability of using port ρ conditional on using the mode m, i.e., $\mu_{ij,\rho|m}^s$ times the probability of using transportation m, i.e., $\mu_{ij,m}^s$. The latter is affected by $d_{ij,m}^s \equiv \left(\sum_{\rho'}\left(\tau_{ij,\rho' m}^s\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\frac{-\theta^s}{\vartheta^s}}$, which captures the average trade cost for mode m. In the exponents of the two partial probabilities, ϑ^s/θ^s indicates the elasticity of substitution across ports within a given transportation mode, while ϑ^s measures the sector-specific elasticity of substitution across transport modes. Greater values of these elasticities entail a higher responsiveness of firms to a change in the mode- and port-specific costs $\tau_{ij,\rho m}^s$.

Following the characterization above, the expected costs of shipping goods from sector s from a Chinese region i to a foreign destination j are given by:[22]

$$d_{ij}^s = E\left[\min_{\rho,m}\frac{\tau_{ij,\rho m}^s}{\varepsilon_{kij,\rho m}}\right] = \xi^s\left[\sum_{m'}\left(\sum_{\rho'}\left(\tau_{ij,\rho' m'}^s\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right]^{-\frac{1}{\vartheta^s}} = \xi^s\left[\sum_{m'}\left(d_{ij,m'}^s\right)^{-\vartheta^s}\right]^{-\frac{1}{\vartheta^s}}. \tag{12}$$

It depends on firms' transportation mode and port choice, which is determined by common

[22]For trade across Chinese regions, across foreign countries, and from foreign countries to Chinese regions, we assume constant trade costs common to all firms and exogenously determined. See Equation (C.5) for a full specification of bilateral trade costs.

costs $\tau^s_{ij,\rho m}$ and the shape parameters θ^s, ϑ^s of the nested Fréchet distribution. The parameter ξ^s reflects a sector-specific constant, which involves the Gamma function and ϑ^s.

To reconcile the importance of the elasticity ϑ^s, we consider a change in the costs for using a specific mode m and characterize its impact on the costs of exporting faced by a firm. Using a second-order approximation of the log change in d^s_{ij}, we can decompose this effect into two components:

$$d\ln d^s_{ij} \approx \underbrace{\mu^s_{ij,m}(d\ln d^s_{ij,m})}_{\text{direct impact}} - \underbrace{\vartheta\mu^s_{ij,m}\left(1-\mu^s_{ij,m}\right)\left(d\ln d^s_{ij,m}\right)^2}_{\text{indirect impact from mode switching}}. \tag{13}$$

The first component captures the direct effect, which depends on the share of shipments that is already carried via that mode, $\mu^s_{ij,m}$. The second term captures the indirect impact, which results from switching to the now relatively lower-cost mode. A larger ϑ^s implies a higher responsiveness to the cost change and more exporters adjusting their modal choice, implying a greater reduction in the overall bilateral trade costs. However, for products that can only be shipped via a certain mode of transport, ϑ^s is small and a reduction in the costs of using other modes will result in minor or no adjustments of the overall bilateral trade costs (both directly and indirectly). The parameter ϑ^s therefore co-determines how reductions in modal trade costs result in actual improvements of market access of regions, as their prevalent industry structure and specialization patterns might not necessarily reflect products that can easily switch to a different mode.

4.2 Equilibrium

Before moving on to calibrating and evaluating our model, we describe its equilibrium and discuss two propositions that follow.

Zero Profit Cutoff Condition and Free Entry of Firms. Due to the presence of fixed operating costs, we can use the equilibrium conditions for prices and quantities derived before to determine the threshold quality level at which a firm's profits are exactly equal to zero. That is, considering the case where $i \neq j$ and setting $\pi_{kij}(\bar{z}^s_{ij}) = 0$, we obtain

$$\bar{z}^s_{ij} = \left(\frac{(\sigma^s)^{\sigma^s}\left(Q^s_j\right)^{\sigma^s-1}}{L_j(\sigma^s-1)^{\sigma^s-1}(\alpha^s w_j)^{\sigma^s}}\right)^{\frac{1}{\sigma^s-1}} c_i w_i d^s_{ij}\left(w_j f_j\right)^{\frac{1}{\sigma^s-1}}, \tag{14}$$

which suggests that a reduction in shipping costs d^s_{ij} results in more firms exporting from i and in an overall increase in the variety of exports.

Since firms pay a fixed cost for entering the market and to make their quality draw from the known distribution $H_i(z)$, free entry implies that the expected operating profits of a firm are equal to these entry costs. Using Equations (7) and (14), and the assumption that $H_i(z)$ is Pareto distributed, we derive the following equilibrium condition

$$E_z\left[\pi_{kij}(z)\right] = \sum_j (b_i)^\kappa \left(\bar{z}_{ij}^s\right)^{-\kappa} \bar{\pi}_{ij}^s = \frac{\sigma^s - 1}{\sigma^s \kappa} \sum_j (b_i)^\kappa \left(\bar{z}_{ij}^s\right)^{-\kappa} \bar{r}_{ij}^s = w_i f_E. \tag{15}$$

which relates the zero profit cutoff levels of quality to the fixed costs of operating in a specific market (f_j) and the fixed entry costs (f_E).

Trade Balance and Market Clearing. To close the model, we require that all entities obey their budget constraints, that markets clear, and that trade is balanced (see Appendix C).

Let λ_{ij}^s denote the share of region j's total expenditure in sector s on goods from market i. In this share, integrating over sales of all firms in s from i to j yields the numerator, and summing over all markets i gives the denominator. We can obtain the following expressions for the expenditure share:

$$\lambda_{ij}^s = \frac{J_i^s (b_i)^\kappa \left(d_{ij}^s c_i w_i\right)^{-\kappa}}{\sum_v J_v^s (b_v)^\kappa \left(d_{vj}^s c_v w_v\right)^{-\kappa}} \tag{16}$$

where J_i^s is the number of entrants in sector s and region i, d_{ij}^s is the expected sector-specific trade cost, c_i and w_i denote the region-specific marginal production costs and the wage rate. The parameter b_i denotes the lower bound of the Pareto distribution.

Combining the free entry condition with the market clearing condition, we solve for the equilibrium mass of entrants:

$$J_i^s = \frac{\sigma^s - 1}{\sigma^s \kappa w_i f_E} \sum_j \alpha^s \lambda_{ij}^s w_j L_j, \tag{17}$$

while, with trade balanced, the market clearing condition can be derived as followings:

$$\sum_s \sum_j \alpha^s \lambda_{ij}^s w_j L_j = w_i L_i, \tag{18}$$

where α^s is the share of sector s in total expenses.

Without loss of generality, we normalize the wage of region j to unity and use its labor as the numéraire. The equilibrium is pinned down by equations (16), (17), (18), which endogenously determines the equilibrium values of λ_{ij}^s, J_i^s, and w_i. In the system b_i, c_i, σ^s, α_s, f_E and d_{ij}^s are model primitives. Notably, the expected trade cost d_{ij}^s is determined by

the set of mode- and port-specific transporting costs $\tau_{ij,\rho m}$ and their respective elasticities, ϑ^s and ϑ^s/θ^s.

Comparative statics. To develop intuition on how CRE connections affect overall exports and those shipped by different transportation modes, we briefly analyze the comparative statics of a simplified version of the model. Considering only one sector and full symmetry across regions in terms of their initial economic conditions, we can set $L_i = L$, $c_i = c$, $b_i = b$, $f_i = f, \forall i$. This symmetry implies equal equilibrium wages across regions, which we normalize to unity, i.e., $w_i = w = 1$. Also trade costs are the same across regions initially.

We model the launch of a CRE connection as a reduction in railfreight-specific trade costs, starting from an initial scenario without any rail exports. Cities connected to CRE consequently face lower cost of exporting when shipping their goods via their railway ports. As a result, expected bilateral trade costs from connected cities decrease, which is summarized by Proposition 1:

Proposition 1 *In the simplified model with a single sector and initially symmetric regions, a reduction in trade costs for a specific mode of transport (i.e., rail freight) and port of exit results in lower average bilateral exporting trade costs for port cities and increases the proportion of their exports that are carried by that mode.*

As the mass of entrants is fixed in the single-sector model, the declining trade cost lowers the entry quality cutoff, and increasing export at both the intensive and extensive margin, as in Melitz (2003). Rising exports and intensifying rail-freight use will increase the volume trade that is shipped by rail. However, the effects on alternative transportation mode, such as sea transportation, remain ambiguous, which we summarize in Proposition 2.

Proposition 2 (Spillover effect on sea transportation) *In the simplified model with a single sector and initially symmetric regions, a reduction in trade costs for a specific mode of transport (i.e., rail freight) and port of exit can increase or decrease the volume of exports carried by other modes (e.g. sea), depending on the elasticity of substitution across transportation modes and dispersion parameters.*

While we provide formal proofs of these propositions in Appendix C.5, Proposition 2 follows from the overall increase in export volumes and the fact that firms decide on transport modes and routes only after they decide to export. Indeed, lower railfreight costs result in larger proportion of exports via rail, and correspondingly declining shares for other transport modes. However, as total exports increase and more firms start exporting, their idiosyncratic trade-route productivity draw $\varepsilon_{ijk,\rho m}$, as well as the modal and port-specific transport cost

elasticities, can result in increased utilization of all transportation modes[23]. Our model, hence, describes a mechanism that can explain the modal spillover of CREs documented in our empirical analysis.

5 Model Calibration

5.1 Estimation strategy

To calibrate our model and apply it to welfare analyses, we estimate its key parameters, θ^s and ϑ^s. Doing so, requires an additional assumption on the structure of general trade costs $\tau^s_{ij,\rho m}$. The estimation procedure broadly follows Bonadio (2022) and is implemented in two steps. First, we estimate trade costs $\tau^s_{ij,\rho m}$, relying on our auxiliary model structure and observable trade data in a fixed effects regression. With those at hand we recover the average mode-specific trade costs, $d^s_{ij,m}$, as well as expected export costs, d^s_{ij}. In the second step, we plug our trade cost estimates into the mode-port-choice equation (11), to estimate θ^s, and subsequently into the exports equation (8), to back out ϑ^s.

Trade Costs. We assume that the common term in the numerator of the trade-cost equation (9) can be separated into two components:

$$\tau^s_{ij,\rho m} = \tau^s_{i,\rho m}\tau^s_{j,\rho m}. \tag{19}$$

The first portion, $\tau^s_{i,\rho m}$, captures the cost of shipping a good from its origin i to port ρ to use mode m. The second component, $\tau^s_{j,\rho m}$, captures the cost of shipping the good from the port of exit to destination j using mode m.[24] The conditional probability of port choice becomes $\mu^s_{ij,\rho|m} = \left[\tau^s_{i,\rho m}\tau^s_{j,\rho m}/d^s_{ij,m}\right]^{-\frac{\vartheta^s}{\theta^s}}$, which corresponds to the expected value of a dummy variable that indicates firm k's choice to use port ρ for exporting a good using mode m.

We take this port-choice equation to the data and evaluate it separately for each transport mode using a Poisson pseudo-maximum-likelihood (PPML) estimator with high dimensional

[23]The utilization of alternative modes can be explained by co-ordination or de-congestion effect between difference choices, as in Brancaccio, Kalouptsidi and Papageorgiou (2024), who document that investment in one port can decongest a wider set of ports.

[24]As we do not focus on quality of ports, there is no port-specific term in (19) which appears in that of Bonadio (2022). In the context of our paper, shipping costs $\tau^s_{j,\rho m}$ from port ρ to Europe decrease. Keeping the change of $\tau^s_{j,\rho m}$ constant, the closer from origin i to port ρ, i.e., the smaller $\tau^s_{i,\rho m}$, the larger reduction of $\tau^s_{ij,\rho m}$. This is in line with our empirical evidence on regional spillovers.

fixed effects:

$$E\left[1_{kij,\rho}|m\right] = \frac{\left(\tau^s_{i,\rho m}\tau^s_{j,\rho m}\right)^{\frac{-\vartheta^s}{\theta^s}}}{\left(d^s_{ij,m}\right)^{-\frac{\vartheta^s}{\theta^s}}} = \exp\left(\underbrace{-\frac{\vartheta^s}{\theta^s}\ln\tau^s_{i,\rho m}}_{f^s_{i\rho m}\text{FE}} \underbrace{-\frac{\vartheta^s}{\theta^s}\ln\tau^s_{j,\rho m}}_{f^s_{j\rho m}\text{FE}} + \underbrace{\frac{\vartheta^s}{\theta^s}\ln d^s_{ij,m}}_{f^s_{ijm}\text{FE}}\right) \tag{20}$$

The dependent variable, $1_{kij,\rho}$, is a dummy variable that equals unity if firm k from region i uses port ρ to export to destination j, given that it chooses transportation mode m.

The sum of the estimated fixed effects $f^s_{i\rho m}$ and $f^s_{j\rho m}$ have the structural interpretation of $\frac{\vartheta^s}{\theta^s}\ln(\tau^s_{i,\rho m}\tau^s_{j,\rho m})$.[25] We construct average modal export costs by aggregating over ports, using $g^s_{ij,m} = \sum_\rho \exp\left(f^s_{i\rho m} + f^s_{j\rho m}\right)$, where $\left(g^s_{ij,m}\right)^{-\frac{\theta^s}{\vartheta^s}}$ converges in probability to $d^s_{ij,m}$, since $(f^s_{i\rho m} + f^s_{j\rho m})$ converges to $\frac{\vartheta^s}{\theta^s}\ln(\tau^s_{i,\rho m}\tau^s_{j,\rho m})$ and the definition implies that $d^s_{ij,m} \equiv \left(\sum_{\rho'}\left(\tau^s_{ij,\rho' m}\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\frac{-\theta^s}{\vartheta^s}}$. The expected bilateral trade costs d^s_{ij} can, hence, be written as a function of the estimated average modal costs $d^s_{ij,m}$, with unknown parameters ϑ^s and ξ^s, as specified in Equation (12).

Estimating Shape Parameters. To avoid estimating the constant term ξ^s, we take the ratio of the share of exports carried by the rail to that by the sea. We take logs on both sides, which derive the regression equations for estimating the unknown shape parameter θ^s and ϑ^s:

$$\ln\left(\frac{\mu^s_{ij,Sea}}{\mu^s_{ij,Rail}}\right) = -\vartheta^s\ln\left(\frac{d^s_{ij,Sea}}{d^s_{ij,Rail}}\right) = -\theta^s\ln\left(\frac{g^s_{ij,Sea}}{g^s_{ij,Rail}}\right). \tag{21}$$

The first equality holds since $\mu^s_{ij,m} = \left(d^s_{ij,m}\right)^{-\vartheta^s} / \left(d^s_{ij}/\xi^s\right)^{-\vartheta^s}$, while the second equality comes from the fact that $\left(g^s_{ij,m}\right)^{-\theta^s/\vartheta^s}$ converges in probability to $d^s_{ij,m}$, as explained above. Since $g^s_{ij,m}, \quad m \in \{Rail,\ Sea\}$ are observable, we estimate θ^s using the second equation of (21), by regressing relative share of rail transportation $\ln(\mu^s_{ij,Sea}/\mu^s_{ij,Rail})$ on $\ln(g^s_{ij,Sea}/g^s_{ij,Rail})$.

