High-speed Rail and the Demand for Skill: Evidence from Chinese Exports*

Yumin Hu
Nankai University

Mingzhi (Jimmy) Xu
Peking University

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Abstract

We study how China's high-speed rail (HSR) expansion raises firms' demand for skills by easing search and coordination frictions. Exploiting the staggered rollout, we show that connected cities gain skilled employment and skill premia, and their exports become more skill-intensive as firms source inputs from distant domestic suppliers, consistent with task outsourcing. A spatial-equilibrium model with frictional sourcing, trade, and mobility implies that HSR-induced matching gains equal a 9.3% drop in domestic trade costs and generate welfare gains of 3.4% of 2011 GDP, concentrated in coastal, skill-abundant cities, widening disparities. Conditional on stations, the network is near welfare-maximizing.

Keywords: Transport infrastructure, outsourcing, skill demand

JEL Classification: F14, F16, L16

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1 Introduction

Improved buyer-seller linkages are redefining firm boundaries, altering the relative returns to factors such as skilled and unskilled labor and contributing to rising inequality (Bernard and Moxnes, 2018; Antràs and Chor, 2022). While a large literature studies how globalization and falling trade costs reshaped sourcing and factor demand (Feenstra and Hanson, 2003; Feenstra, 2007) and how contract enforcement governs inter-firm transactions (Boehm and Oberfield, 2020), this paper examines a new aspect: how enhanced matching efficiency between firms, driven by China's rapid expansion of its high-speed rail (HSR) passenger transportation network, affects the demand for skills and skill premiums. By reducing coordination costs and improving access to specialized suppliers, HSR facilitates faster business travel and strengthens firm-to-firm linkages. This shift encourages outsourcing, reducing demand for unskilled labor in easily separable tasks while increasing reliance on skilled labor for tasks retained in-house.

In this paper, we make two key contributions. First, we provide novel evidence on how HSR, a modern infrastructure designed primarily for rapid passenger travel, reshapes China's trade patterns and firms' relative demand for skilled labor. The key mechanism is that HSR lowers within-country search and coordination costs, encouraging greater reliance on domestically outsourced intermediate inputs. We focus on exports because they are less directly driven by local demand conditions than domestic sales, which can rise with housing booms, local stimulus, or other place-based shocks that coincide with HSR rollout. Exports still reflect local supply capacity, but precisely because they are disciplined by external markets, they offer a cleaner view of supply-side adjustment and production-network reorganization. Second, because these partial-equilibrium patterns do not capture the economy-wide impacts of interconnected market responses, we develop a general-equilibrium model with spatial sourcing, frictional mobility, and trade. The model allows us to quantify the impacts of these mechanisms on the overall distribution and aggregate demand for skills within the Chinese context. To our knowledge, this is the first study to establish a causal link between HSR connectivity, export outcomes, and firms' relative demand for skilled labor.

By the end of 2015, China had built the world's largest high-speed rail (HSR) network, with about 19,000 kilometers of track linking roughly 170 cities.[1] The expansion transformed business travel by making medium-distance trips fast, reliable, and easy to schedule. In 2013, HSR carried 672 million passengers, surpassing air travel, and its high frequency and punctuality made it the dominant mode on many corridors (Ou et al., 2014). Survey evidence in Bullock et al. (2014) points to a strong business-travel margin: business-related trips account

[1] As of 2013, Spain had the second-longest HSR network (2,515 km), followed by Japan (2,388 km) and France (2,036 km).

for a disproportionately large share of HSR riders, rising by 17% on the Changchun–Jilin line and 11% on the Beijing–Shanghai line.[2] Interviews further emphasize that firms use HSR to cut travel time and coordination costs in sales, procurement, and partnership building; many employees report making two to five HSR business trips per month, underscoring its role in sustaining supplier and customer networks. Commuting, by contrast, accounts for only about 15% of HSR ridership and is concentrated in short-distance trips.[3] Accordingly, we view China's HSR less as a migration-cost shock and more as a coordination technology: it makes face-to-face business travel cheap and frequent, strengthening links between firms.

Leveraging the staggered rollout of China's HSR network between 2011 and 2018, we provide robust evidence that HSR connections significantly enhance city-level economic efficiency, primarily by facilitating the use of domestic intermediate inputs. These gains disproportionately benefit skilled labor: connected cities not only experience a rise in total exports, but also see a marked increase in the skill intensity of those exports. Specifically, we find that connectivity to HSR boosts city exports by an impressive 11.9% annually, while also increasing the demand for skilled labor among exporting firms by 13.3% as a share of total employment. To address endogenous HSR placement, we instrument using a least-cost-path spanning-tree network. We further apply the Callaway and Sant'Anna (2021) estimator to accommodate staggered adoption and heterogeneous effects, and an event study shows no differential pre-trends, supporting parallel trends. The results remain robust when major cities are excluded, indicating they are not driven by large urban centers. Importantly, the gains are driven by ordinary exports, which rely more heavily on domestic inputs. In contrast, processing exports—centered on assembling imported intermediates—show no measurable response. The rise in skill content is closely tied to a shift toward domestic outsourcing: firms expand their domestic sourcing networks over longer distances while reducing reliance on imported inputs. This reorientation leads to greater overall input use and reflects an HSR-induced strengthening of domestic production linkages.

To better understand the local development consequences of HSR, we combine supplementary microdata from the China Tax Survey (2011–2016), the Population Census (2010; 2015 1% sample), and the China Family Panel Studies (2010–2018) to trace adjustments at both the firm and city levels. Firms in HSR-connected cities exhibit higher average wages and greater R&D intensity (R&D-to-sales), indicating a shift toward more complex, skill-

[2]HSR ridership grew at an average annual rate of 39% (vs. 13% for air travel); business travelers account for 40% of riders on the Changchun–Jilin route and 63% on the Beijing–Shanghai corridor.

[3]Bullock et al. (2014); Ren et al. (2023) report that commuting trips account for about 15% of HSR journeys on the Changchun–Jilin and Beijing–Tianjin lines. This share is much lower for trips exceeding one hour. In smaller countries, HSR can meaningfully reduce commuting costs and affect residential and workplace choices (Heuermann and Schmieder, 2019).

intensive production. In local labor markets, connected cities also show larger employment shares of skilled workers and higher skill premia. These results point to rising demand for skills driven by HSR-enabled outsourcing and tighter firm-to-firm linkages. However, the productivity gains from improved connectivity are unevenly distributed: they accrue disproportionately to skilled workers and skill-abundant cities, reinforcing pre-existing wage and spatial inequality. To our knowledge, this is the first study to provide causal evidence linking the rollout of China's HSR network to changes in skill demand embedded in city exports.

To quantify the general equilibrium effects of improved production networks from HSR expansion and assess its distributional implications, we develop a quantitative spatial trade model grounded in Eaton et al. (2016). Our model incorporates costly trade, frictional labor mobility, and spatial outsourcing, allowing us to analyze regions with varying technology and outsourcing capabilities. We demonstrate that HSR connections increase the demand for skilled labor by enabling unskilled tasks to substitute for manufacturing through outsourcing (Feenstra and Hanson, 1996; Baumgarten et al., 2013). By linking outsourcing capabilities to the efficiency of firm-to-firm matching, we show that HSR enhances this efficiency via faster transportation. A key aspect of our model is that increased outsourcing does not necessarily reduce the relative demand for unskilled labor. In fact, it can raise both the marginal product and the demand for unskilled workers in core, non-outsourced tasks, as noted by Wright (2014); Bilal and Lhuillier (2021). The interaction between production and regional outsourcing influences the demand for various labor types and the supply of goods for both final consumption and intermediate tasks across regions. Workers choose their residences based on expected utility, shaped by local amenities, prices, wages, and personal preferences. This migration behavior ultimately determines labor supply and demand for goods, leading to equilibrium where labor distribution and factor prices ensure market clearance.