Having obtained estimates of θ^s, we can construct $h^s_{ij} = \sum_m (g^s_{ij,m})^{\theta^s}$, where $\xi^s(h^s_{ij})^{-1/\vartheta^s}$ converges in probability to d^s_{ij}. In the last step, we substitute d^s_{ij} with $\xi^s(h^s_{ij})^{-1/\vartheta^s}$ into the bilateral exports equation:

$$E\left[r_{kij}(z)\right] = \underbrace{\frac{L_j(\sigma^s-1)^{\sigma^s-1}\left(w_j\right)^{\sigma^s}}{\left(\sigma^s\right)^{\sigma^s-1}\left(Q^s_j\right)^{\sigma^s-1}}}_{\equiv\beta^s_j} \underbrace{\left(c_i w_i\right)^{-(\sigma^s-1)}\xi^s(z)^{\sigma^s-1}}_{\equiv\alpha^s_k} \left(h^s_{ij}\right)^{\frac{\sigma^s-1}{\vartheta^s}}, \tag{22}$$

[25] As discussed in Weidner and Zylkin (2021); Bonadio (2022), the fixed effects f^s_{ijm} are not consistent estimators of $\frac{\vartheta^s}{\theta^s}\ln d^s_{ij,m}$ and cannot be directly used. A consistent estimator of $\frac{\vartheta^s}{\theta^s}\ln(\tau^s_{i,\rho m}\tau^s_{j,\rho m})$ also requires a large number of destination or origin regions while the number of ports remains constant, which holds in our sample.

The set of parameters summarized by α_k^s captures marginal costs of a firm producing in sector s. The ratio summarized under β_j^s captures the aggregate demand conditions in destination j. Equation (22) provides a way to estimate $(\sigma^s - 1)/\vartheta^s$, by regressing exports on h_{ij}^s in a log-linear model, while controlling for the exporter (α_k^s) and destination (β_j^s) fixed effects. Using estimates of trade elasticities σ^s from the literature, we can recover our own estimates of the shape parameter ϑ^s, which characterizes how easily exports can switch from one transport mode to another.

5.2 Implementation

Data. To implement the estimation strategy outlined above, we use the information from the China Customs database in which we observe disaggregated transactions at the origin-port-destination level. As we do not observe individual firms k, we proxy them by considering the distinct products code, which is reported at the 8-digit level of the Chinese combined nomenclature. Exploiting the hierarchical nature of this nomenclature, and its compatibility with the Harmonized System (HS) at 6-digits or higher, we define sectors s as groups of products that share the same first digits and subsequently form the basis of our sector-specific parameters $\hat{\theta}$ and $\hat{\vartheta}$. To back out the latter parameter, we use estimates of σ^s from Macedoni and Xu (2022) who adopt the same preference structure and industry classification in their calibration. Finally, since our empirical strategy relies on exploiting different transport modes, we focus on a subset of cities that features sufficient observations and variation across all relevant dimensions. Our calibration, hence, relies on a sample that comprises China's top 30 exporting cities in 2018 that ship their exports via 10 main ports, using either rail freight or sea transport. The top 30 exporting cities account for nearly 69.6% and 76.2% of China's exports carried by sea and rail, respectively, while the 10 main port cities account for 86.6% and 77.3% of China's total export using these modes.[26]

Results. Table 5 presents the results of our calibration exercise. Column (4) indicates how the estimated transport-mode elasticity varies across sectors, ranging from 0.276 for Miscellaneous goods to 1.746 for Chemical & Allied industries. Column (5) suggests that port elasticities are typically quite larger, ranging from 2.936 for Textiles to 196.071 for Foodstuffs. Indeed, column (1) shows that the within-transport mode correlation in productivity θ (see Eq. (10)), is generally quite small, which implies a high correlation in port productivity, all other things equal. This suggests that ports using the same transportation mode have

[26] In 2018, the percentages of exports to the EU by sea and by rail were 72.6% and 4.6%, respectively.

very similar capacity and efficiency in shipping goods, which makes them close substitutes.[27] Overall, the results suggest that the substitutability of transportation modes is much lower than that of ports. In other words, exporters appear to choose from different ports more flexibly, while their transport-mode choice is rather rigid.

Table 5: Estimation of cross-transportation elas. ϑ^s and cross-ports elas. ϑ^s/θ^s

		(1)	(2)	(3)	(4)	(5)
Industry Category	2-digit HS codes	θ^s	$(\sigma^s-1)/\vartheta^s$	σ^s	ϑ^s	ϑ^s/θ^s
Vegetables Products	06-15	0.039	0.687	1.777	1.131	29.000
Foodstuffs	16-24	0.006	0.832	1.844	1.014	169.071
Chemicals & Allied	28-38	0.012	0.990	2.729	1.746	145.539
Textiles	50-63	0.130	1.795	1.685	0.382	2.936
Metals	72-83	0.019	2.653	1.913	0.344	18.113
Machinery & Electrical	84-85	0.015	2.465	2.252	0.508	33.861
Transportation	86-89	0.057	1.660	2.000	0.602	10.569
Miscellaneous	$\geq$90	0.014	2.704	1.746	0.276	19.706

Notes: Values reported in columns (1), (2), (4) and (5) are estimated by the authors. Values in column (3) are borrowed from Macedoni and Xu (2022).

Our estimated cross-modal elasticities are also consistent with anecdotal evidence on the flexibility of certain industries to switch transportation modes due to regulatory, safety, or volume constraints. For instance, the shipment of electrical devices, especially those containing lithium batteries classified as dangerous goods, is bound by stringent regulations that vary significantly by transport mode, leading to a small elasticity of substitution for the Machinery & Electrical industry. Similarly, industries with goods that require large volume shipments, such as metals or vehicles, would also be expected to have lower elasticities as the substantial carrying capacity of ships makes sea transport more indispensable for such goods. In addition, the vast difference in the number of containers that can be carried by ships compared to trains or aircraft reinforces the relative reliance on maritime transport and their limited substitution with other modes.[28]

[27] Seaport capacities along China's extensive coastline reveal remarkable similarities. For instance, the Port of Shenzhen in the south, the Port of Ningbo-Zhoushan in the east, and the Port of Qingdao in the north have similar annual container throughput—27.7 million TEUs for Shenzhen, 27.5 million TEUs for Ningbo-Zhoushan, and 18.26 million TEUs for Qingdao. The workforce sizes of these ports are also similar, approximately 12,454 for Shenzhen, 17,425 for Ningbo-Zhoushan, and 9,218 for Qingdao. These figures demonstrate a notable uniformity in operational capacity and closely matched scale of these ports. For detailed information, see "Top Major Ports in China" at https://www.gocomet.com/blog/top-major-ports-in-china/..

[28] As reported in https://containerfaqs.com/how-many-containers-cargo-ship/ and https://traintrackshq.com/how-many-containers-can-a-train-carry/, the average number of containers carried on a ship is around 15,000, while the maximum loading capacity of trains is 200 containers, much smaller than that of a ship.

Modal substitution and product characteristics reconsidered. We relate our estimated elasticity of substitution between transportation modes to characteristics of exported products, as previously done in our empirical analysis. Doing so, we compute the weighted average unit-value of products in each sector s, using as weights the share of each 8-digit product in total exports during 2010-2018. We subsequently plot these unit-values against our ϑ^s-estimates from Column (4) of Table 5. As displayed in panel (a) of Figure B.5, we find an inverted-U relationship between the average unit-value of products in a sector and the corresponding substitutability between transport modes. This pattern is consistent with our empirical findings. Panel (b) of Figure B.5 indicates a positive correlation between ϑ^s and the average time-sensitivity of products in this sector, suggesting that more time-sensitive goods (e.g., goods with a short shelf life) are more likely to switch from one mode of transportation to another. Overall, we obtain relatively less complete picture for this dimension, as not all sectors obtain estimates for either ϑ^s or time-sensitivity.[29]

6 Quantitative Analysis

We use the results of our calibration exercise to investigate how the CRE facilitated regional export and welfare. To do so, we express the equilibrium conditions of our model in relative changes, using the "hat" notation for the ratio of after-versus-before levels of a variable in response to a given perturbation: $\hat{x} \equiv x'/x$ for any variable x (Dekle, Eaton and Kortum, 2008). As shown in Appendix C.6, we relate observed allocations to a given base year and can solve the model without having to rely on estimates of fixed costs and other parameters that are not directly observable.

6.1 Main findings

Data requirements. To carry out the analysis, we need to supplement our data with information on region-level population and trade shares. In our model, regions are Chinese cities, Europe and ROW, so the trade shares include also domestic transactions, i.e. intra-national trade, which is typically not available or systematically reported by customs authorities or other government agencies. We derive this information from a novel dataset that covers China's 100 largest exporting cities in 2010 (the year before the first CRE train was launched), representing 94.4% of total exports in that year. We use information from

[29] Indeed, time-sensitivity cannot be observed for vegetable products and foodstuffs, while we do obtain an estimate for ϑ^s in five categories with available time-sensitivity measures. Specifically, these are plastic and rubbers, raw hides, skins, leather and furs, wood and wood products, footwear and headgear, and stone and glass.

transaction records of one of China's largest e-commerce platforms, *Taobao*, to proxy city-sector-level trade flows based on the repoted location of buyers and sellers.[30]

Since *Taobao* only accounts for online transactions on its platforms, we have to rescale these flows to match the absolute magnitudes of the domestic trade volumes. To do so, we first obtain China's total output from I-O tables published by the National Bureau of Statistics,[31] as well as total exports from the Chinese Statistical Yearbook. We then calculate aggregate domestic trade as the difference between total output and foreign sales. Meanwhile, we also need information on aggregate online transaction volume on *Taobao* platform to calculate the ratio of online transaction to domestic trade in China. Given that we only observe 100 cities in the *Taobao* database, we use a proportionality assumption and divide the aggregate online transactions observed by the 100 cities' share in national GDP in 2011, to derive the aggregate online transaction volume. Finally, we divide our disaggregated *Taobao* city-sector-level online transactions by the ratio of online transaction to match domestic trade.

Having obtained cities' domestic trade flows, we combine this information with the international trade data from the China Customs database and the WTO to calculate trade shares. The China Customs database provides sectoral trade flows between China and Europe, and between China and the rest of the World (RoW), while WTO provides sectoral trade flows between Europe and RoW. We aggregate city-level exports to Europe from the China Customs database at the city-sector-mode level in 2018, with which we calculate sufficient statistics for the change in bilateral trade cost to Europe.

Sufficient Statistics for Trade Cost Changes. Our interest centers around the general equilibrium effects of opening the China-Europe Railway Express, which requires us to determine how much the cost of exporting has effectively changed in every location. To achieve this, we derive a sufficient statistic for the reduction in trade costs that results from the introduction of a new transportation mode.

Introduction of the CRE enables port cities to ship their goods to Europe via railway, but without it only non-rail modes are available. Hence, Chinese cities i initially face exporting costs to j that are equal to $d_{ij}^s = \xi^s \left[\sum_{m\in\mathbb{M}}(d_{ij,m}^s)^{-\vartheta^s}\right]^{-1/\vartheta^s}$ where $\mathbb{M}$ is

[30] *Taobao* platforms include a B2C platform (Tmall.com) and a C2C platform (Taobao.com). The total outflow and inflow for each city on the Taobao platform are displayed in Figure B.6. Sector categories reported in *Taobao* include Food, Tobacco and Alcohol; Clothing; Housing, Household Goods and Services; Transportation and Communication; Education, Culture and Entertainment; Healthcare; and Others. We map these categories to other sector classifications as detailed in Table B.8. Because the earliest year of data provided by *Taobao* is 2011, we set 2011 as initial year. The initial-year information on region-level population and trade shares is all in 2011.

[31] The total output in 2011 is approximated by the average of output in the years 2010 and 2012 from the I-O table.

the set of transport modes *excluding* rail freight. After a CRE connection is established, exporters have additional transportation mode choices and the trade cost becomes $d_{ij}^{s\prime} = \xi^s \left[\sum_{m\in\mathbb{M}\cup\{Rail\}}(d_{ij,m}^s)^{-\vartheta^s}\right]^{-1/\vartheta^s}$. The ratio $d_{ij}^{s\prime}/d_{ij}^s$ denotes the change in bilateral trade costs due to the CRE, which can be summarized as follows:

$$\hat{d}_{ij}^s = \begin{cases} \left(\mu_{ij,\mathbb{M}}^{s\prime}\right)^{\frac{1}{\vartheta^s}} & \text{if } i \in CHN \text{ and } j \in Europe \\ 1 & \text{Otherwise} \end{cases} \tag{23}$$

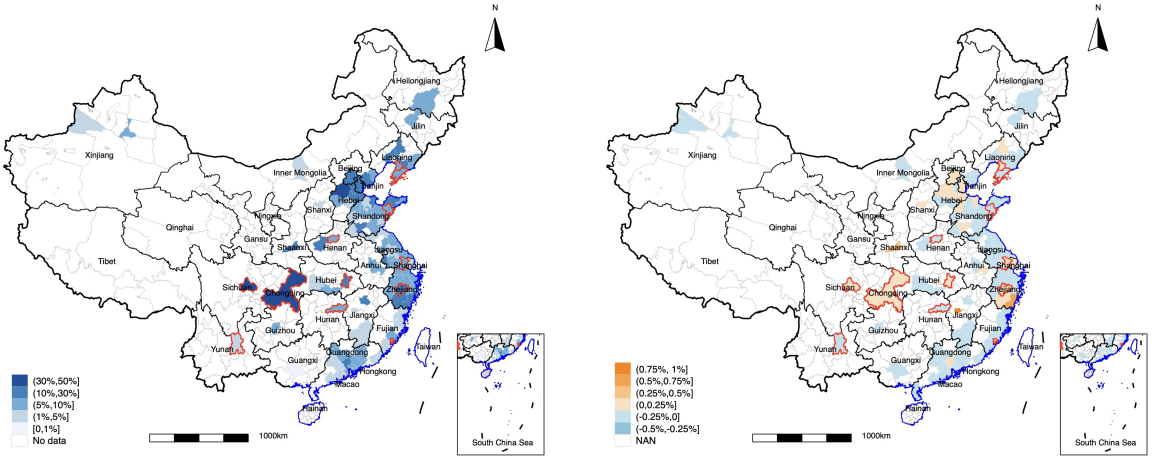
where $\mu_{ij,\mathbb{M}}^{s\prime}$ is the share of non-rail exports in sector s from city i to destination j in total sales. Whenever the destination of a shipment is not in Europe, transport mode choices and exporting costs remain unchanged and $\hat{d}_{ij}^s = 1$.

The above equation suggests that with our estimated elasticities of substitution between transportation modes ϑ^s, the share of exports shipped by non-rail modes (e.g., sea and air) is sufficient to determine the overall bilateral trade cost change. The derivation is based on the (reasonable) assumption that before regular CRE schedules were taken up, the share of exports to Europe via rail was zero. Our solution is reminiscent of the simple and canonical formulas for the gains from trade derived by Feenstra (1994) and Arkolakis, Costinot and Rodríguez-Clare (2012), where initial expenditure shares and substitution elasticities provide sufficient statistics and share a common structure. Our solution conveniently avoids more complicated approaches to the inference of trade costs changes that typically rely on estimating gravity equations, but entail the risk of model misspecifications and make the calibration a daunting parameter estimation task (e.g. Fan, 2019; Xu and Yang, 2021). To implement our sufficient statistics approach into the welfare analysis, all we need are the estimated elasticities of substitution across transportation modes ϑ^s as well as information on the transport mode and destinations of exports from by Chinese cities.

Results. To provide an overview of the trade cost reductions across Chinese cities, we illustrate in Panel (a) of Figure 5 the estimated reduction in bilateral trade cost for the top 100 Chinese export cities. The overall reduction of bilateral trade cost is computed as the weighted average of the reductions in sector-specific bilateral trade cost, using sector-specific trade in 2010 as weights.[32] The average reduction amounts to about 9%, but is quite unevenly distributed across cities. More substantial reductions are observed for inland

[32]The detailed reduction in bilateral trade cost for all Chinese cities is reported in Appendix Figure B.7. As a robustness check, we also compute the bilateral trade cost reduction by estimating a single-sector model. The corresponding elasticity parameter ϑ is 1.957, and we follow Bonadio (2022) and let σ be 5. Appendix Figure B.9 compares trade cost reduction inferred from the single-sector model to that from the multi-sector model.

Figure 5: Trade cost reductions and welfare effects of CRE adoption, top 100 exporting cities



(a) Trade cost reduction (b) Welfare change in GE

Notes: Cities with CRE are outlined in red, and coastal cities are outlined in blue.

cities, which are geographically closer to the EU markets but farther away from the seaports. We illustrate this relationship more explicitly in Appendix Figure B.8, which plots cities' distance to the closest sea port against our simulated change in trade costs.[33] The positive correlation is consistent with the empirical finding that more pronounced effect of CRE connections on exports can be observed among cities- located in inner regions of China.

To quantify the importance of CRE connections on regional development, we solve for all endogenous variables and obtain the implied welfare change in each of the 100 cities in our sample. The resulting magnitudes and signs are displayed in Panel (b) of Figure 5. Again, the pattern is quite mixed. Some cities report welfare gain amounting to up to 1 percent of their local GDP, whereas the population-weighted average resides at only 0.016 percent. Generally, welfare changes are positively related to the reduction in export costs, but we also note that some cities (including ones with a CRE connection) experience welfare losses instead of gains. Indeed, trade cost reductions in these cities were minimal, which can be explained partly by their sectoral structure and the result that their produced goods have become less competitive compared to those from regions with larger trade cost reduction. This results in reduced labor demand and lower wages, whereas cities benefiting from greater reductions in trade costs see increased labor demand and rising wages. This shift in competitive patterns engenders welfare losses for cities that achieve only limited reductions in trade costs to the EU, highlighting the nuanced economic impacts of trade

[33] In Appendix Figure B.8, we group cities into 30 equal-sized bins by their distance to the closest seaport and compute the mean of the reduction of trade cost and the mean of the distance within a bin.

cost reductions on local economies. Nonetheless, the magnitude of the welfare effects is small, given that rail-freight adoption is overall limited and good produced for European markets account for only a fraction of China's GDP.

Robustness checks. To see whether the inferred spatially distributional welfare consequences of the CRE as well as the moderate size of the welfare effects are robust, we use two alternative approaches for our calculations. First, we recalculate the welfare changes using trade shares from the multi-regional input-output (MRIO) table, as employed by Zheng et al. (2022).[34] Second, we examine the welfare impact using a single-sector model instead of our multi-sector baseline. Comparing these new estimates with our baseline results in Appendix Figures B.10 and B.11, we find that all three approaches deliver very similar results in terms of the distribution of welfare effects, although individual cities might reveal significant deviations. The dispersion of welfare changes in the single-sector model appears smaller than in the baseline results (see Table B.9), which we will discussed in further detail below.

6.2 Further results

Entry into exporting. A core finding in our empirical analysis has been the adjustments at the extensive margin, suggesting that increasing numbers of firms start to export following the connection of their city to the CRE. Our model incorporates this mechanism and allows us to explore where firm-entry dominates.[35] To do so, we simulate our model to document the implied growth in the number of exporters by city and sector groups, as displayed in Appendix Figure B.12. There is substantial heterogeneity in how the CRE facilitates entry into exporting across sectors. For instance, Machinery & Electrical and Transportation sectors exhibit quite widely spread increases, whereas changes for Textiles and Miscellaneous product sectors are more geographically concentrated. Foodstuffs as well as Chemicals and Allied industries reveal on average more modest entry which, in spite of a relatively higher modal elasticity could indicate higher general entry barriers (e.g. due to regulatory market access barriers). Overall, cities with more pronounced entry into exporting across different industries are also the ones that appear to benefit most from the CRE in terms of our inferred welfare effects.

[34]The estimated city-industry level MRIO table for 2012 is constructed following the framework outlined by Zheng et al. (2022). To ensure consistency between the industry classifications in the MRIO table and the sectors used in Table 5, we map the MRIO table's classifications to the HS2-digit industries, as detailed in Table B.8

[35]See equilibrium conditions in Equations (C.38)-(C.40) in the Appendix.

Dispersion explained by sectoral differences. Another key finding of our empirical analysis is the differential responsiveness of rail export growth across industries, which we incorporate into our model as a sector-specific elasticity of substitution between transport modes ϑ^s and sector-specific shipping costs $\tau^s_{ij,\rho m}$. The elasticities indicate the flexibility to switch transport mode while the shipping costs capture the level of specific-transport expense reduction. These two elements contribute to the overall changes in bilateral trade cost, which is reflected by our sufficient statistic in Equation (23). We consequently observe that the CRE entails significant (spatial) distributional effects that are driven partly by the initial sectorial composition of a city, its access to alternative trade routes, and the fact that some sectors are more responsive than others.

When shutting down the sectoral composition channel by using a single-sector model, the city-level welfare effects are reported in the Appendix Table B.9 while summary statistics are summarized in the Appendix Table B.10. Without sectoral differences, the simple average of welfare gains is higher but the populated-weighted average is much lower. It suggests the gains of large cities with a potentially more complex and diversified industry structure are underestimated if we close the sectoral composition channel. The total welfare gain is also underestimated since these larger cities have a higher share in total welfare. The dispersion of welfare gains, defined by the variation coefficient as the standard deviation over simple average, is around 26.2% of that in our baseline. This implies that almost 75% of the dispersion in welfare effects across cities can be attributed to the differential sectoral responsiveness to the CRE, while the remainder can be attributed to other city characteristics, such as their location and access to alternative transport routes.

Cost-benefit Analysis. Both our reduced-form estimates as well as our model implicitly consider the CRE as a form of trade liberalization that resulted primarily from administrative alignments and made exporting less costly for firms. While this assumption conveniently simplified the empirical analysis and subsequent quantification, a complete evaluation of the CRE warrants acknowledgment also of the substantial public expenditures it entailed. Especially in its early years, CRE connections were heavily subsidized to incentivize firms of their utilization and to scale up these services to economically sustainable levels.[36] While there is no complete or systematic information about the amount and allocation of CRE subsidies, the total subsidy costs during our period of investigation (2011-2018) can be estimated to reach about $840 million, using 335,954 FEU shipments (8,194 block trains, each with an estimated 41 FEUs) and Besharati et al. (2017)'s numbers of an average of

[36]Since 2012, China has operated a decentralized subsidy system for rail transport, with the Ministry of Finance setting limits on the share of transport costs that can be subsidized. Local governments are then able to adjust the level of subsidy provided within these limits.

$2,500 per FEU.[37] Our welfare estimates suggest a monetary equivalent of $507.64 million across the top 100 cities, which indicates subsidies exceeded welfare gains from 2010 to 2018.[38] However, as subsidies were announced to be gradually phased out by 2022, while trade and CRE rail-freight statistics suggest continuous growth up until today (Table B.11), the benefits are expected to exceed subsidy costs after 2021, as displayed in Figure B.13.

7 Conclusion

In this paper, we analyzed the trade and economic development effects of enhanced access to foreign markets, facilitated by an improved international transport infrastructure. Focusing on the China-Europe Railway Express (CRE), a new transport route for rail freight between China and Europe, we consider an infrastructure that is only locally accessible, destination-specific and (to some extent) also product-specific. Leveraging these unique features we study novel margins of adjustment, which provide insights beyond the specific case we have analyzed and shed light on mechanisms that are difficult to observe and disentangle.

Utilizing information from a comprehensive China Custom database, reporting trade flows at the city-level and by mode of transportation, we document that Chinese cities becoming connected to Europe via the CRE experience significant export growth, which materializes largely at the extensive firm margin. Increased market access and exporting activity can be observed within connected and geographically nearby cities, while, overall, cities located in inner China and farther away from coastal sea ports benefit the most. Next to increased exporting activity, we document positive changes also in firms' total sales, profits, employment and wage payments. Altogether, these findings suggest that improved market access increases economic activity along various dimensions not only in "port" cities, but also in their surroundings.

A specific feature of the CRE is that it enables us to identify a heterogeneous responsiveness to rail-based market access across products. In particular, we document that very heavy and very light goods (i.e. goods with high or low weight-value ratios) produce similar coefficients, while products ranging at intermediate levels are significantly more responsive. A similar relationship is documented for the "time-sensitivity" of goods (Hummels and Schaur, 2013), which suggests that firms face different trade-offs when deciding which transport mode

[37] In some studies, the reported numbers are higher for individual cities and that average subsidy rates peak in 2018 at around $5,000 per container (FEU) (ERAI, 2022). They nevertheless, differ remarkably across time and cities, at rates of $6,400 per FEU in Chongqing, $7,000 in Chengdu, $7,400 in Zhengzhou, $5,600 in Wuhan, but only $1,000 in Suzhou (Jiang et al., 2018).

[38] See Appendix C.6 for detailed calculations, using 2010 GDP as baseline income and an exchange rate of 6.77 ¥/$.

to choose depending on the goods they produce. We incorporate this mechanism together with our other empirical findings into a spatial quantitative general equilibrium model of international trade with multiple regions, sectors, transport modes and ports, to analyze the complex mechanisms at work. We calibrate the model to estimate sector specific trade-cost elasticities of transport mode and route choices that determine the effective change in trade costs for every Chinese cities, depending on their location within China and the goods they desires to sell abroad.

Results from calibrating our model suggest that firms can switch between different ports relatively easily, which suggests that domestic transportation costs play a minor role and that ports are qualitatively similar in terms of their efficiency and capacity (Bonadio, 2022). On the other hand, we find that modal switching, e.g. from ocean shipping to rail freight, is much less common and feasible, while there is also dispersion across sectors.

We further demonstrate that our model yields a solution for the effective change in modal trade costs between two locations, which summarizes sufficient statistics in a simple expression that is reminiscent of the canonical formulas for the gains from trade derived by Feenstra (1994) and Arkolakis, Costinot and Rodríguez-Clare (2012). Applying this formula to moments in our data, our model predicts an uneven distribution of effective trade cost reductions across Chinese, following the CRE, which is in line with our earlier empirical findings. Combining these results with novel and unique data on sector-specific domestic trade flows, derived from transactions realized via platforms of the online retailer *Taobao*, we calculate the implied changes in city level and aggregate welfare, following the introduction of CRE services.

The most noticeable finding of our quantification exercise are the pronounced distributional effects, which imply winners and losers of the CRE. The reasons for this result can be found in the sectorial and spatial heterogeneity of effective trade cost reductions, but also in general equilibrium effects that induce a reallocation of resources from one city to another. Cities with only modest trade cost reductions face a comparative disadvantage, which has real implication as labor demand and wages decline. While the overall magnitude of these effects is limited in the context of our study (below 1 percent of GDP locally and only about 0.016 % in the aggregate), the underlying mechanisms are important as they are likely at work also in other contexts, such as place-based policies that aim to promote local economic activity.

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A Detail on sources

China Customs Database

Information on city exports and imports is derived from the China Customs Database, which covers the universe of Chinese exports and imports, and was harmonized and generously provided by the University of California, Davis, Center for International Data (Feenstra et al., 2018). The export data reports the annual trade information on values, quantities, and destination countries at the HS 8-digit level for all Chinese cities in the period under investigation (i.e., 2001 to 2018). Besides, we can also observe transport modes, the ports from which the exporting goods leave China and city-level location of exporter. In similar structure, the import data reports the annual trade information on values, quantities, and origin countries at the HS 8-digit level for all Chinese cities during 2001-2018.

China Tax Survey

The tax survey is jointly implemented by the Ministry of Finance of China and the State Administration of Taxation, with local tax authorities responsible for specific tasks such as data filling, collection, and verification. The annual survey sample encompasses approximately 600,000 or more enterprises, comprising both key surveys and sampling surveys. Of this total, 80% are designated as key surveyed enterprises, encompassing essential tax sources and export-oriented entities, among others. The remaining 20% are categorized as stratified sampling surveyed enterprises. This comprehensive survey encompasses a diverse range of businesses, spanning from sizable manufacturing enterprises to smaller-scale service industry establishments, as well as specific individual operators. The tax survey data contains comprehensive indicators, mainly including the characteristic information and financial information of the enterprise, such as tax identification number, location, industry, number of employee, and other individual information of the enterprise. It also includes multiple financial indicator information in tax declaration forms, cash flow statements, balance sheets, and income statements. In this paper, we use the following variables, firm's tax ID, industry, location, number of employees at the beginning and end of the year, domestic sales revenue of general goods and services, sales revenue of exported goods, operating profit, total salaries and bonuses, and expenses incurred for researching new products, new technologies, and new processes.

Belt and Road Portal

The Belt and Road Portal is an official website run by the China Economic Information Service and the State Information Center, under the supervision of China's National Development and Reform Commission and Xinhua News Agency. The website refers to https://www.yidaiyilu.gov.cn in Chinese and https://eng.yidaiyilu.gov.cn in English. The website reveals the operation of China Railway Expresses, including regular expresses to Europe, i.e., CRE. The information on operation includes route, first date of operation, origin and destination. Besides, it reports the number of China Railway Expresses each year.

China Stock Market & Accounting Research (CSMAR) Database

The China Stock Market & Accounting Research (CSMAR) database provides access to a comprehensive collection of data on China's stock market, financial statements, and various financial indicators. It also includes data on city-level economic indicators in China, such as GDP, the proportion of the secondary industry to GDP, employment, the proportion of the secondary industry to employment and total freight volume, for 2001-2018.