For precision in counterfactual analyses, we calibrate our model to the initial equilibrium of the Chinese economy and assess the impact of HSR with detailed disaggregated data while maintaining a tight connection with our reduced-form regression. In particular, to capture China's economic geography of goods flow, we utilize transaction records from the Taobao Platform to create a novel dataset of trade flows between cities. Migration patterns for skilled and unskilled labor are sourced from the 2010 Population Census, while regional outsourcing shares are tracked using firm-level data from the Chinese Tax Survey. The impact of HSR on matching efficiency between firms is calibrated to match the coefficients from the reduced-form estimates in the empirical section. This analysis reveals that the cost savings from improved production networks due to HSR connections are equivalent to a 9.28% reduction in iceberg trade costs for domestic intermediate inputs.

Our quantitative analysis indicates that the construction of HSR between 2011 and 2017

increased China's overall welfare by 3.4% of GDP in 2011, accounting for 26.82% of the total welfare change during this period, which also includes broader economic shifts such as technological advancements. However, the gains from HSR disproportionately benefit skilled labor, resulting in a welfare increase of 5.09%. In contrast, unskilled labor experiences a decline of 0.62% due to decreased demand as outsourcing rises. This widening skill gap means that regions with higher concentrations of skilled labor benefit most from HSR, exacerbating the inequality between cities. Overall inequality, measured by the Theil index, increased by 1.5%. Finally, further policy experiments suggest that this rising inequality could be mitigated through reforms aimed at reducing domestic migration costs and trade barriers.

Finally, we assess the efficiency of HSR hub placement by solving a social planner's problem that reallocates the same number of stations observed in the actual network between 2011 and 2017 to maximize aggregate welfare. The optimal configuration yields a welfare gain of 3.78 percent, 0.38 percentage points higher than the realized network. It prioritizes coastal provinces such as Jiangsu and Shandong while reducing coverage in areas near Beijing—highlighting a trade-off between economic efficiency and political or regional development goals. Despite these differences, the observed network captures about 90 percent of the potential gain, suggesting that its placement, while not fully optimal, was broadly effective given the number of hubs actually constructed.

Related Literature. This paper contributes to several key areas of the literature, with the first being the rapidly growing research on the economic impacts of HSR. Bernard et al. (2019) show that HSR enhances firm productivity by lowering search and outsourcing costs, which allows firms to engage more efficiently with higher-quality suppliers, thereby reducing marginal costs. Similarly, Charnoz et al. (2018) document that the reduced travel times from HSR restructure firms, encouraging functional specialization—where remote affiliates handle production and headquarters focus on management—resulting in productivity gains. Tian and Yu (2023) find that improved domestic market integration driven by HSR significantly enhances firms' export performance, as reflected in higher export sales and volumes, broader market reach, and improved product quality. However, these firm-level gains do not consistently translate into welfare growth at the aggregate level. For instance, using reduced-form regressions, Lin (2017) finds that HSR connections have no significant effect on city-level GDP in China, while Qin (2017) reports that non-urban counties along upgraded railway lines even saw declines in GDP per capita after HSR integration. By contrast, Ahlfeldt and Feddersen (2018) finds that HSR access in Germany is linked to increases in GDP. We contribute by showing that HSR connections raise the relative demand for skilled labor through domestic outsourcing. This mechanism helps reconcile mixed findings in the

literature within a unified spatial general-equilibrium framework. Our model links HSR's productivity effects to its distributional consequences for skilled and unskilled workers, and quantifies the aggregate trade-off between efficiency gains and widening skill gaps.[4]

Second, this study contributes to the existing literature on how infrastructure investments shape the demand for skilled labor and impact inequality. Prior research demonstrates that the U.S. Interstate Highway System boosted the relative demand for skilled labor by fostering the agglomeration of trade-related activities and reducing migration costs, which disproportionately benefited skilled workers (Michaels, 2008; Cucu, 2022). Similarly, China's National Trunk Highway System raised capital intensity, which in turn increased the skill premium (Lu, 2018). Narayanan and Lebesmuehlbacher (2023) further demonstrate that the effects of capital-skill complementarity, driven by public investment, can vary depending on local labor market frictions. In Switzerland, Fretz et al. (2022) document a rise in inequality following highway construction. However, improved transportation can also expand access to education, helping reduce regional disparities by increasing the supply of skilled labor (Aggarwal, 2018; Adukia et al., 2020). Building on this, we investigate how HSR—a modern infrastructure distinct from previous developments such as highways—shapes the demand for skilled labor. We present the first reduced-form evidence that HSR increases the skill content of exports, which we explain through a general equilibrium spatial model that highlights how improved transportation enhances the outsourcing of manufacturing tasks—a key mechanism driving our empirical findings.

Our analysis reveals that the distributional effects of HSR stem from an increased capacity to outsource manufacturing tasks. This connects our findings to the broader literature on outsourcing's influence on productivity and income distribution. While productivity gains from outsourcing typically reduce demand for unskilled labor (Feenstra and Hanson, 2003; Geishecker and Görg, 2008; Keuschnigg and Ribi, 2009; Hummels et al., 2014; Acemoglu et al., 2015; Carluccio et al., 2019; Bilal and Lhuillier, 2021; Bergeaud et al., 2024), this does not necessarily lead to greater inequality among different skill groups.[5] Outsourcing also generates output effects that boost demand for core manufacturing tasks performed by unskilled labor (Wright, 2014; Bilal and Lhuillier, 2021). As goods producers employ more service workers, the marginal product of unskilled labor can increase. In our model, the

[4]HSR fosters local economic development through several channels. It heightens competition, improving airline service quality (Fang et al., 2025), stimulates growth in peripheral cities, raising property values (Zheng and Kahn, 2013), and reduces travel times, facilitating knowledge exchange and academic collaboration (Dong et al., 2020)

[5]Previous studies on productivity gains from outsourcing (Feenstra and Hanson, 1996; Amiti and Konings, 2007; Goldberg et al., 2010; Bøler et al., 2015; Halpern et al., 2015; Antras et al., 2017; Halpern et al., 2015) primarily attribute the rise in offshoring activities to reduced trade costs. In contrast, our analysis emphasizes the role of improved firm-to-firm matching efficiency as a key driver of these gains.

distributional impact of HSR depends on the interaction between outsourcing's distributional and productivity effects, which we calibrate carefully using detailed city-level economic data.

Finally, the quantitative framework of this paper builds on the recent trade literature, notably pioneered by Eaton and Kortum (2002).[6] Standard policy instruments in these models typically focus on trade costs for shipping goods or migration costs for labor movement. However, these approaches do not directly account for the improvement in firm-to-firm matching efficiency resulting from HSR connections—a critical driver of firm performance and growth, as documented by Cristea (2011), Giroud (2013), Cai and Szeidl (2017), Charnoz et al. (2018), and Bernard et al. (2019). To better capture this effect in China's economic context, we extend Eaton et al. (2016)'s framework by allowing matching efficiency to depend on both the location of the outsourcing task's origin and its destination, while introducing frictional labor mobility across regions. This adaptation quantifies the trade cost equivalent of improved matching efficiency between buyers and suppliers within a tractable model that integrates trade, migration, and outsourcing.