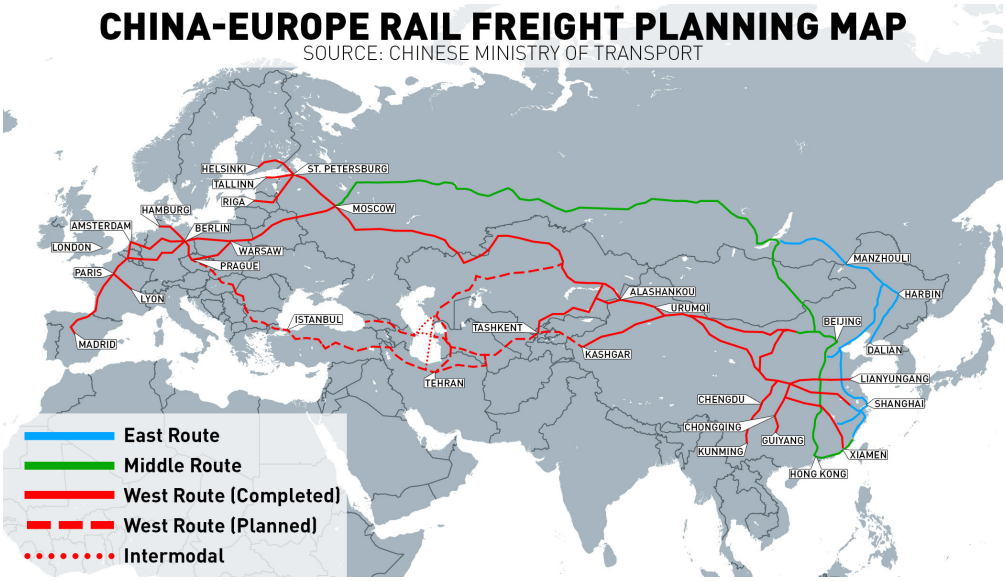
Taobao Database

Taobao is one of the biggest E-commerce platforms in China. Taobao consists of two platforms, a B2C platform (Tmall.com) and a C2C platform (Taobao.com). The online sales of the two platforms account for 82 percent of China's total online retail sales in 2014 (Fan et al., 2018). Taobao provides city-level trade flow within China in 2011. The trade flow is aggregated over the origin and destination cities of delivery according to all online transaction records on the platform.

B Tables and figures

B.1 China Railway Express

Figure B.1: Routes of China-Europe Railway Express



Source: CGTN America. The figure displays the main routes of CRE on a map.

Table B.1: Trade costs and flows from China to Germany, by transport mode

	2006			2017		
Transport mode	Sea	Rail	Air	Sea	Rail	Air
Transport time (days)	30	47	5	32	16	4
Transport cost (dollars/FEU)	2,740	8,450	25,000	2,410	6,350	32,490
Share in total imports (%)	57.7	0.05	37.7	62.3	4.38	31.9

Source: Schramm and Zhang (2018) and Eurostat data. The table presents transport time and cost to export a forty-foot equivalent unit (FEU) from Shanghai to Hamburg by sea, by rail and by air in 2006 and 2017. Import shares reflect Germany's imports from China.

Table B.2: Regular China-Europe Railway Express

Origin	Operating since	Destination	Route	Duration (days)	Length (km)	Seaport (km)
Chongqing	2011/03	Duisburg, GER	YuXinOu	16	11179	893
Wuhan	2012/10	Melink Pardubice, CZE	HanXinOu	23	10863	454
Chengdu	2013/04	Lodz, POL	RongOu	11	9826	1091
Zhengzhou	2013/07	Hamburg, GER	ZhengOu	15	10245	527
Suzhou	2013/09	Warsaw, POL	SuManOu	18	11800	10
Yingkou	2014/10	Moscow, RUS	YingManOu	14	10500	44
Changsha	2014/10	Duisburg, GER	XiangOu	18	6476	569
Yiwu	2014/11	Madrid, ESP	YiXinOu	21	13000	168
Jiaozhou	2015/07	KAZ	Qingdaohao	8	7900	4
Xiamen	2015/08	Lodz, POL	XiaRongOu	15	12733	4
Kunming	2015/10	POL	KunRongOu	12	10198	695
Dalian	2016/07	Moscow, RUS	LiaoManOu	12	8600	4

Notes: The Belt and Road Portal reports regular China Railway Expresses, including twelve expresses to Europe and one express to Vietnam. The table reports information on the twelve regular China-Europe Railway Expresses, including the first month of operation, origin, destination, name of route, duration and length of the route. The origin is at city level. Chongqing is province-level city. Yiwu and Jiaozhou are county-level cities. Other origins are prefecture-level cities. The duration of the XiangOu is 16-18 days, reported by the Belt and Road Portal. We present the upper bound, 18 days, in the table. The last column displays the distance from origin to its nearest sea port. The distribution of sea ports in China refers to *China coastal port layout planning* issued in 2006.

B.2 Data Sample

Table B.3: Summary statistics

	N	Mean	S.D.	Min	Median	Max
Panel A: City-industry-year level outcome variables						
Export to Europe	192,565	12.76	201.97	0.00	0.00	23,478.65
Export to others	192,565	53.11	917.11	0.00	0.03	144,589.31
Export to Europe by sea	192,565	9.54	116.49	0.00	0.00	11,642.85
Export to Europe by rail	192,565	0.23	9.48	0.00	0.00	1,995.62
Export to Europe by air	192,565	2.54	99.98	0.00	0.00	11,978.42
Export to Europe locally	192,565	11.05	195.24	0.00	0.00	23,383.91
Export to Europe non-locally	192,565	1.71	19.56	0.00	0.00	1,943.58
Panel B: Firm-year level outcome variables						
Indicator of exporter	2,850,236	0.49	0.50	0.00	0.00	1.00
Log of sales	1,575,008	9.50	2.37	-1.11	9.61	19.81
Log of R&D	87,232	7.90	1.96	0.00	8.16	16.21
Log of profit	1,414,756	6.50	2.84	0.00	6.44	18.92
Log of payroll	2,466,588	6.83	2.05	0.00	6.81	23.89
Log of employment	2,794,388	3.49	1.67	-0.69	3.40	33.00
Panel C: Main explanatory variables						
Indicator of CRE	2,027	0.01	0.11	0.00	0.00	1.00
Connection year of CRE	2,027	0.03	0.32	0.00	0.00	5.00
Panel D: Control variables						
Global export	192,565	65.88	1,086.86	0.00	0.05	155,415.34
GDP	2,027	2,153.31	2,990.34	105.80	1,235.83	33,106.00
GDP of secondary industry	2,027	1,019.09	1,181.49	22.68	637.84	8,642.25
Employment	2,027	69.55	109.54	5.01	35.50	986.87
Employment of secondary industry	2,027	30.36	42.34	0.43	15.39	429.09

Notes: The table reports summary statistics of our main variables used for the empirical analysis. The second column to the last column show number of observations, mean, standard deviation, minimum, median and maximum respectively. In panel A, the unit of all variables is million dollars. Export to others are the export value from China to countries other than European countries. In panel B, the unit of sales, R&D, profit, payroll is thousand Chinese yuan and the unit of employment is person. We define indicator of exporter to be one if the export is positive and zero otherwise. In panel C, we define indicator of CRE to be one if the city is an origin of regular CRE and the year is larger than the first operating year, and zero otherwise. Connection year is the number of years since operation for origins of regular CRE. It equals to zero if it is before the operation or if it is not origin of regular CRE. In panel D, the unit of GDP is 100 million Chinese yuan and the unit of employment is 10 thousand persons.

B.3 Robustness Checks

Propensity Score Matching. The procedure of PSM is as follows: First, we estimate the probability/propensity score to be treated (to open regular CRE) by

$$Pr\{origin_i = 1|X\} = \phi(X'\beta) \tag{B.1}$$

where covariates X used in estimation include GDP, proportion of the secondary industry to GDP, GDP of secondary industry, growth rate of GDP of secondary industry, employment, proportion of the secondary industry to employment and total freight volume. Data comes from CSMAR database. We use the average of covariates over 2008-2010 to estimate a probit model equation (B.1).

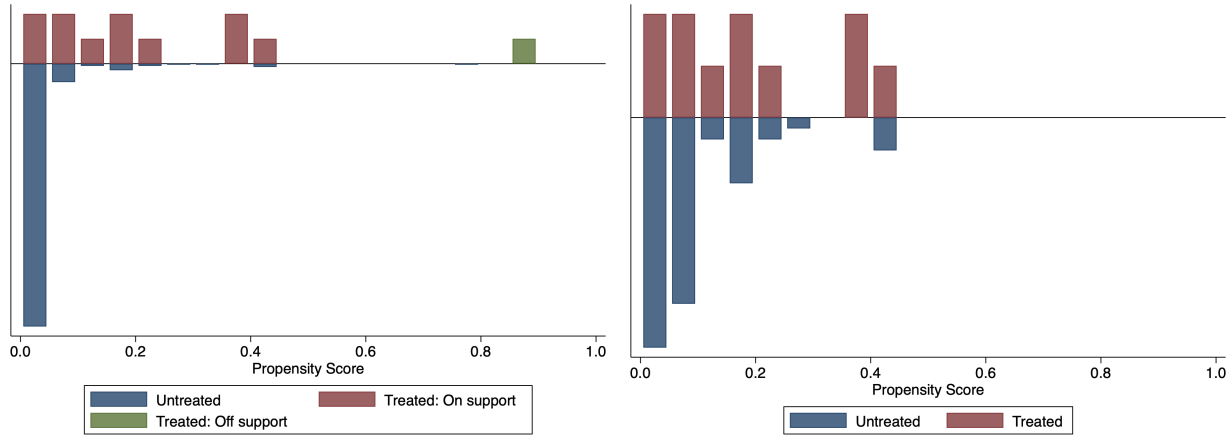
Second, according to the estimated propensity scores, we match the treated with the control cities with replacement under the principles of ten-nearest-neighbor matching and 0.05-caliper matching. The distribution of estimated propensity scores before and after matching is shown in Figure B.2. The treated and control groups highly overlap and the process of matching balances the propensity scores. Table B.4 reports a balanced test of matching. The characteristics on exports are more balanced between treated and control groups after matching from the evidence of a t-test.

Finally, with the matched samples, we estimate the following specification:

$$Export_{ikt} = exp(\beta CRE_{it} + \gamma'\mathbf{X}_{ikt} + \mu_{ik} + \mu_{kt} + \mu_{gt}) \times \epsilon_{ikt} \tag{B.2}$$

where the definitions of $Export_{ikt}$, CRE_{it}, $\mathbf{X}_{ikt}$, μ_{ik} and μ_{kt} are the same as the baseline specification. The only difference is that we limit the observations to the matched samples and we allow for time trend across different groups by μ_{gt}. g denotes the group which a treated city and its corresponding matched controls belong to. The results of estimation are reported in Table 1.

Figure B.2: Distribution of propensity scores



(a) Before matching (b) After matching

Notes: The figure shows distributions of propensity scores of samples before and after matching. The propensity score is estimated over covariates including the average of GDP, GDP of secondary industry, proportion of the secondary industry to GDP, growth rate of GDP of secondary industry, employment, proportion of the secondary industry to employment and total freight volume. We take average of the coveriates over 2008-2010. We follow the principle of 10-nearest-neighbor matching and 0.05-caliper matching.

Table B.4: PSM: balanced test

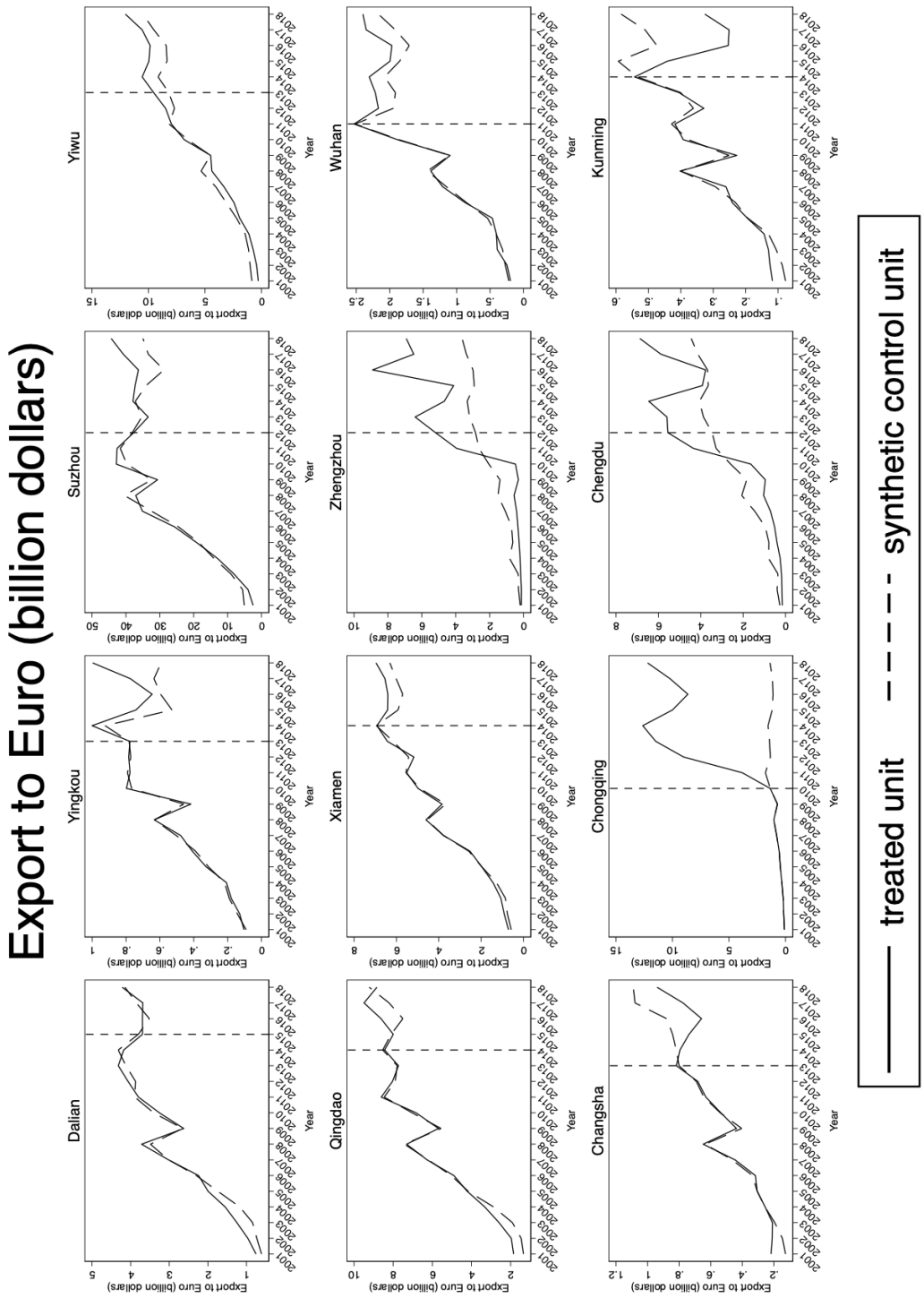
		Mean		T - test	
Covariates		Treated	Control	t	p>|t|
GDP (billion yuan)	Unmatched	392.630	118.870	5.460	0.000
	Matched	365.850	291.480	0.870	0.394
Proportion of the secondary industry to GDP (%)	Unmatched	50.497	49.908	0.180	0.856
	Matched	50.990	51.700	-0.220	0.830
GDP of secondary industry (billion yuan)	Unmatched	200.000	59.352	6.210	0.000
	Matched	190.000	160.000	0.700	0.491
Growth rate of GDP of secondary industry (%)	Unmatched	18.195	19.885	-0.850	0.397
	Matched	18.264	17.125	0.400	0.692
Employment (thousands)	Unmatched	1147.100	386.880	4.920	0.000
	Matched	1027.300	936.620	0.390	0.701
Proportion of the secondary industry to employment (%)	Unmatched	51.561	42.036	2.340	0.020
	Matched	51.991	55.013	-0.490	0.628
Total freight volume (million tons)	Unmatched	252.710	91.306	5.930	0.000
	Matched	211.150	187.230	0.470	0.640

Notes: The table reports balanced test of covariates used to estimate propensity score with samples before matching and after matching. The covariates are taken average over 2008-2010 for each city. The second column indicates unmatched or matched sample. The third and fourth column presents mean of covariates for the treated group and control group. The five and sixth column report results of T-test for the difference between treated group and control group.