The paper is structured as follows: Section 2 provides an overview of China's HSR, while section 3 analyzes its causal impact on exports and skilled labor demand. Section 4 introduces a multi-regional spatial model, calibrated in section 5, with quantitative results discussed in section 6. We conclude in section 7.

2 China's HSR Network

The term "high-speed rail" refers to railways capable of supporting trains with top speeds exceeding 250 km/h. While early discussions of HSR development in China date back to the 1990s, it wasn't until 2002—when the newly appointed governor of the Ministry of Railways proposed the "Great Leap Forward" strategy—that concrete plans to expand railway capacity and introduce HSR gained traction. Prior to the construction boom in 2007, the only passenger-dedicated HSR line, connecting Qinhuangdao and Shenyang, was introduced in 2003, with a modest operating speed of 200 km/h.[7] In 2008, the State Council set ambitious targets through the *Mid- to Long-Term Railway Development Plan*, aiming to expand the traditional railway network to 120,000 kilometers and establish 16,000 kilometers of HSR,

[6] Other recent studies on this topic include Alvarez and Lucas (2007); Arkolakis et al. (2012); Hsieh et al. (2019); Di Giovanni et al. (2014); Caliendo and Parro (2015); Caliendo et al. (2017); Ramondo et al. (2016); Edmond et al. (2015), among others, with a broader literature review provided in Costinot and Rodríguez-Clare (2014). Notably, two prominent applications of these quantitative methods to China are found in the contemporaneous works of Fan (2019) and Tombe and Zhu (2019), who examine the relative importance of domestic migration and trade costs in explaining China's export performance.

[7] Technically, the Qinhuangdao-Shenyang line didn't qualify as HSR since its speed fell below the minimum criteria. Instead, it functioned as a pilot line to test the feasibility of HSR operations, as noted by Ou et al. (2014). China's earlier efforts focused on accelerating traditional trains through five waves of speed increases from 1997 to 2004, though these improvements only raised average speeds to 65.7 km/h by 2004.

forming four north-south and four east-west corridors.[8]

The *Mid- to Long-Term Railway Development Plan* set the primary objective of the HSR system as providing faster transportation links between capital cities. Most HSR lines are designed to accommodate bullet trains operating at average speeds of 350 km/h, substantially outpacing typical intercity lines (200–250 km/h, like the Guangzhou-Zhuhai Intercity Line) and traditional express routes (120–160 km/h).[9] HSR tickets are competitively priced, with second-class fares on 300–350 km/h lines averaging $0.077 per kilometer. This makes them cheaper than discounted airfare and only about three times the cost of traditional express rail, reinforcing HSR's appeal as a cost-effective travel option.[10] Notably, China's HSR fares are about one-quarter the price of comparable HSR systems in other countries. This affordability is underpinned by the system's high passenger density, strong occupancy rates, and relatively low construction and operating costs.

3 Empirical Analysis

To what extent do expanding supply chains and customer networks reshape firms' production efficiency and their demand for skilled labor? We focus on exports because they provide a cleaner gauge of production-side adjustment: external markets discipline export demand, making exports less mechanically tied to local demand shocks. Enhanced intercity transportation increases matching efficiency by lowering the cost of face-to-face interactions, facilitating the efficient creation of firm-to-firm relationships and outsourcing partnerships. This effect is particularly significant for manufacturing tasks, which often employ unskilled labor.[11] We expect HSR connections to raise city productivity, showing up as stronger exports and more skill-intensive production. Using prefecture-level cities and the staggered rollout of HSR across China, we estimate its effects on city exports and skill demand.[12]

[8]The *Mid- to Long-Term Railway Development Plan* was updated in 2015, setting targets of 175,000 kilometers for conventional rail and 45,000 kilometers for HSR by 2030. By the end of 2015, China's HSR network spanned roughly 19,000 kilometers and linked 170 cities—including virtually all provincial capitals and most cities with populations above five million. Additional background on the system's development is provided by Ou et al. (2014), Lin (2017), and Qin (2017). Appendix Figure A.1 documents the network's expansion from 2011 to 2018.

[9]For instance, the launch of the Jinghu HSR in 2011 cut travel time between Beijing and Shanghai from 13 hours to just 5, significantly boosting connectivity between these major economic hubs.

[10]Traditional express train tickets are often difficult to obtain, and the service quality is significantly lower.

[11]The suitability of a supplier's product for the buyer's needs is crucial in forming buyer-supplier linkages. Without HSR, it is less convenient for buyers (e.g., firm managers on the eastern coast of China where wages are high) to frequently travel to the supplier's location (e.g., inland China where wages are low) to ensure the quality and appropriateness of outsourced inputs.

[12]A four-layer hierarchy system governs the geographical administrative units in China. The country is first categorized into provincial units, including provinces (e.g., Jiangsu Province), autonomous regions (e.g., Tibet), and municipalities directly under the central government (e.g., Beijing, Shanghai, Chongqing, and Tianjin). Prefecture-level divisions are the second level of the administrative structure. Large prefectures are

3.1 Specification

We estimate the effect of HSR connection on city exports and on the skill content of exports using a two-way fixed effects (TWFE) specification:

$$y_{it} = \beta \, Connect_{it} + \eta X_{it} + \delta_i + \delta_t + \epsilon_{it}, \tag{1}$$

Our primary outcome variable y_{it} measures the total exports and their skill content from city i in year t. The explanatory variable of interest is a dummy variable, $Connect_{it}$, indicating whether city i was connected to the HSR network in year t. We include a vector of city control variables, X_{it}, which may affect trade and communication between producers. In addition, we include city fixed effects (δ_i) to capture time-invariant city characteristics, and year fixed effects (δ_t) to absorb nationwide business cycle fluctuations. To further account for potential regional macroeconomic shocks, we augment the regression with geographic group-by-year fixed effects $\delta_{g(i)t}$, where cities are grouped by population size: fewer than 1 million, between 1 and 10 million, and more than 10 million residents.[13] Robust standard errors are used throughout the analysis. We begin by detailing the construction of each variable and the corresponding data sources. Appendix C provides comprehensive details on all data sources. The final dataset consistently tracks 227 prefecture-level cities over time, encompassing nearly 99 percent of China's total export volume.

3.1.1 City Exports and Skill Content, y_{it}

Our dependent variable captures both the total volume of exports and their skill content. We source data on Chinese exports by product and city from the China Customs Database (2011-2018), compiled by the General Administration of Customs of China. This extensive dataset covers all Chinese import and export transactions, with each entry providing detailed information on trade values in US dollars at the eight-digit Harmonized System (HS) product level, encompassing over 7,000 products. We aggregate these data to calculate total exports, further breaking them down by exporting regime—specifically distinguishing between ordinary and processing modes—at the city-year level. In our regression analysis, city exports are logged to ensure consistency and comparability.

We measure the skill content of city-level exports from 2011 to 2018 in two steps. First,

subdivided into (autonomous) counties and county-level cities. Finally, townships or towns are at the fourth level of the administrative structure. In this study, the unit of analysis is the prefecture city. Our analysis includes the four municipalities (Beijing, Shanghai, Chongqing, and Tianjin) and provides robustness checks without these super-large cities. For details, see http://xzqh.mca.gov.cn/statistics/2018.html.