Synthetic Control Method. For the point estimate of the treatment effects, our outcome variable is city-level export to European countries. Predictors include (i) export to European countries, yearly data from 10 years before the shock to the last pre-intervention year; and (ii) global export, GDP, GDP of secondary industry, proportion of the secondary industry to GDP, the yearly growth rate of GDP of secondary industry, employment, proportion of the secondary industry to employment, which are taken average from 2001 to the last pre-intervention year. The export data comes from the China Customs database and the other data comes from the CSMAR database. Using the predictors, we construct control for each treated city. The treatment effects is measured by the post-intervention gap between treated and control unit. We are able to calculate the average treatment effects by averaging out the treatment effects of all the treated units.

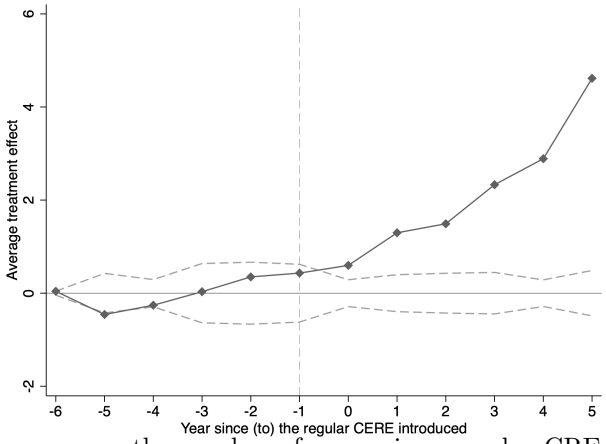
The procedure of estimation inference is as follows. First, we use all the cities in our sample, excluding treated cities, as our whole placebo pool. Second, for each treated city and corresponding connection year, we do the Synthetic Control Method with respect to each placebo in the pool, as if the placebo is connected in the same year. Then, for each treated city, we have corresponding pool of placebo effects. Last, we also calculate an average of placebo effects, because we average out the treatments effects of all connected cities. We draw a placebo from each pool of the connected cities and take average of the placebo effects, which is replicated for 50 times. Therefore, we are able to calculate the standard deviation of the 50-time placebo effects as reference for the evaluation of no policy shocks.

Figure B.3: Treated and synthetic control groups



Notes: The figure shows export to Europe from treat unit and synthetic control. The treat unit is the origin of regular CRE. The synthetic control is estimated by synthetic control method. The dash line indicates the last pre-intervention year.

Figure B.4: Average treatment effect



Notes: The horizontal axis measures the number of years since regular CRE established. The solid line indicates the average differences of export to Europe between treated cities and synthetic control, i.e., average treatment effects. Export to Europe of treated cities and synthetic controls refer to Figure B.3. The dash lines exhibit the ±1.96 times the standard deviation derived by bootstrapping. The calculation of standard deviation is as follows. We bootstrap for 50 times. Within a bootstrapping, for each treated city, we bootstrap an untreated city and estimate treatment effect by synthetic control method as if it is connected in the same year. The average treatment effect within a bootstrapping is calculated as average of treatment effects of these untreated cities. We define the standard deviation as the standard deviation of 50-time bootstrapping average treatment effects. The synthetic control method is performed over covariates including (i)export to European countries, yearly data from 10 years before the shock to the last pre-intervention year; and (ii) global export, GDP, GDP of secondary industry, proportion of the secondary industry to GDP, growth rate of GDP of secondary industry, employment, proportion of the secondary industry to employment and total freight volume, which are taken average from 2001 to the last pre-intervention year. Table B.5 reports the estimates and the standard deviation of boostrapping.

Table B.5: Average treatment effect estimation

Year	Average treatment effect	Standard deviation
-6	0.041	0.022
-5	-0.458	0.217
-4	-0.259	0.150
-3	0.032	0.325
-2	0.350	0.340
-1	0.432	0.317
0	0.597	0.147
1	1.297	0.202
2	1.491	0.218
3	2.330	0.227
4	2.889	0.146
5	4.616	0.249

B.4 Local Exports

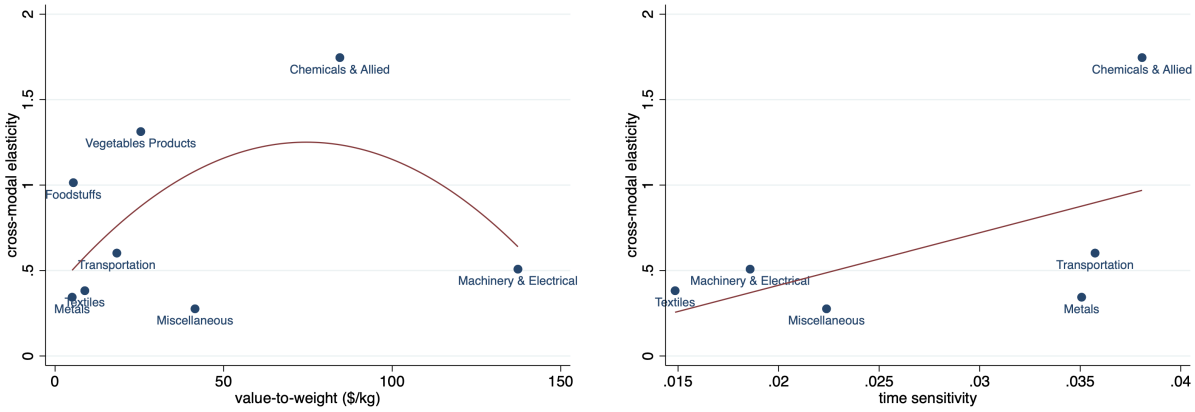
Table B.6: Self-contained export versus inter-city cooperation

Dep. Var.: $Export_{ikt}^{EUR}$	(1)	(2)	(3)	(4)
Intermediary	local		non-local	
CRE_{it}	0.124***		-0.126	
	(0.038)		(0.166)	
Years since $CRE_{it} = 1$		0.057***		-0.044
		(0.020)		(0.080)
Observations	192,565	192,565	192,565	192,565

Notes: The table reports PPML estimates. Observations are at the city-industry-year level. Industry is classified by HS 2 digit. Dependent variables are export values to Europe, but by different types of intermediaries, which are reported in the column heading. Local denotes export activities are finished completely by producer themselves or under the cooperation with local export intermediary. Non-local denotes export activities are finished under the cooperation with non-local intermediary. CRE_{it} is a dummy variable that equals one if city i is an origin of regular CRE and year t is larger than the first operating year, and zero otherwise. Years since $CRE_{it} = 1$ is the number of years since operation for origins of regular CRE. It equals to zero if it is before the operation or if it is not origin of regular CRE. Robust standard errors are reported in parentheses, clustered by city. In all columns, we control for city-year level variables, GDP, GDP of secondary industry, employment, employment of secondary industry. Additionally, we control for city-industry-year level global export, city-industry fixed effects and year-industry fixed effects. Statistical significance: *** = 0.01; ** = 0.05, * = 0.10.

B.5 Elasticities

Figure B.5: Heterogeneity of elasticities



(a) Unit value

(b) Time sensitivity

Notes: Each point represents a category classified in Table 5. The y-axis is the cross-modal elasticity in both figures. The x-axis is average value-to-weight ratio in figure (a) and time sensitivity in figure (b). We take average of value-to-weight ratio of each product (HS 8 digit) within each category, weighted by total China's exports of each product (HS 8 digit) in 2010-2018. The value-to-weight ratio is defined as the total value over total quantity of China's exports of each product (HS 8 digit) from 2010 to 2018 as in section 3.3. We take average of time sensitivity of each industry (HS 2 digit) within each category, weighted by total China's exports of each industry (HS 2 digit) in 2010-2018. In figure (b), the data of time sensitivity is unavailable for vegetable products and foodstuffs. The red lines are quadratic and linear fitted values.

Table B.7: Firm ownership

Dep. Var.	$Export_{ikt}^{Europe,rail}$					
Ownership	SOE		Foreign		Domestic private	
	(1)	(2)	(3)	(4)	(5)	(6)
$CERE_{it}$	-0.524		1.619***		0.730***	
	(0.324)		(0.274)		(0.185)	
$Connectionyear_{it}$		-0.122		0.490***		0.488***
		(0.143)		(0.106)		(0.104)
Observations	192,565	192,565	192,565	192,565	192,565	192,565
Controls	Y	Y	Y	Y	Y	Y
City-Industry FE	Y	Y	Y	Y	Y	Y
Year-Industry FE	Y	Y	Y	Y	Y	Y

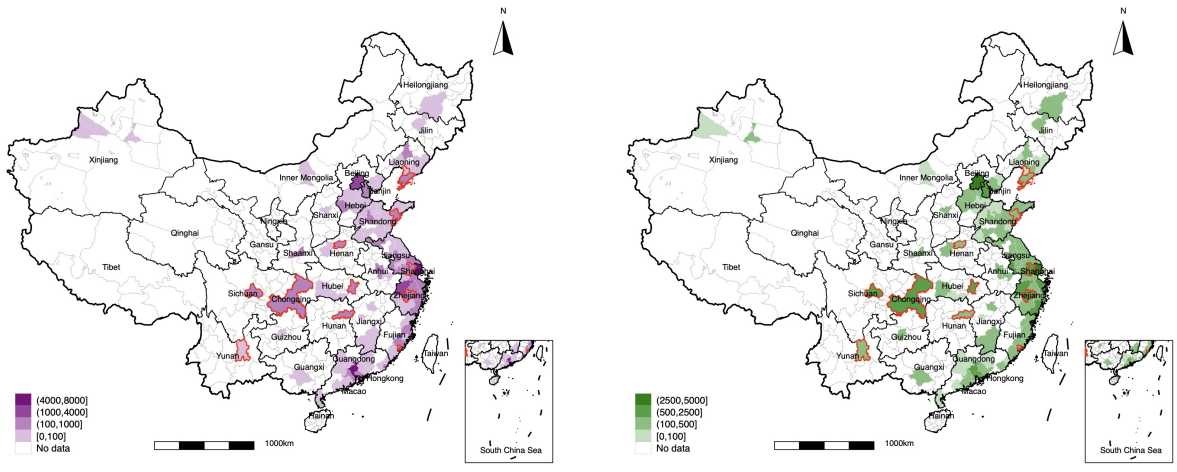
Notes: The table reports PPML estimates. Observations are at the city-industry-year level. Industry is classified by HS 2 digit. Dependent variable is export to Europe by rail, but exported by firms with different types of ownership, which is reported in the column heading. $CERE_{it}$ is a dummy variable that equals one if city i is an origin of regular CERE and year t is larger than the first operating year, and zero otherwise. $Connectionyear_{it}$ is the number of years since operation for origins of regular CERE. It equals to zero if it is before the operation or if it is not origin of regular CERE. Robust standard errors are reported in parentheses, clustered by city. In all columns, we control for city-year level variables, GDP, GDP of secondary industry, employment, employment of secondary industry. Additionally, we control for city-industry-year level global export, city-industry fixed effects and year-industry fixed effects. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

B.6 Welfare Analysis

Table B.8: Harmonization of sectors provided by Customs Database, Taobao and I-O table

Custom Database	Taobao	MRIO
Vegetables Products		Agricultural, Forestry, Animal Husbandry & Fishery Products & Services
Foodstuffs	Food, Tobacco & Alcohol	Food & Tobacco
Chemical & Allied	Household Goods & Services	Chemical Products
Textiles	Clothing	Textiles Textile Clothing, Shoes, Hats, Leather, Down & Related Products
Metals		Metal Smelting & Rolling Processing Products Metal Products
Machinery & Electrical	Education, Culture & Entertainment	Specialized Equipment Electrical Machinery & Equipment Communication Equipment, Computers, & Other Electronic Devices General Equipment
Transportation	Transportation & Communication	Transportation Equipment
Miscellaneous	Healthcare Others	Instruments & Meters Other Manufactured Products Wood Products & Furniture

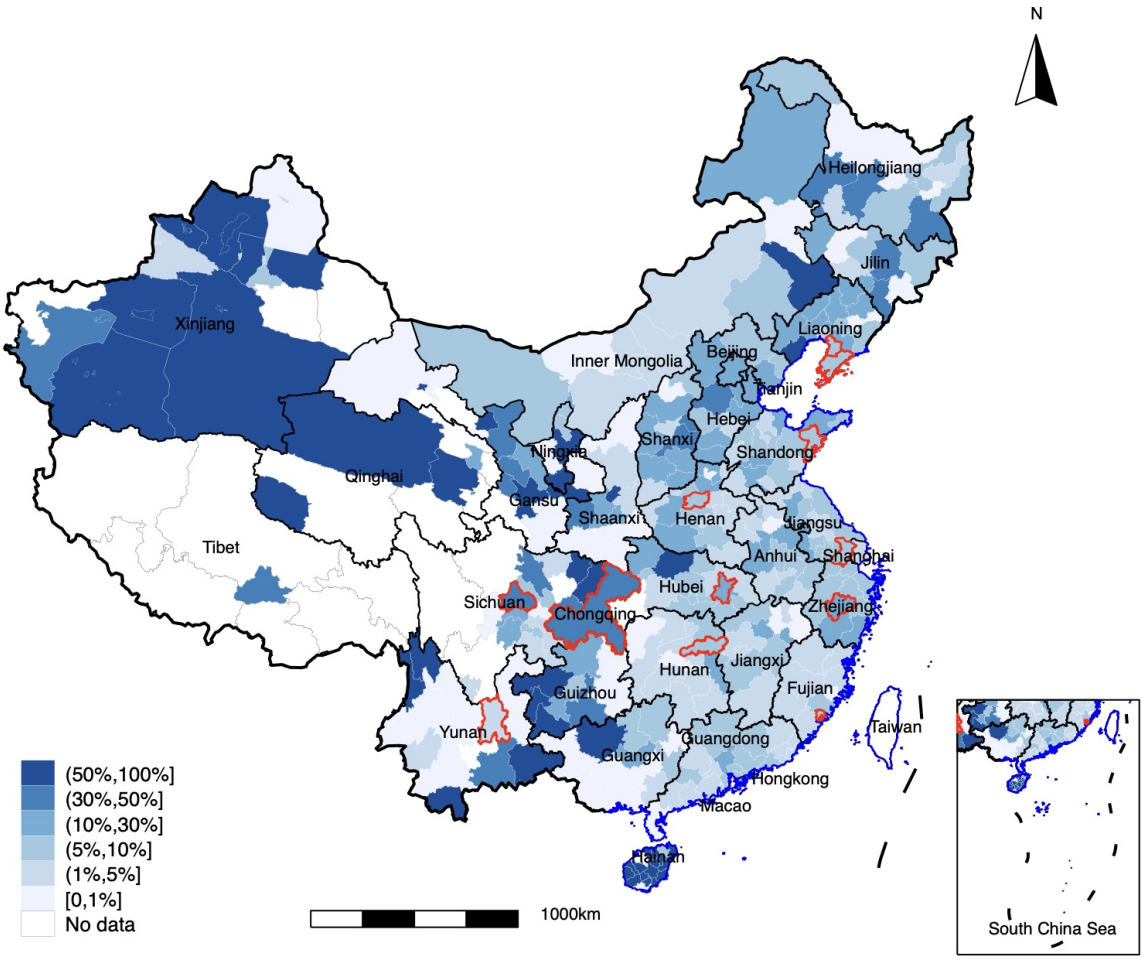
Figure B.6: Transaction on the Taobao platform



(a) Outflow (b) Inflow

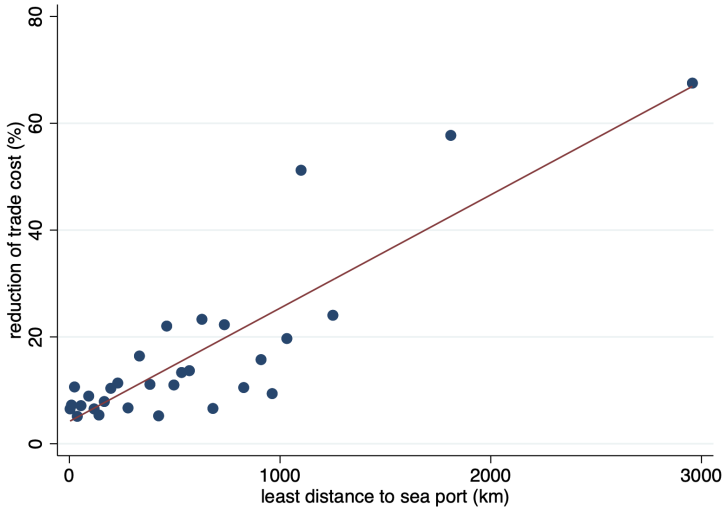
Notes: The unit is million dollars. The outflow and inflow value is aggregated over counterparts, i.e., the other 99 cities in our dataset. The cities with regular CRE are outlined in red.