[13] Cities are grouped into three geographic categories based on population size: Group 1 includes cities with populations under 1 million; Group 2 includes those with populations between 1 and 10 million; and Group 3 includes cities with populations exceeding 10 million.

following Zhu and Trefler (2005) and Amiti and Freund (2008), we construct a product-level skill intensity measure ($SkillEmp_{p,1990}$) based on the share of college-educated workers in total employment using the 1990 Population Census. This dataset provides detailed information on individuals' industry and education, classified under the China Industrial Classification (CIC). We map CIC industries to the International Standard Industrial Classification (ISIC) and then to HS 6-digit product codes. In the second step, we compute the annual skill content of a city's exports using the aggregation formula in (2):

$$SkillContent_{it} = \sum_{p} SkillEmp_{p,1990} \times \frac{X_{ipt}}{X_{it}} \tag{2}$$

where X_{ipt} represents city i's exports of HS-6 digit product p in year t, and X_{it} denotes the total exports of city i in the same year, i.e., $X_{it} = \sum_p X_{ipt}$. An increase in $SkillContent_{it}$ indicates a rising skill content in the city's exports.

3.1.2 City Connection to HSR, $Connect_{it}$

The initial connection time of each city to the HSR network was carefully gathered through multiple sources to ensure both accuracy and comprehensiveness. Our primary reference is the "Major Events" section of the China Railway Statistical Yearbook, where we identified the documented connection dates by searching for each city's name. To enhance this dataset, we supplemented it with information from online news sources. Using Google's advanced search features, we employed specific keywords, including city names, "Dongchezu," and "Hexiehao," to pinpoint the earliest documented connection times. This dual approach allowed us to cross-verify and compile a robust dataset of HSR connection times for all cities. In our study, we focus on HSR connections established prior to 2018.[14] Using this data, we construct the policy variable $Connect_{it}$. This dummy variable equals one for periods after city i first connects to the HSR in year t, and zero otherwise.

3.1.3 Other Control Variables, X_{it}

Other city-level socio-economic variables are primarily sourced from the China City Statistical Yearbooks for the years 2011 to 2018. These variables include city-specific data on population, average income in the manufacturing and service sectors, and the number of internet users.[15] To control for the impact of tariffs on Chinese city exports, we utilize tariff

[14] As shown in Appendix Figure A.1, 65 cities were connected to the HSR network by 2011, and this number grew to 214 by 2018. The year 2014 marks a particularly notable period of expansion, with 40 additional cities joining the network.

[15] In the Yearbooks, average wages in services are slightly below those in manufacturing (Appendix Table A.1). This gap is best viewed as a classification artifact: the Yearbooks' services category is very broad and combines low-wage personal services with higher-skill business services. Our mechanism concerns the latter.

data from the WTO's Integrated Database (IDB). Let $\tau_{n,p,t}^{CHN}$ represent the tariffs imposed by country n on imports from China at the HS 6-digit product level (p) for year t. We calculate the tariff exposure for each city c as the weighted average tariff rate, using the city's initial-year product-level export shares as weights, as shown in the following equation:

$$\text{Tariff}_{it} = \sum_{n,p} \frac{X_{inp,t0}}{X_{i,t0}} \tau_{n,p,t}^{CHN} \tag{3}$$

where $X_{inp,t0}$ is city i's exports to country n for product p in 2011, and $X_{i,t0}$ denotes the total exports of city i in that year. The estimation sample covers 227 prefecture-level cities across 31 provinces in mainland China. Summary statistics for 2011–2018 are reported in Appendix Table A.1, panel (a).

3.2 Results

Table 1 presents the baseline estimates of the impact of HSR connections on a city's total exports and the skill content of its exports. Columns (1) and (2) report OLS estimates for total exports, without and with group-by-year fixed effects, respectively, both showing a significant increase in export volume following the introduction of an HSR connection. Columns (5) and (6) report the corresponding effects on the skill content of exports, indicating that HSR connections significantly raise the skill intensity of a city's export basket.

Instrumental Variable Approach The selection of nodal cities in the HSR network may not be random, as it may be influenced by the socio-economic characteristics of a city, leading to potential endogeneity issues. However, official documents from the Ministry of Railways of China indicate that the HSR grid was initially designed to connect all provincial capitals and other major cities with faster transportation, with a focus on politically significant cities. This strategic design provides an opportunity to construct a least-cost path network as an instrumental variable for actual HSR placement. To address the endogeneity issue, we construct a least-cost path (LCP) spanning tree network as an instrument variable for actual HSR placement. Since the set of cities included in the LCP network is time-invariant, we interact the LCP-based dummy with year fixed effects to generate time variation and construct a city-year-specific instrument for actual HSR connection. The validity of this instrument relies on the assumption that, conditional on city and year fixed effects and other controls, the timing of HSR arrival across cities in the LCP network is uncorrelated

As a measurement check, we compute sectoral wages using the China Family Panel Studies (CFPS) for 2010, 2012, 2014, 2016, and 2018; in the CFPS, the average log wage in services is about 0.14 log points higher than in manufacturing. Because the CFPS is available only in selected years, we rely on the City Statistical Yearbooks for our annual city panel.

Table 1: Impact of HSR Connection on City Exports and Skill Content, 2011-2018

Dependent Variable:	City Exports				Skill Content			
	(1) TWFE	(2) TWFE	(3) IV	(4) CSDID	(5) TWFE	(6) TWFE	(7) IV	(8) CSDID
$Connect_{it}$	0.043*	0.050**	0.119**	0.105**	0.094***	0.091***	0.133**	0.094**
	(0.025)	(0.025)	(0.060)	(0.045)	(0.027)	(0.028)	(0.065)	(0.047)
Observations	1,709	1,709	1,709	1,709	1,709	1,709	1,709	1,709
R-squared	0.982	0.983	-	-	0.846	0.848	-	-
City FE	Y	Y	Y	-	Y	Y	Y	-
Year FE	Y	Y	Y	-	Y	Y	Y	-
Group-Year FE	-	Y	Y	-	-	Y	Y	-
City Controls	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table reports the effects of HSR connections on export outcomes. Columns (1)–(4) present results for total city exports, while columns (5)–(8) show the corresponding effects on the skill content of exports. Columns (1) and (5) estimate the baseline two-way fixed effects model specified in equation (1) without group-year fixed effects, while columns (2) and (6) incorporate group-year fixed effects. Columns (3) and (7) instrument for HSR connections using the least-cost path spanning tree. Columns (4) and (8) employ the CSDID estimator proposed by Callaway and Sant'Anna (2021). Cities are grouped by population size: Group 1 includes cities with fewer than 1 million residents, Group 2 includes those with populations between 1 and 10 million, and Group 3 includes cities with more than 10 million residents. City-level controls include average wages in manufacturing and services, tariff rates, population size, and internet penetration. Robust standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

with unobserved determinants of export performance. A more detailed description of the spanning tree instruments can be found in Appendix D.[16]

Columns (3) and (7) of Table 1 report results using the least-cost path instrument, constructed from predicted construction costs. The first-stage F-statistic is 35.4, indicating a strong and reliable correlation between the instrument and actual HSR placements. The 2SLS estimates are modestly larger than the OLS estimates in columns (2) and (6), respectively. This difference suggests that policymakers may have prioritized HSR construction in prefectures with weaker expected export growth or limited prospects for skill upgrading, introducing a downward bias in the OLS estimates. Importantly, the IV estimates reinforce the main conclusions: HSR connections lead to a significant increase in export activity and a measurable rise in the skill content of those exports.