Figure B.7: Reduction in bilateral trade cost in exporting to Europe



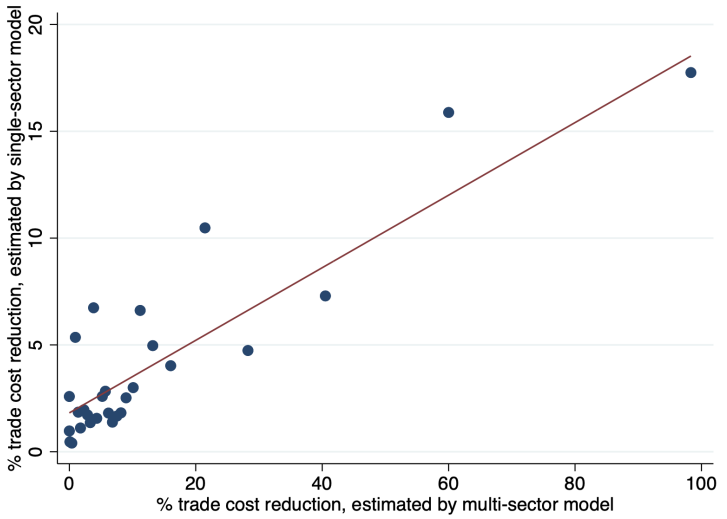
Notes: Cities with CRE are outlined in red, and coastal cities are outlined in blue.

Figure B.8: The reduction of trade cost and distance to sea port



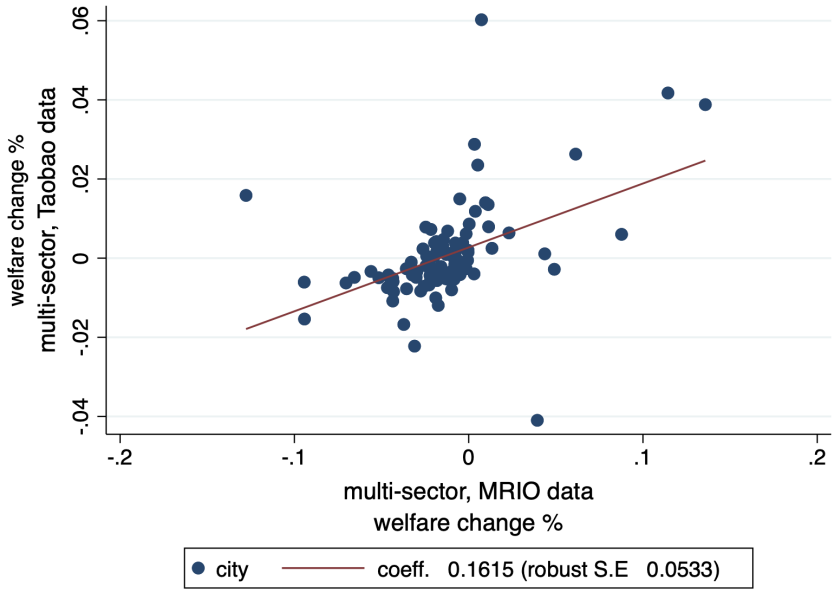
Notes: The x-axis is the least distance to sea port. The y-axis is the reduction of trade cost. We group Chinese cities into 30 equal-sized bins by the least distance to sea port and compute the mean of the x-axis and y-axis variables within each bin. Each point represents a bin. The red line is the linear fitted values at bin level.

Figure B.9: Correlation of trade cost reduction, estimated by multi-sector and single-sector model



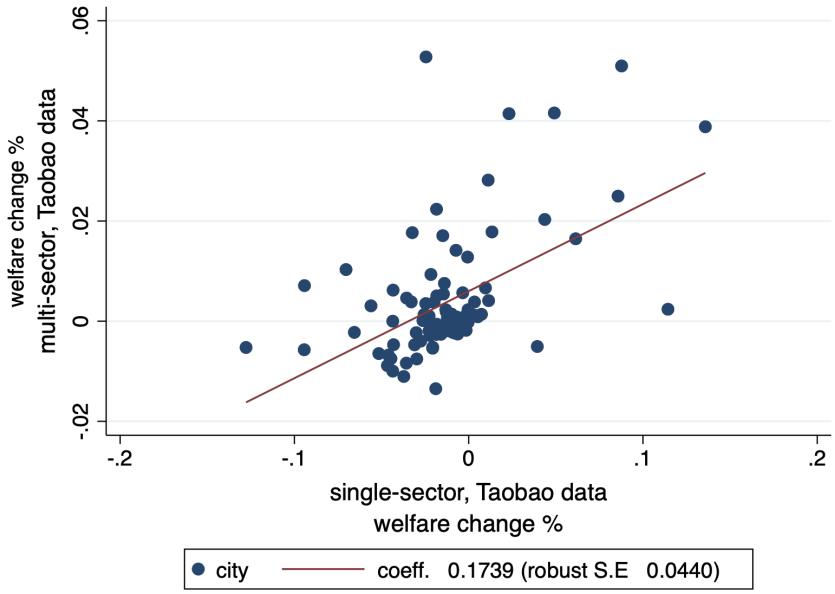
Notes: The x-axis is the trade cost reduction, estimated by multi-sector model. Under the multi-sector framework, we calculate sector-level change and take average of the reduction, weighted by exports of the sector to Europe in 2010. The y-axis is the trade cost reduction, estimated by single-sector model. We group Chinese cities into 30 equal-sized bins by the x-axis variable and compute the mean of the x-axis and y-axis variables within each bin. Each point represents a bin. The red line is the linear fitted values at bin level.

Figure B.10: Correlation between welfare estimation using Taobao data and MRIO data



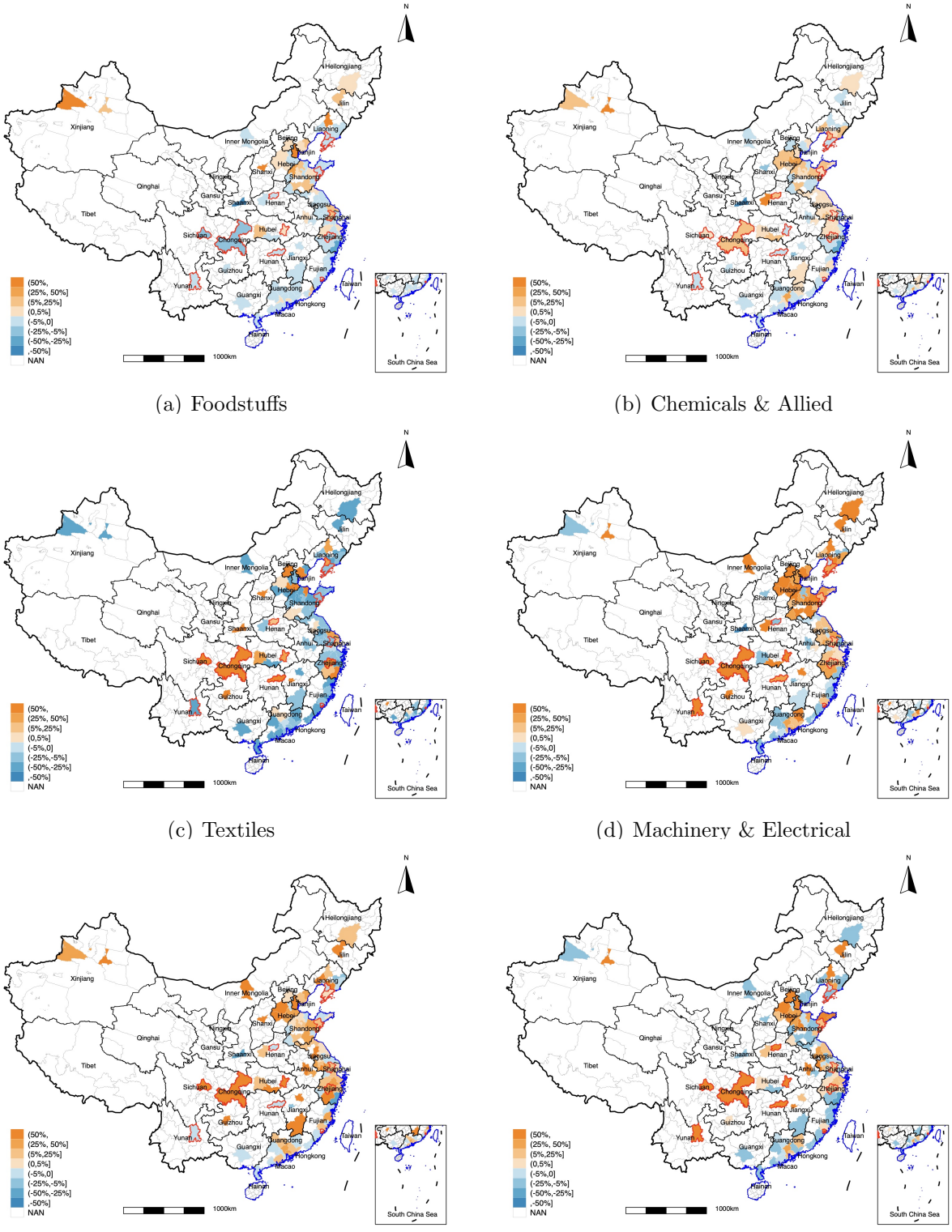
Notes: Each scattered dot represents a city. We fix mass of entrants when we solve out the multi-sector model. We drop outliers that have welfare change larger than 0.2% when draw the dots. The line stands for correlation.

Figure B.11: Correlation between welfare change under single- and multi-sector model



Notes: Each scattered dot represents a city. We drop outliers that have welfare change larger than 0.2% when draw the dots. The line stands for the correlation. The specific results are displayed in Table B.9

Figure B.12: Change in the number of exporters into the European market (%)



(a) Foodstuffs

(b) Chemicals & Allied

(c) Textiles

(d) Machinery & Electrical

(e) Transportation

(f) Miscellaneous

Notes: The figure shows the geographical distribution of the change in the number of EU exporters for each sector. The change in the number of EU exporters is computed by solving the model with the exact hat algebra.

Table B.9: Welfare change (%)

City	Single-sector	Multi-sector	City	Single-sector	Multi-sector
Beijing	0.001	0.007	Tianjin	0.016	0.061
Shijiazhuang	0.001	-0.026	Tangshan	0.000	-0.008
Qinghuangdao	-0.002	-0.020	Baoding	0.028	0.011
Cangzhou	0.020	0.044	Langfang	0.000	-0.026
Hengshui	-0.006	-0.094	Taiyuan	-0.005	0.039
Baotou	-0.007	-0.045	Shenyang	0.004	0.011
Dalian	0.001	-0.009	Anshan	0.014	-0.007
Benxi	-0.013	-0.019	Dandong	0.010	-0.070
Jingzhou	0.000	-0.044	Yingkou	0.343	0.003
Changchun	0.006	-0.003	Harbin	-0.003	-0.006
Shanghai	0.001	0.005	Nanjing	0.001	-0.001
Wuxi	0.004	-0.025	Xuzhou	-0.002	-0.008
Changzhou	0.017	-0.015	Suzhou	0.007	0.010
Nantong	0.002	-0.013	Lianyungang	0.000	-0.008
Huai'an	0.004	-0.020	Yancheng	-0.002	-0.021
Yangzhou	0.001	-0.023	Zhenjiang	0.001	-0.012
Taizhou	-0.003	-0.019	Hangzhou	-0.001	-0.005
Ningbo	0.005	-0.036	Wenzhou	0.036	0.632
Jiaxing	0.001	-0.010	Huzhou	-0.002	-0.030
Shaoxing	0.007	-0.094	Jinhua	0.004	0.003
Quzhou	-0.001	-0.020	Zhoushan	-0.011	-0.037
Taizhou	0.005	-0.014	Lishui	0.018	0.013
Hefei	-0.002	-0.008	Wuhu	0.041	0.023
Fuzhou	-0.002	-0.008	Xiamen	0.002	0.000
Putian	0.000	-0.010	Quanzhou	0.005	-0.018
Zhangzhou	-0.008	-0.036	Ningde	-0.003	-0.016
Nanchang	-0.002	-0.015	Xinyu	-0.008	0.819
Ganzhou	-0.006	-0.052	Jinan	-0.001	-0.010
Qingdao	0.002	-0.013	Zibo	0.000	-0.024
Dongying	0.002	0.114	Yantai	0.053	-0.024
Weifang	0.003	-0.056	Jinning	0.051	0.088
Weihai	-0.002	-0.009	Rizhao	0.009	-0.022
Laiwu	0.006	-0.043	Linyi	0.001	-0.007
Dezhou	0.042	0.049	Liaocheng	0.004	-0.033
Binzhou	-0.002	-0.066	Heze	-0.005	-0.021
Zhengzhou	-0.002	-0.001	Luoyang	0.013	-0.001
Wuhan	0.001	0.000	Yihan	0.022	-0.018
Jinzhou	0.018	-0.032	Changsha	0.000	0.000
Guangzhou	0.001	0.004	Shenzhen	0.000	-0.005
Zhuhai	-0.001	-0.018	Shantou	-0.001	-0.017
Foshan	-0.002	-0.013	Jiangmen	-0.005	-0.043
Zhanjiang	-0.004	-0.028	Zhaoqing	-0.008	-0.030

Continued on next page

Table B.9 – Continued

City	Single-sector	Multi-sector	City	Single-sector	Multi-sector
Huizhou	-0.002	-0.023	Heyuan	-0.007	-0.046
Yangjiang	-0.003	-0.022	Qingyuan	-0.010	-0.044
Dongguan	-0.001	-0.008	Zhongshan	0.001	-0.012
Chaozhou	-0.005	-0.031	Jieyang	-0.009	-0.047
Nanning	-0.002	-0.012	Chongqing	0.039	0.136
Chengdu	0.025	0.086	Guiyang	-0.005	-0.021
Kunming	-0.003	-0.022	Xi'an	-0.002	0.376
Urumqi	0.008	-0.014	Yili	-0.005	-0.128

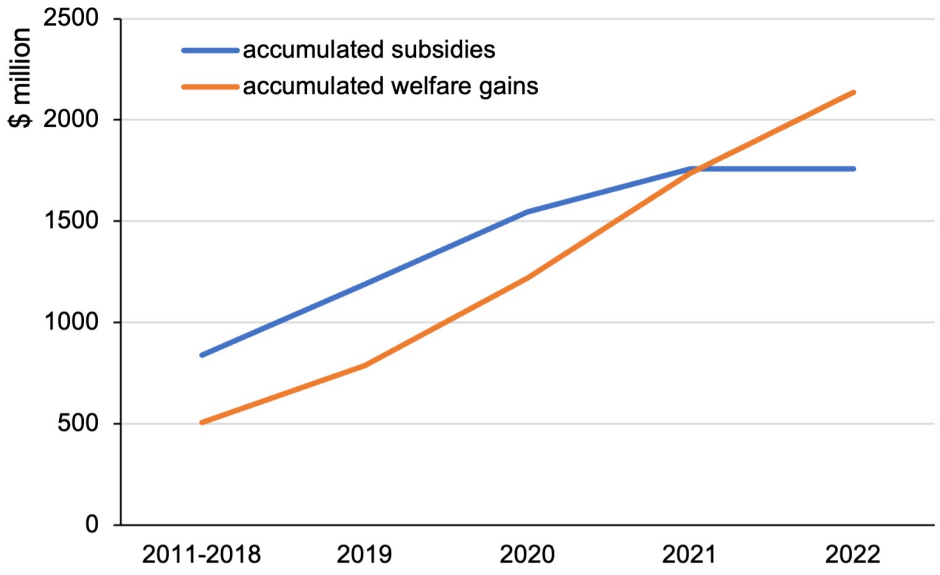
Notes: Cities that are underlined have regular CRE. In this table, we use Taobao data for inter-city trade flow.

Table B.10: Welfare gains dispersion

Welfare gains (%)	Single-sector	Multi-sector
Simple average	0.00734	0.006218
Population-weighted average	0.0083027	0.0157684
Standard deviation	0.0361478	0.1168017
Variation coefficient= standard deviation / simple average	4.924798	18.78458
Total welfare gain (0.1billion RMB)	19.26101	34.36707

Notes: The population-weighted average is weighted by city-level population in 2010. Total welfare is monetary equivalent. See Appendix C.6 for detailed calculations. We use 2010 GDP as baseline income.

Figure B.13: Trend in subsidies and welfare gains for CRE



Notes: The specific numbers are detailed in Table B.11

Table B.11: Projection of subsidies and welfare gains

(1) Year	(2) # of Trains	(3) Subsidy	(4) Accumulated subsidies	(5) Accumulated gains
2011-2018	8194	2500	839.89	507.64
2019	4525	1875	1187.74	787.98
2020	6982	1250	1545.57	1220.53
2021	8364	625	1759.90	1738.70
2022	6395	0	1759.90	2134.89

Notes: Column (2) presents the number of westbound trains. The subsidy per FEU from 2019 to 2022 is estimated by the authors, aligned with the government's plan to reduce the subsidy to zero by 2022. We assume each train carries 41 FEUs. Based on our calculations, the welfare gain per FEU is $507.64/(8194\times41)$ million, which we use to project welfare gains for 2019–2022.

C Model Derivations

C.1 Inverse Demand Function

Maximizing consumer's utility yields the inverse demand for variety ω in sector s and region j, supplied from i:

$$p_{ij}(\omega) = X_j^s \left(Q_j^s\right)^{\frac{1-\sigma^s}{\sigma^s}} z(\omega)^{\frac{\sigma^s-1}{\sigma^s}} q_{ij}(\omega)^{-\frac{1}{\sigma^s}}, \tag{C.1}$$

The term X_j^s denotes the total expenditure on sector s varieties, such that $X_j^s = \alpha^s w_j L_j$.

C.2 Expectation of Export Cost

For the export from China to Europe, the CDF of minimum export cost is given by:

$$\begin{aligned} G(b) &= \mathbb{P}\left(\min_{\rho,t} \frac{\tau_{ij,\rho t}^s}{\varepsilon_{kij,\rho t}} < b\right) = 1 - \mathbb{P}\left(\frac{\tau_{ij,\rho t}^s}{\varepsilon_{kij,\rho t}} \geq b, \forall \rho, t\right) = 1 - \mathbb{P}\left(\varepsilon_{kij,\rho t} \leq \frac{\tau_{ij,\rho t}^s}{b}, \forall \rho, t\right) \\ &= 1 - \exp\left[-\sum_t \left(\sum_\rho \left(\frac{\tau_{ij,\rho t}^s}{b}\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right] = 1 - \exp\left[-b^{\vartheta^s} \sum_t \left(\sum_\rho \left(\tau_{ij,\rho t}^s\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right]. \end{aligned} \tag{C.2}$$

So the PDF of the export cost is given by:

$$g(b) = \vartheta^s b^{\vartheta^s - 1} \sum_t \left(\sum_\rho \left(\tau_{ij,\rho t}^s\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s} \exp\left[-b^{\vartheta^s} \sum_t \left(\sum_\rho \left(\tau_{ij,\rho t}^s\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right]. \tag{C.3}$$

We denote $A = b^{\vartheta^s} \sum_t \left(\sum_\rho \left(\tau_{ij,\rho t}^s\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}$, then $g(b) = \exp(-A)\frac{\mathrm{d}A}{\mathrm{d}b}$.

The expectation of export cost is given by:

$$
\begin{aligned}
E\left[\min_{\rho,t}\frac{\tau^s_{ij,\rho t}}{\varepsilon_{kij,\rho t}}\right] &= \int_0^\infty b\cdot g(b)\mathrm{d}b = \int_0^\infty b\exp(-A)\frac{\mathrm{d}A}{\mathrm{d}b}\mathrm{d}b \\
&= \left[\sum_t\left(\sum_\rho\left(\tau^s_{ij,\rho t}\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right]^{-\frac{1}{\vartheta^s}}\int_0^\infty A^{\frac{1}{\vartheta^s}}\exp(-A)\mathrm{d}A \\
&= \Gamma(1+\frac{1}{\vartheta^s})\left[\sum_t\left(\sum_\rho\left(\tau^s_{ij,\rho t}\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right]^{-\frac{1}{\vartheta^s}}.
\end{aligned}
\tag{C.4}
$$

Combined with trade costs across Chinese regions, across foreign countries and from foreign countries to Chinese regions, the bilateral trade cost is summarized in the following equation:

$$
d^s_{ij} = \begin{cases}
1 & \text{if } i=j, \\
m^s_{ij} & \text{if } i,j\in CHN \text{ or } i,j\notin CHN, \\
\tilde{m}^s_{ij} & \text{if } i\notin CHN \text{ and } j\in CHN, \\
\xi^s\left[\sum_{m'}\left(\sum_{\rho'}\left(\tau^s_{ij,\rho'm'}\right)^{-\frac{\vartheta^s}{\theta^s}}\right)^{\theta^s}\right]^{-\frac{1}{\vartheta^s}} & \text{if } i\in CHN \text{ and } j\notin CHN.
\end{cases}
\tag{C.5}
$$

C.3 Firm's Problem

Solving firm's problem, i.e., maximizing equation (7), yields optimal price given by:

$$
p_{kij}(z) = \frac{\sigma^s}{\sigma^s-1}c_i w_i d^s_{ij}. \tag{C.6}
$$

Substituting the optimal price into the demand function which is implicitly given by equation (C.1) and into the profit function equation (7), we derive the optimal (expected) quantity and profit:

$$
q_{kij}(z) = z^{\sigma^s-1}\left[\frac{\sigma^s-1}{\sigma^s}\frac{\alpha^s w_j}{c_i w_i d^s_{ij}\left(Q^s_j\right)^{\frac{\sigma^s-1}{\sigma^s}}}\right]^{\sigma^s}, \tag{C.7}
$$

$$
\pi_{kij}(z) = \frac{L_j(\sigma^s-1)^{\sigma^s-1}(\alpha^s w_j)^{\sigma^s}}{(\sigma^s)^{\sigma^s}\left(Q^s_j\right)^{\sigma^s-1}}\left(c_i w_i d^s_{ij}\right)^{-(\sigma^s-1)}z^{\sigma^s-1} - w_j f_j. \tag{C.8}
$$

We define the quality cutoff that sets profits to zero as:

$$
\bar{z}^s_{ij} = \left(\frac{(\sigma^s)^{\sigma^s}\left(Q^s_j\right)^{\sigma^s-1}}{L_j(\sigma^s-1)^{\sigma^s-1}(\alpha^s w_j)^{\sigma^s}}\right)^{\frac{1}{\sigma^s-1}} c_i w_i d^s_{ij}\left(w_j f_j\right)^{\frac{1}{\sigma^s-1}}. \tag{C.9}
$$

Then the expected profits and revenues can be written as:

$$\pi_{kij}(z) = w_j f_j \left[\left(\frac{z}{\bar{z}_{ij}^s} \right)^{\sigma^s - 1} - 1 \right], \tag{C.10}$$

$$r_{kij}(z) = \sigma^s w_j f_j \left(\frac{z}{\bar{z}_{ij}^s} \right)^{\sigma^s - 1}. \tag{C.11}$$

Average revenues and profits in the sector equal to:

$$\bar{r}_{ij}^s = \int_{\bar{z}_{ij}^s}^{\infty} r_{kij}(z) h_i(z|\bar{z}_{ij}^s) \mathrm{d}z = \frac{\sigma^s \kappa w_j f_j}{\kappa - \sigma^s + 1}, \tag{C.12}$$

$$\bar{\pi}_{ij}^s = \int_{\bar{z}_{ij}^s}^{\infty} \pi_{kij}(z) h_i(z|\bar{z}_{ij}^s) \mathrm{d}z = \frac{(\sigma^s - 1) w_j f_j}{\kappa - \sigma^s + 1}. \tag{C.13}$$

The free entry condition in each sector is given by:

$$E_z \left[\pi_{kij}(z) \right] = \sum_j (b_i)^{\kappa} \left(\bar{z}_{ij}^s \right)^{-\kappa} \bar{\pi}_{ij}^s = \frac{\sigma^s - 1}{\sigma^s \kappa} \sum_j (b_i)^{\kappa} \left(\bar{z}_{ij}^s \right)^{-\kappa} \bar{r}_{ij}^s = w_i f_E, \tag{C.14}$$

where $(b_i)^{\kappa} \left(\bar{z}_{ij}^s \right)^{-\kappa}$ is the probability of entering the market (destination) j, and the $\bar{\pi}_{ij}^s$ is the expected profits conditional on market entry. We plug in $\bar{\pi}_{ij}^s = \frac{\sigma^s - 1}{\sigma^s \kappa} \bar{r}_{ij}^s$, implied by equation (C.12) and (C.13). The right-hand side stands for the establishment cost.

C.4 Aggregation and Equilibrium

Aggregate revenues are given by:

$$R_{ij}^s = J_i^s (b_i)^{\kappa} \left(\bar{z}_{ij}^s \right)^{-\kappa} \bar{r}_{ij}^s, \tag{C.15}$$

which is trade flow of sector s. J_i^s is the number of entrants in sector s, and $J_i^s (b_i)^{\kappa} \left(\bar{z}_{ij}^s \right)^{-\kappa} \triangleq N_{ij}^s$ is the number of exporters to destination j. The trade by rail is then given by $\mu_{ij,Rail}^s \cdot R_{ij}^s$.

The trade shares within sector is given by:

$$\lambda_{ij}^s = \frac{R_{ij}^s}{\sum_v R_{vj}^s} = \frac{J_i^s (b_i)^{\kappa} \left(\bar{z}_{ij}^s \right)^{-\kappa} \bar{r}_{ij}^s}{\sum_v J_v^s (b_v)^{\kappa} \left(\bar{z}_{vj}^s \right)^{-\kappa} \bar{r}_{vj}^s}. \tag{C.16}$$

Plugging equation (14) and (C.12) plugged into trade shares, we derive equation (16) in the

equilibrium. With equation (C.15) plugged in, the free entry condition can be written as:

$$\begin{aligned} E_z\left[\pi_{kij}(z)\right] &= \frac{\sigma^s - 1}{\sigma^s \kappa} \sum_j \frac{R_{ij}^s}{J_i^s} \\ &= \frac{\sigma^s - 1}{\sigma^s \kappa} \sum_j \frac{\alpha^s \lambda_{ij}^s w_j L_j}{J_i^s} \\ &= w_i f_E. \end{aligned} \tag{C.17}$$

Here we use $R_{ij}^s = \lambda_{ij}^s \sum_v R_{vj}^s = \lambda_{ij}^s X_j^s = \lambda_{ij}^s \alpha^s w_j L_j$, where $\sum_v R_{vj}^s = X_j^s$, the expenditure of region j on sector s.

The trade balance condition is given by:

$$\sum_s \sum_j R_{ij}^s = \sum_s \sum_j \alpha^s \lambda_{ij}^s w_j L_j = w_i L_i \quad \forall i = 1, \ldots, I. \tag{C.18}$$

The left-hand side is total revenue and the right-hand side is total expenditure of region i.

C.5 Simple Case

In the simplified version of the model, trade costs are homogeneous across regions and are specified by the following equations:

$$d_{ij}^s = \begin{cases} 1 & \text{if } i = j, \\ \xi^s \left[\sum_{t'} \left(\sum_{\rho'} \left(\tau_{ij,\rho' t'}^s \right)^{-\frac{\vartheta^s}{\theta^s}} \right)^{\theta^s} \right]^{-\frac{1}{\vartheta^s}} = \xi^s \left[\sum_{t'} \left(\sum_{\rho'} \left(\tau_{\rho' t'}^s \right)^{-\frac{\vartheta^s}{\theta^s}} \right)^{\theta^s} \right]^{-\frac{1}{\vartheta^s}} & \text{if } i \neq j, \end{cases} \tag{C.19}$$

where $\tau_{ij,\rho t} = \tau_{ji,\rho t} = \tau_{\rho t}, \forall i \neq j$.