Addressing Bias in Staggered Adoption Settings Our empirical setting features staggered treatment adoption, as cities are connected to the HSR network at different times between 2011 and 2018. In such cases, the conventional TWFE estimator can be interpreted

[16]The approach follows the methodology of Faber (2014), with a key distinction: the objective of the HSR network, as stated in official reports, is to link all provincial capitals within a single network. In particular, the generation of the LCP involves two steps. First, we calculate the least-cost paths between all pairs of capital cities using remote sensing data on land elevation, land cover, and land use. We employ a straightforward construction cost function that increases linearly with land slope gradients and areas covered by water, wetlands, or built structures. Dijkstra's optimal route algorithm is then applied to determine the least-cost HSR paths between all bilateral destinations. In the second step, we use Kruskal's minimum spanning tree algorithm to create a single continuous network, minimizing the overall construction cost.

as a weighted average of all possible two-group difference-in-differences (DID) comparisons (Goodman-Bacon, 2021). When treatment effects vary over time or across units, this weighting may yield a so-called "bad average," potentially leading to biased or misleading inference. To address this issue, we re-estimate the baseline specification using the method proposed by Callaway and Sant'Anna (2021), commonly referred to as CSDID. This framework is designed for settings with multiple time periods and variation in treatment timing, allowing for treatment effect heterogeneity and offering alternative aggregation schemes that yield more credible and interpretable estimates. Columns (4) and (8) of Table 1 present results based on the CSDID method. The estimates consistently show that HSR connections lead to significant increases in both export volume and the skill intensity of exports. The magnitudes are closely aligned with those from the TWFE specification and the least-cost path IV approach, providing complementary evidence that reinforces the core pattern of effects identified throughout the analysis.

3.2.1 Robustness Checks

We perform a series of robustness checks, including a placebo test with processing exports, an event study for parallel trends, a sample excluding major cities, and a falsification test for unobserved shocks. All use our preferred specification with group-specific time trends.

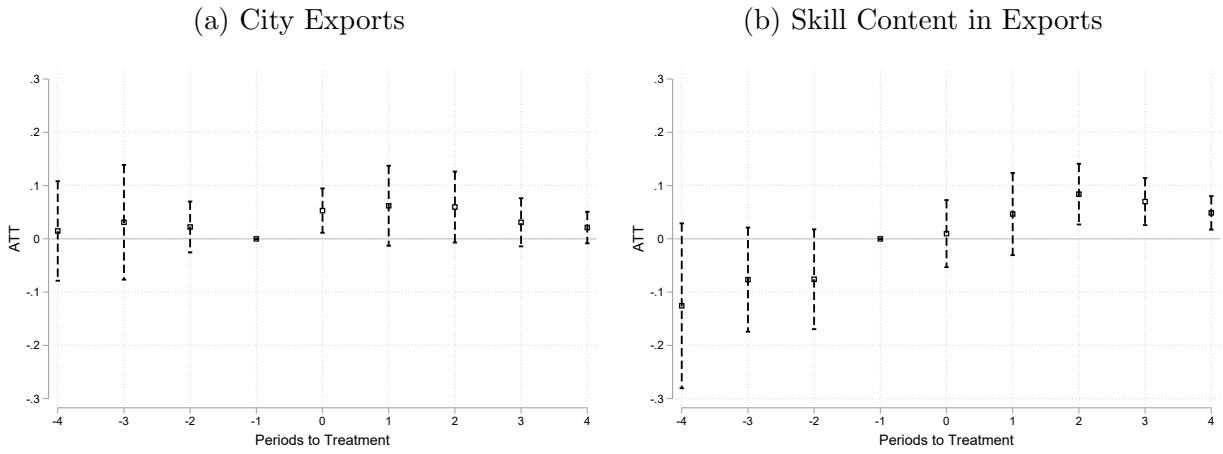
Placebo Test Using Processing Exports We separate a city's total exports into ordinary and processing trade regimes, using the latter as a placebo test. Processing exports typically involve international contract manufacturing, in which Chinese firms assemble final goods using intermediate inputs supplied by foreign partners (Kee and Tang, 2016). These operations are heavily reliant on imported materials and embedded within foreign-controlled supply chains, making them largely insulated from the domestic sourcing environment. As such, they are unlikely to benefit from improved access to domestic input suppliers enabled by HSR connections. We therefore expect no significant effect of HSR on processing exports. Appendix Table A.2 presents the results using the TWFE specification, the least-cost path IV approach, and the CSDID method. Across specifications, HSR connections robustly raise ordinary exports but leave processing-trade exports unchanged, a contrast that supports our identification strategy.

Pre-trend Test To check the parallel trends assumption, we run a variation of specification (1), incorporating the leads and lags of the initial connection dummies as controls:

$$\ln y_{it} = \sum_{m=2}^{4} \beta_m FirstConnect_{i,t-m} + \sum_{n=0}^{4} \beta_n FirstConnect_{i,t+n} + \eta X_{it} + \delta_i + \delta_t + \delta_{g(i)t} + \epsilon_{it} \quad (4)$$

where $FirstConnect_{i,t}$ is a dummy variable indicating whether city i first connected to the HSR network in year t, switching to unity only if the HSR line opens that year. The variable $FirstConnect_{i,t-m}$ represents the m-th lead, while $FirstConnect_{i,t+n}$ represents the n-th lag. Including leads controls for pre-HSR effects as a placebo, helping to distinguish anticipatory effects from actual connection impacts. Controlling for lags allows us to trace the treatment effects following the HSR's introduction. We expect anticipatory effects to be negligible for exports, with a significant positive impact expected in the lags. Figure 1 presents the results of an event study based on equation (4). The lack of significant coefficients in the pre-treatment periods supports the parallel trends assumption, indicating that prior trends in exports and skill composition were not influenced by anticipated HSR connections. For city exports, the estimated effects become positive in the year of connection, whereas for skill content, the impact emerges with a two-year lag. As a robustness check, Appendix Figure A.2 reports analogous results using the CSDID method, which yields a similar dynamic pattern.

Figure 1: Event Study of HSR Connection



Notes: The figure reports point estimates and 95% confidence intervals for both pre-treatment and post-treatment periods, based on equation (4), using city exports and the skill content of exports as the respective dependent variables.

Excluding Major Cities To ensure the estimates are not confounded by agglomeration in very large cities, we re-estimate the Table 1 specifications on a restricted sample that omits all provincial capitals, the four centrally administered municipalities (Beijing, Shanghai, Chongqing, and Tianjin), and any city with a 2011 population above ten million.[17] Columns

[17]This criterion excludes locations with pronounced pre-existing advantages—dense supplier networks, headquarters and producer services, port and logistics infrastructure, and preferential policy regimes—that

(1)–(2) of Appendix Table A.3 show that the IV coefficients remain stable and statistically significant: HSR connections continue to raise total exports and the skill content of exports, indicating that the findings do not hinge on big-city agglomeration.

Controlling for Other Modes of Transport China's highway and airline networks also expanded over our sample period, potentially facilitating interregional trade alongside HSR.[18] Because the spatial footprints of highways, air routes, and HSR may be correlated, a concern is that the HSR coefficients could partly reflect the influence of other modes. We address this by augmenting the baseline with city–year controls for air passenger traffic and for highway passenger and freight traffic, drawn from the *China Statistical Yearbook*, and re-estimating on the same restricted sample. As reported in columns (3)–(4) of Appendix Table A.3, the coefficients remain stable after adding these controls, indicating that the estimated effects are not merely proxies for concurrent expansions in other transport modes.

Measuring HSR Exposure In the baseline, treatment is a binary indicator equal to one in years when a city is connected to the HSR network. Because exposure plausibly accumulates with time since the initial connection, we replace $Connect_{it}$ with a continuous measure—the *years since first HSR connection*.[19] Under this specification, the coefficient is interpreted as the *average annual marginal effect* of HSR exposure. As reported in Columns (5)–(6) of Appendix Table A.3, city exports rise by about 2% per year after the initial connection, while the skill content of exports increases by roughly 3.6% per year—consistent with a progressively strengthening impact as integration deepens over time.

Randomization-based Test To ensure the robustness of our findings and rule out the possibility that our results are driven by unobserved stochastic trends common to both HSR connections and exports, we conduct a falsification test. In this test, we randomly reassign HSR connections across cities and replicate the TWFE specification from column (2) of Table 1 over 200 iterations. Appendix Figure A.3 shows the distribution of placebo estimates, centered around zero. Our actual estimate, marked by a vertical line, lies well

can raise exports and skill intensity regardless of HSR access. By removing these hubs, we limit the risk that the estimates load on agglomeration rents or endogenous station siting in already thriving centers, and shift identification toward margins more relevant for mid-sized cities. Our approach is related in spirit to exclusion strategies in the Chinese railroad literature (e.g., Banerjee et al. (2020)), but our objective here is to purge agglomeration-intensive locations so that the estimated effects are not conflated with pre-existing urban advantages.

[18] For clarity, see Fang et al. (2025), who show that HSR entry intensifies competition in aviation markets and is associated with measurable improvements in airline service quality (e.g., capacity adjustments and on-time performance), indicating that developments in other modes can move in tandem with HSR.

[19] If a city first connects in year t_0, the measure equals 0 for all $t < t_0$, 1 in t_0, 2 in $t_0 + 1$, and so on.

outside the 95th percentile—providing strong evidence that the observed effect of HSR on exports is not driven by chance. These findings confirm that HSR connections significantly enhance a city's ordinary exports and skill content, indicating a factor-biased transformative impact on the production structure.

3.3 Extended Analysis

We proceed to analyze the potential mechanisms behind the surge in city exports and the heightened skill content of these exports following HSR connections, focusing on whether the time-varying changes across Chinese cities are driven by improved buyer-supplier matching efficiency, which facilitated the outsourcing of manufacturing tasks, and, in turn, boosted the demand for skilled labor.

Skill Demand Columns (1) through (2) of Table 2 examine changes in the employment share of skilled workers—defined as those with education beyond high school—using data from the 2010 Population Census and 2015 1% Population Survey. The analysis adopts a long-difference specification, controlling for each city's pre-HSR employment composition. Column (1) shows that cities connected to the HSR network experienced, on average, a 0.9 percentage-point increase in the share of skilled employment between 2010 and 2015. However, this rise was not uniform. Column (2), which interacts treatment status with the initial share of skilled workers ($Skill_{i,2010}$), indicates that HSR connections disproportionately increased the skilled employment share in cities that already had a more skilled workforce, revealing a pattern of HSR-induced specialization.

Columns (3)–(4) of Table 2 analyze the impact of HSR connections on the skilled wage premium. We estimate city-year-specific skilled premiums using data from the China Family Panel Studies (CFPS), resulting in valid estimates for 224 city-year pairs.[20] The panel regression analysis indicates that HSR connections significantly raised the relative wage premium for skilled labor, widening the wage gap between skilled and unskilled workers. This finding suggests that cities connected by HSR have seen an increased demand for skilled labor relative to unskilled labor. The rise in the skill premium is consistent with a parallel shift in the occupational structure. As shown in columns (5)–(8), HSR-connected cities experienced, on average, a 0.4 percentage-point decline in manufacturing employment and a 0.5 percentage-point increase in services, with larger movements in cities that had higher

[20]The skill premium is the wage difference between skilled and unskilled workers, estimated using data from the CFPS, a nationally representative survey initiated in 2010 by the Institute of Social Science Survey at Peking University. We calculate it by regressing individual wages on a college education dummy, controlling for experience and age. The coefficient on this dummy indicates how much more skilled workers earn on average compared to their unskilled counterparts. For more details, see Appendix C.1.

baseline skill shares. Because services are typically less outsourceable and more intensive in highly educated labor, these shifts reinforce an HSR-driven specialization and a skill-biased reallocation of employment.

Table 2: High-Speed Rail, Skill Demand, and Urban Employment Structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-Difference Model		Two-Way Fixed Effects Model					
Dependent Variable:	ΔSkilledEmpShare		Skill Premium		EmpShare: Manufcturing		EmpShare: Service	
$Connect_{i,2010}$	0.009*	-0.022*						
	(0.004)	(0.011)						
$Connect_{i,2010} \times Skill_{i,2010}$		0.294**						
		(0.121)						
$Skill_{i,2010}$		-0.405***						
		(0.140)						
$Connect_{it}$			0.714***	0.497	-0.004	0.012***	0.005**	-0.008**
			(0.254)	(0.392)	(0.002)	(0.004)	(0.002)	(0.004)
$Connect_{it} \times Skill_{i,2010}$				2.452		-0.174***		0.145***
				(3.684)		(0.038)		(0.037)
Observations	276	276	217	217	1,670	1,670	1,670	1,670
R-squared	0.493	0.546	0.570	0.571	0.964	0.964	0.963	0.963
Province FE	Y	Y	Y	Y	Y	Y	Y	Y
City FE	-	-	Y	Y	Y	Y	Y	Y
Year FE	-	-	Y	Y	Y	Y	Y	Y
Group-Year FE	-	-	Y	Y	Y	Y	Y	Y
City Controls	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table reports the estimates of the impact of HSR on skill demand and occupational structure across cities. Columns (1)-(2) evaluate the impact of HSR on changes in the skilled employment share between 2010 and 2015, using a first-difference model with province-fixed effects. Columns (3)-(8) examine the effect of HSR on the skill wage premium and occupational structure from 2010 to 2018, using a two-way fixed effects model with fixed effects for cities, years, and group-years. Cities are grouped by population size: cities with fewer than 1 million residents are labeled as Group 1, those with 1 to 10 million residents as Group 2, and cities with more than 10 million residents as Group 3. City controls include average annual wage rates in the manufacturing and services sectors, tariff rates, population size, and internet coverage at the city level. Robust standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Firm Sourcing and Talent Utilization. Following Bernard et al. (2019), HSR lowers domestic search and coordination frictions, encouraging manufacturing firms to outsource more within China and thereby increasing their relative demand for skilled labor. Given data limitations, we proxy skill demand with firms' average wages. This measure is standard and, within manufacturing, tends to track shifts toward more skill-intensive tasks. Because our specification absorbs broad local wage movements, the residual wage response is naturally interpreted as within-firm changes in skill intensity.