Regions have the same measure for wage rate in the equilibrium due to symmetry. Plugging the market clearing condition (with $S = 1$) into the free entry condition, we solve out that the mass of entrants is fixed for each region:

$$J_i = \frac{L}{f_E} \frac{\sigma - 1}{\sigma \kappa} \triangleq J, \forall i = 1, \ldots, I, \tag{C.20}$$

Substituting the wage rate and the fixed entrants into the trade shares, we have:

$$\lambda_{ij} = \frac{(d_{ij})^{-\kappa}}{\sum_v (d_{vj})^{-\kappa}} = \begin{cases} \frac{1}{1+(N+1)d^{-\kappa}} & \forall i = j, \\ \frac{d^{-\kappa}}{1+(N+1)d^{-\kappa}} & \forall i \neq j, \end{cases} \tag{C.21}$$

where $d \triangleq \xi \left[\sum_{t'} \left(\sum_{\rho'} \left(\tau_{\rho' t'}^s \right)^{-\frac{\vartheta}{\theta}} \right)^{\theta} \right]^{-\frac{1}{\vartheta}}$ denotes the inter-region trade cost.

Proof of Proposition 1

The average rail transport cost is represented by:

$$d_{Rail} = \left(\sum_{\rho'} \left(\tau_{\rho', Rail} \right)^{-\frac{\vartheta}{\theta}} \right)^{-\frac{\theta}{\vartheta}}. \tag{C.22}$$

We derive $\frac{\partial d_{Rail}}{\partial \tau_{\rho, Rail}} > 0$ easily. The connections to CRE, modeled by decline in $\tau_{\rho, Rail}$, are captured by a uniform reduction in rail transportation trade costs.

The average trade cost is given by:

$$d = \xi \left[\sum_{t'} \left(\sum_{\rho'} \left(\tau_{\rho' t'} \right)^{-\frac{\vartheta}{\theta}} \right)^{\theta} \right]^{-\frac{1}{\vartheta}} = \xi \left[\sum_{t'} \left(d_{t'} \right)^{-\vartheta} \right]^{-\frac{1}{\vartheta}}. \tag{C.23}$$

Hence $\frac{\partial d}{\partial d_{Rail}} > 0$ (or $\frac{\partial d}{\partial \tau_{\rho, Rail}} > 0, \forall \rho$). The average bilateral exporting trade costs decreases.

The share of rail transport is:

$$\mu_{Rail} = \frac{\left(d_{Rail} \right)^{-\vartheta}}{\sum_{t'} \left(d_{t'} \right)^{-\vartheta}}. \tag{C.24}$$

By the chain rule, we derive $\frac{\partial \mu_{Rail}}{\partial \tau_{\rho, Rail}} = \frac{\partial \mu_{Rail}}{\partial d_{Rail}} \cdot \frac{\partial d_{Rail}}{\partial \tau_{\rho, Rail}} < 0, \forall \rho$. The proportion of exports carried by rail increases.

Plugging the equilibrium $w_j = 1$, $R_{ij} = \lambda_{ij} w_j L_j = \lambda_{ij} L$, we derive

$$\frac{\partial R_{ij}}{\partial \tau_{\rho, Rail}} = \frac{\partial R_{ij}}{\partial \lambda_{ij}} \cdot \frac{\partial \lambda_{ij}}{\partial \tau_{\rho, Rail}} = \frac{\partial R_{ij}}{\partial \lambda_{ij}} \cdot \frac{\partial \lambda_{ij}}{\partial d} \cdot \frac{\partial d}{\partial \tau_{\rho, Rail}} < 0, \forall i \neq j, \forall \rho, \tag{C.25}$$

where $\frac{\partial \lambda_{ij}}{\partial d} < 0$ is directly implied by equation (C.16). The aggregate revenue increases. The rising exports and intensifying rail choice improve the volume of rail transportation.

The declining trade cost lowers the entry quality cutoff, since

$$R_{ij} = J b^{\kappa} \left(\bar{z}_{ij} \right)^{-\kappa} \bar{r}_{ij} = J b^{\kappa} \left(\bar{z}_{ij} \right)^{-\kappa} \frac{\sigma \kappa w f}{\kappa - \sigma + 1}, \tag{C.26}$$

we have $\frac{\partial \bar{z}_{ij}}{\partial \tau_{\rho, Rail}} > 0$ as $\frac{\partial R_{ij}}{\partial \tau_{\rho, Rail}} < 0$. Note that the number of exporters to destination j is given by $N_{ij} = J b^{\kappa} \left(\bar{z}_{ij} \right)^{-\kappa}$ and the incumbent's revenue and profit is given by equation (C.11) and (C.10). As the cutoff decreases when the cost goes down, we obtain $\frac{\partial N_{ij}}{\partial \tau_{\rho, Rail}} < 0$, $\frac{\partial \pi_{ij}}{\partial \tau_{\rho, Rail}} < 0$ and $\frac{\partial r_{ij}}{\partial \tau_{\rho, Rail}} < 0, \forall i \neq j, \forall \rho$ by chain rule. The connection of CRE increases both intensive and extensive margins of exports.

Proof of Proposition 2

The export by different transport mode is given by the export revenue multiplied by the fraction of the transportation:

$$R_{ij,t} = R_{ij} \cdot \mu_t \tag{C.27}$$

For non-rail transportation t, $\frac{\partial R_{ij,t}}{\partial \tau_{\rho,Rail}}$ depends on the parameters κ and ϑ:

$$\begin{aligned} R_{ij,t} = R_{ij} \cdot \mu_t &= \lambda_{ij} L \cdot \mu_t \\ &= \frac{d^{-\kappa}}{1+(N+1)d^{-\kappa}} L \cdot \frac{d_t}{\sum_{t\prime}(d_{t\prime})^{-\vartheta}} \\ &= \frac{d^{-\kappa}}{1+(N+1)d^{-\kappa}} L \cdot \frac{d_t}{(\frac{d}{\xi})^{-\vartheta}} \\ &= \frac{d^{\vartheta-\kappa}}{1+(N+1)d^{-\kappa}} \frac{d_t}{\xi^{\vartheta}} L \\ &= \frac{1}{d^{\kappa-\vartheta}+(N+1)d^{-\vartheta}} \frac{d_t}{\xi^{\vartheta}} L \end{aligned} \tag{C.28}$$

where we plug in $d = \xi(\sum_{t\prime}(d_{t\prime})^{-\vartheta})^{-\frac{1}{\vartheta}}$.

C.6 Welfare (Hat Algebra)

To express the welfare with λ, J and w, we combine the following equations:

$$R^s_{jj} = J^s_j \left(b_j\right)^{\kappa} \left(\bar{z}^s_{jj}\right)^{-\kappa} \bar{r}^s_{jj} = \lambda^s_{jj} \alpha^s w_j L_j, \tag{C.29}$$

$$\bar{r}^s_{jj} = \frac{\sigma^s \kappa w_j f_j}{\kappa - \sigma^s + 1}, \tag{C.30}$$

$$\bar{z}^s_{jj} = \left(\frac{\left(\sigma^s\right)^{\sigma^s} \left(Q^s_j\right)^{\sigma^s - 1}}{L_j (\sigma^s - 1)^{\sigma^s - 1} (\alpha^s w_j)^{\sigma^s}} \right)^{\frac{1}{\sigma^s - 1}} c_j w_j d^s_{ij} \left(w_j f_j\right)^{\frac{1}{\sigma^s - 1}}, \tag{C.31}$$

Finally, we derive the welfare as:

$$\begin{aligned} U_j &= \prod_{s=1}^{S} \left(Q^s_j\right)^{\alpha^s}, \\ Q^s_j &= \left(\frac{\sigma^s \kappa w_j J^s_j \left(b_j\right)^{\kappa}}{(\kappa - \sigma^s + 1)\alpha^s w_j L_j} \right)^{\frac{1}{\kappa}} \frac{(\sigma^s - 1)\left(L_j (\alpha^s w_j)^{\sigma^s}\right)^{\frac{1}{\sigma^s - 1}}}{\left(\sigma^s\right)^{\frac{\sigma^s}{\sigma^s - 1}} c_j w_j d_{jj} \left(w_j\right)^{\frac{1}{\sigma^s - 1}}} \left(f_j\right)^{-\frac{\kappa - \sigma^s + 1}{\kappa}} \left(\lambda^s_{jj}\right)^{-\frac{1}{\kappa}}. \end{aligned} \tag{C.32}$$

Applying the hat algebra technique on the welfare expression (C.32) and the equilibrium system (16), (17) and (18), we obtain:

$$\hat{U}_j = \prod_{s=1}^{S} \left(\hat{Q}_j^s\right)^{\alpha^s} \tag{C.33}$$

$$\hat{Q}_j^s = \left(\hat{J}_j^s\right)^{\kappa} \left(\hat{\lambda}_{jj}^s\right)^{-\frac{1}{\kappa}} \tag{C.34}$$

$$\hat{\lambda}_{ij}^s = \frac{\hat{J}_i^s (\hat{d}_{ij}^s \hat{w}_i)^{-\kappa}}{\sum_v \lambda_{vj}^s \hat{J}_v^s (\hat{d}_{vj}^s \hat{w}_v)^{-\kappa}} \tag{C.35}$$

$$\hat{J}_i^s \hat{w}_i = \frac{\sum_j \lambda_{ij}^s \hat{\lambda}_{ij}^s \hat{w}_j w_j L_j}{\sum_j \lambda_{ij}^s w_j L_j} \tag{C.36}$$

$$\hat{w}_i = \frac{\sum_s \sum_j \alpha^s \lambda_{ij}^s w_j L_j \hat{\lambda}_{ij}^s \hat{w}_j}{\sum_s \sum_j \alpha^s \lambda_{ij}^s w_j L_j} \tag{C.37}$$

We calibrate the initial wage w_j under the equilibrium, using the equation (18). We feed in the consumption share α^s, trade flow share λ_{ij}^s, and population L_j. Consider a change in trade cost d_{ij}^s[39], we solve out the "hat" by the following steps:

- Step 1: Guess a vector of wages $\hat{\mathbf{w}} = (\hat{w}_1, \ldots, \hat{w}_{N+2})$.
- Step 2: Given $\hat{\mathbf{w}}$, guess a $N \times S$ matrix of entrants $\hat{\mathbf{J}}$. Use equilibrium (C.35) to solve for expenditure shares $\hat{\lambda}_{ij}^s(\hat{\mathbf{w}}, \hat{\mathbf{J}})$.
- Step 3: Substitute $\hat{\lambda}_{ij}^s(\hat{\mathbf{w}}, \hat{\mathbf{J}})$, $\hat{\mathbf{J}}$ and $\hat{\mathbf{w}}$ into (C.36) and verify if it holds. If not, we adjust our guess of $\hat{\mathbf{J}}$ and proceed to step 2 until free entry condition (C.36) is obtained.
- Step 4: Given $\hat{\mathbf{w}}$, we obtained $\hat{\mathbf{J}}(\hat{\mathbf{w}})$ and $\hat{\lambda}_{ij}^s(\hat{\mathbf{w}})$ after step 2-3. We substitute them into the market clearing condition (C.37) and very if it holds. If not, we adjust our guess of $\hat{\mathbf{w}}$ and proceed to step 1 until equilibrium condition (C.37) is obtained.

We can also solve out the change of export revenue and decompose it into change of entrants and change of average revenue, applying the hat algebra technique on the equations (C.12) and (C.15).

$$\hat{R}_{ij}^s = \hat{N}_{ij}^s \times \hat{\bar{r}}_{ij}^s \tag{C.38}$$

where

$$\hat{N}_{ij}^s = \hat{J}_i^s (\hat{\bar{z}}_{ij}^s)^{-\kappa} = \hat{J}_i^s \frac{\hat{Q}_j^s}{\hat{w}_j} \hat{w}_i \hat{d}_{ij}^s \tag{C.39}$$

$$\hat{\bar{r}}_{ij}^s = \hat{w}_j \tag{C.40}$$

Monetary Equivalent. The welfare expressed in equivalent income is derived from the following equation:

$$U_j = \prod_{s=1}^{S} \left(Q_j^s\right)^{\alpha^s} = \underbrace{w_j L_j}_{X_j} \prod_{s=1}^{S} \left(\frac{\alpha^s}{\mathbb{P}_j^s}\right)^{\alpha^s} \tag{C.41}$$

[39] We censored the d_{ij}^s to 0.2 if it is smaller than 0.2.

where the sub-utility is given by the following:

$$Q_j^s = \frac{X_j^s}{\mathbb{P}_j^s} = \frac{\alpha^s w_j L_j}{\mathbb{P}_j^s} \tag{C.42}$$

and the price index is:

$$\mathbb{P}_j^s = \left[\sum_i \int_{\omega \in \Omega_{ij}^s} z(\omega)^{\sigma^s - 1} p_{ij}(\omega)^{1-\sigma^s} d\omega \right]^{\frac{1}{1-\sigma^s}} \tag{C.43}$$

To maintain the initial situation (constant prices), the equivalent variation, that is, the counterfactual income X_j^* that raises welfare to U_j', satisfies the following condition:

$$U_j' = X_j^* \prod_{s=1}^{S} (\frac{\alpha^s}{\mathbb{P}_j^s})^{\alpha^s}. \tag{C.44}$$

Thus, under homothetic preferences, the equivalent variation in monetary income directly reflects the change in welfare.

$$\frac{X_j^*}{X_j} = \frac{U_j'}{U_j} = \hat{U}_j \tag{C.45}$$

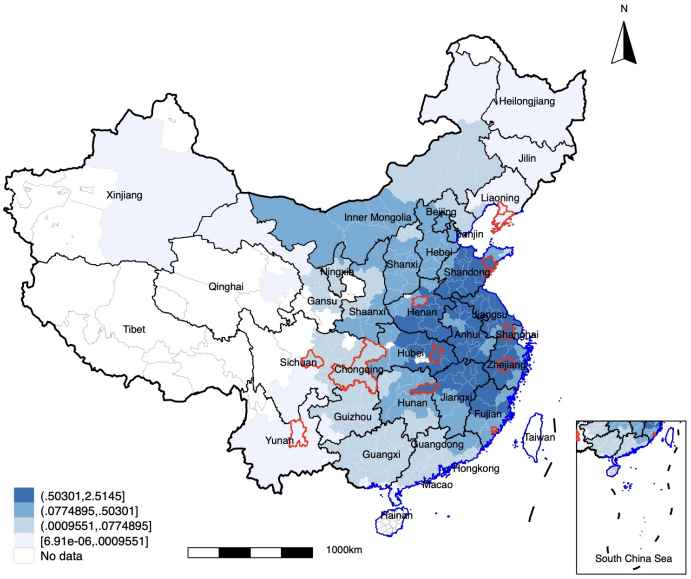
D Eigenvector Centrality

The eigenvector centrality calculation follows two main steps. We first create a city-level adjacency matrix based on the 2010 Chinese expressway network (illustrated in panel (a) of Figure B.14), where each element is set to 1 if two cities are connected by an expressway and 0 otherwise. Next, we calculate the principal eigenvector of this matrix, which represents each city's relative centrality within the network. This eigenvector is then normalized by its norm and scaled by a factor of 100. Panel (b) of Figure B.14 displays the resulting centrality values, excluding cities not connected by expressways from the analysis.

Figure B.14: Centrality of Chinese cities based on 2010 Chinese expressway network



(a) Chinese expressway network in 2010



(b) Eigenvector Centrality

Notes: The red line represents expressway in 2010