Table 3 examines how manufacturing firms adjust after gaining HSR access. Columns (1)–(4) focus on sourcing margins. Column (1) reports the share of *business mobility expenditure* in total costs; columns (2) and (3) report the shares of domestic intermediate purchases and foreign intermediate purchases, respectively; column (4) measures average sourcing distance—defined as the cost-weighted distance to a firm's top five suppliers—using

a matched sample from the China Tax Survey and WIND.[21] The results in columns (1)–(3) indicate that firms in HSR-connected cities allocate a larger cost share to business mobility—consistent with intensified supplier search and relationship-building, increase reliance on domestic inputs, and reduce dependence on foreign suppliers—evidence of a shift toward domestic outsourcing, consistent with Kee et al. (2024). Column (4) shows that HSR also lengthens average sourcing distances within China, pointing to expanded domestic supplier networks, in line with Bernard et al. (2019). In line with the results in Table 2, columns (5)–(6) turn to talent utilization. Column (5) shows that HSR connection raises average firm wages—our proxy for skill demand—while column (6) documents a parallel increase in R&D intensity (R&D expenditures over total costs). These patterns echo Charnoz et al. (2018), who find that faster travel improves managerial efficiency and fosters functional specialization. The evidence suggests that HSR not only improves sourcing efficiency but also tilts firms toward more skill-intensive production. Overall, the evidence suggests that HSR improves sourcing efficiency and steers firms toward more skill-intensive production.[22]

Table 3: Impact of HSR on Firm Sourcing and Talent Utilization, 2011-2016

	(1)	(2)	(3)	(4)	(5)	(6)
	Firms sourcing pattern				Firms employment	
Dependent Variable:	Travel Expenses	Input Materials	Foreign Inputs	Sourcing Distance	Wage	R&D Share
$Connect_{it}$	0.001*	0.004***	-0.001***	0.300**	0.008***	0.006**
	(0.000)	(0.001)	(0.000)	(0.132)	(0.002)	(0.002)
Observations	2,559,358	2,559,358	2,559,358	650	2,559,358	121,128
R-squared	0.556	0.543	0.582	0.841	0.624	0.788
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Group-Year FE	Y	Y	Y	Y	Y	Y

Notes: The table reports the estimates of the impact of HSR connection on firm outcomes. Columns (1)–(3) examine business mobility expenditure, domestic intermediate purchases, and foreign intermediate purchases—each measured as a share of operating costs and transformed using log(x+1) transformation. Column (4) evaluates the effect on the weighted average sourcing distance to a firm's top five suppliers. Columns (5)–(6) report the effects on the firm's average wage and on R&D expenditure as a share of operating costs. All regressions incorporate fixed effects for firms, years, and group-years. Cities are categorized into three groups according to their population levels: those with populations below 1 million are labeled as 1, those with populations between 1 million and 10 million are labeled as 2, and cities with populations exceeding 10 million are denoted as 3. Other controls include employment and capital per employment at the firm level. Robust standard errors are clustered at the firm level and reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

[21] The matched sample contains 650 firm–year observations; see Appendix C.2 for construction and variable definitions.

[22] As a robustness check, we augment the specification with firm-level controls—employment and capital per worker. As reported in Appendix Table A.4, the coefficients are virtually unchanged in magnitude and significance, indicating that the sourcing and talent results are not driven by concurrent shifts in firm scale or capital intensity.

4 Quantitative Model

Motivated by this empirical evidence, we extend the firm-to-firm trade model of Eaton et al. (2016) to quantify the aggregate and distributional effects of improved firm sourcing driven by HSR network expansion. Our extension makes task outsourcing contingent on the locations of both suppliers and buyers, capturing the heterogeneous impact of HSR connections on bilateral trade patterns. We further adapt the model to a multi-region context, incorporating individual migration decisions and frictional labor mobility.

4.1 Model Environment

The economy consists of N regions indexed by $i = 1, 2, \ldots, N$, each initially endowed with two types of workers—skilled ($\bar{L}_i^W$) and unskilled ($\bar{L}_i^B$). Labor can move across regions but faces frictions discussed below. Firms require both services (e.g., management) and manufacturing tasks as inputs. Service tasks must be performed in-house, while manufacturing tasks can be outsourced.[23] Final output is used either for consumption or as an intermediate input in other firms, with the two uses non-substitutable. Firms source inputs through random matching with suppliers across regions, with match quality governed by bilateral matching efficiency. Improvements in matching efficiency (e.g., via HSR connections) enable firms to find more or better suppliers, reducing marginal costs and raising production efficiency. To capture regional disparities and mobility constraints under the Hukou system, we assume heterogeneous technology endowments and frictional labor mobility, allowing us to examine the distributional effects of HSR across regions and skill groups.

4.1.1 Producers

Technology. A firm j in location i can produce a quantity of output $Q_i(j)$ by combining two intermediate tasks: service tasks, denoted as S, and manufacturing tasks, denoted as M, according to the production function:

$$Q_i(j) = z_i(j) \prod_{k \in \{S,M\}} b_k^{-1} \left[\frac{\left(m_{k,i}(j)/\zeta_k\right)^{\zeta_k} \left(L_{k,i}/(1-\zeta_k)\right)^{1-\zeta_k}}{\beta_k} \right]^{\beta_k} \tag{5}$$

[23] While it is difficult to directly observe the outsourcability of service tasks, we provide indirect evidence supporting the assumption that such tasks are largely non-outsourcable. Drawing on the National Firm Tax Survey, we calculate the outsourcing share—defined as the ratio of outsourced materials to total costs—across sectors. Manufacturing firms outsource nearly 90% of their material inputs, whereas service-sector firms outsource only 8%, despite their greater reliance on service-intensive operations. This stark contrast supports our modeling assumption that service tasks are predominantly performed in-house. Sector classifications follow standard industry definitions, as detailed in section 5.1. While one could relax this assumption by allowing service tasks to be outsourced to a lesser extent than manufacturing tasks, such a modification would not affect the core results of the model.

where $z_i(j)$ represents producer j's Hicks-neutral productivity, $m_{k,i}(j)$ denotes the input of task k, b_k is a constant to be specified later, and β_k is the Cobb-Douglas share of task k, which satisfies $\beta_k > 0$ and $\beta_S + \beta_M = 1$. To transform the input of task k into output, an assembly worker specific to that task ($L_{k,i}$) is required. We assume that labor ($L_{k,i}$) and task input ($m_{k,i}(j)$) are aggregated under Cobb-Douglas technology, with $1 - \zeta_k$ denoting the within-task assembly worker share.[24]

Intermediate tasks can be performed either by labor appropriate for that task or by an input produced by another firm. We assume skilled labor is required for the service task, and unskilled labor for the manufacturing task. If a firm uses labor for task k, it pays the wage $w_{k,i} \equiv w_i^{l(k)}$ for labor type $l(k) \in \{W, B\}$, where $k \in \{S, M\}$. The worker productivity in performing a task, $q_{k,i}(j)$, is worker-firm specific and is drawn from an extreme value distribution to be explained later. Producer j can also source intermediate inputs from suppliers to perform the tasks. Due to search frictions, buyers match with an integer number of suppliers. Variable profit is split via Nash bargaining, with buyers having all the bargaining power, as per Eaton et al. (2016). This implies that the price of intermediate input is driven down to its unit cost. We further assume that unskilled labor and intermediate inputs are perfect substitutes for performing the tasks.

The unit cost that firm j pays to perform task k depends on the labor wage and the availability of intermediate inputs. We denote this unit cost as $c_{k,i}(j)$, which is expressed as:

$$c_{k,i}(j) = \min \left\{ \frac{w_{k,i}}{q_{k,i}(j)},\ c_{k,i}^{min}(j) \right\} \tag{6}$$

where $c_{k,i}^{min}(j)$ is the lowest price of the intermediate input available to firm j, resulting in the firm's marginal cost of delivering a unit of its output to destination n being expressed as $c_{ni}(j) = d_{ni}/z_i(j) \times \prod_{k \in S,M} \left[\left(c_{k,i}(j)^{\zeta_k} w_{k,i}^{1-\zeta_k} \right)^{\beta_k} / b_k \right]$. The iceberg transportation cost of delivering one unit of final output from i to n is denoted by $d_{ni} \geq 1$, with $d_{ii} = 1$ for all i. For model tractability, we follow the assumptions made by Eaton et al. (2016) regarding the distributions of productivity, labor productivity in performing tasks, and the distribution of intermediate input prices.

In particular, we assume that the measure of potential producers in each region i with productivity greater than z ($z_i(j) \geq z$) is given by

$$\mu_i^Z(z) = T_i z^{-\theta} \tag{7}$$

[24]Specifically, the production simplifies to $Q_i(j) = z_i(j) \prod_{k \in S,M} b_k^{-1} \left(\frac{m_{k,i}(j)}{\beta_k} \right)^{\beta_k}$ if ζ_k is set to unity, mirroring the production function proposed by Eaton et al. (2016).

where T_i represents the endowment of technology in region i, and $\theta \geq 0$ is the shape parameter governing similarities—higher values of θ imply greater similarities. Additionally, the worker productivity in performing task k in firm j, $q_{k,i}(j)$, is assumed to follow an extreme value distribution with the cumulative distribution function (c.d.f.) given by

$$F(q) = \exp(-q^{-\phi}) \tag{8}$$

where $\phi \geq 0$ reflects the similarity of workers' productivity across tasks and firms, with the restriction $\phi \leq \theta$. Given equations (7) and (8), we will later demonstrate that the measure of sellers sourcing from i with a cost below c in destination n can be derived as:

$$\mu_{ni}(c) = \Upsilon_i d_{ni}^{-\theta} c^{\theta} \tag{9}$$

where Υ_i is an endogenous variable reflecting the overall capacity of the region i, including technology level, labor market conditions, trade barriers, and the efficiency of supplier search. In contrast, the specifications of equations (7) and (8) are primitives of the model, with T_i, θ, and ϕ being exogenous parameters.

Matching with Intermediate Input Suppliers. The matching between buyers and suppliers is random, which can be interpreted as coming into contact with intermediate input suppliers and relates to the suitability of the supplier's product for the buyer's needs. The intensity with which a seller with a unit cost of c encounters a buyer in region n searching to perform task k is governed by the following equation:

$$e_{k,ni}(c) = \lambda_{k,ni} \mu_{ni}(c)^{-\gamma} \tag{10}$$

where $\mu_{ni}(c)$ denotes the measure of suppliers with a marginal cost below c, as defined in (9). The parameter γ, restricted to $\gamma \in (0, 1)$, indicates the degree of congestion caused by lower-cost suppliers. This means that as more firms offer lower costs, the likelihood of matching with an appropriate buyer decreases. The parameter $\lambda_{k,ni}$ reflects the outsourcibility of task k, which improves with an HSR connection. In our model extension, we make this outsourcibility measure dependent on the bilateral locations of both buyers and sellers, whereas in Eaton et al. (2016), it depends unilaterally on the buyer's location. This extension aims to capture the heterogeneous impact of HSR connections on bilateral trade patterns. An HSR link increases $\lambda_{k,ni}$ by facilitating buyer efforts to find and supervise sellers, ensuring the quality of intermediate inputs. Motivated by the very low outsourcing share observed in service sectors, we assume that service tasks are not outsourced, implying

$\lambda_{S,ni} = 0$. The number of quotes a buyer receives for task k at a price no greater than c follows a Poisson distribution. The expected number of quotes per buyer, represented by the Poisson parameter $\rho_{k,ni}(c)$, is calculated by aggregating over all sellers from i to n as shown in (9) and (10):

$$\rho_{k,ni}(c) = \int_0^c e_{k,ni}(x) d\mu_{ni}(x) = \frac{\lambda_{k,ni}}{1-\gamma} \Upsilon_i^{1-\gamma} d_{ni}^{-\theta(1-\gamma)} c^{\theta(1-\gamma)} \tag{11}$$

With the restriction $\gamma \in (0, 1)$, the expected number of price quotes below c increases as c grows. This means that many less-productive suppliers can perform the buyer's task, leading to a higher expected number of price quotes.

Firm j can perform task k at a cost no greater than c if both the labor cost and the lowest price quote for the intermediate input do not exceed c. The probability that firm j in region n does not encounter any suppliers offering a price lower than c for task k is given by $\prod_i \exp(-\rho_{k,ni}(c))$ according to the Poisson distribution. Conversely, the labor cost is no less than c if $w_{k,n}/q_{k,n}(j) \geq c$, and the corresponding probability is $F(w_{k,n}/c)$ as defined in (8). Assuming these two events are independent, the distribution of the lowest cost of performing task k in region n is:

$$G_{k,n}(c) = 1 - \exp\left[-\left(\sum_i \frac{\lambda_{k,ni}}{1-\gamma} \Upsilon_i^{1-\gamma} d_{ni}^{-\theta(1-\gamma)} c^{\theta(1-\gamma)} + w_{k,n}^{-\phi} c^{\phi} \right) \right] \tag{12}$$

We follow Eaton et al. (2016) by setting $\gamma \equiv (\theta - \phi)/\theta$, implying that the parameters affecting cost heterogeneity due to labor efficiency are the same as those governing heterogeneity due to intermediate inputs for a given task and buyer, thereby simplifying the cost distribution for task k as the following equation:

$$G_{k,n}(c) = 1 - exp\left(-\Xi_{k,n} c^{\phi}\right) \tag{13}$$

where

$$\Xi_{k,n} \equiv v_{k,n} + w_{k,n}^{-\phi}, \quad v_{k,n} \equiv \sum_i v_{k,ni}, \quad v_{k,ni} \equiv \frac{\theta}{\phi} \lambda_{k,ni} \Upsilon_i^{\phi/\theta} d_{ni}^{-\phi} \tag{14}$$

The endogenous parameter $\Xi_{k,n}$ captures the technological efficiency of performing task k, influenced by both labor cost ($w_{k,n}^{-\phi}$) and intermediate input efficiency ($v_{k,n}$). Lower labor costs ($w_{k,n}$) and greater overall capacity (Υ_n) in region n imply a higher level of efficiency ($\Xi_{k,n}$) for task k. Additionally, a higher matching efficiency ($\lambda_{k,ni}$) in region i corresponds to greater production efficiency for task k.

The probability that a firm outsources task k to the lowest-cost supplier is given by

$\bar{\omega}_{k,n} = v_{k,n}/\Xi_{k,n}$, while the probability of performing task k in-house by hiring workers is $1-\bar{\omega}_{k,n} = w_{k,n}^{-\phi}/\Xi_{k,n}$.[25] Unlike Eaton et al. (2016), our extended model defines the efficiency of intermediate inputs for task k in location n as the sum of bilateral efficiencies ($v_{k,ni}$, $\forall i$) from all other locations. The likelihood of outsourcing task k increases with improved bilateral matching efficiency (higher $\lambda_{k,ni}$) or higher labor costs ($w_{k,n}$).[26] Since service tasks cannot be outsourced ($\lambda_{S,n} = 0$), the labor share in these tasks is entirely one. The overall labor share in production in region i is derived as follows:

$$\beta_i^L = \sum_{k\in\{S,M\}} \beta_i^{l(k)} = \beta_S + \beta_M \left(1 - \zeta_M + \zeta_M \frac{w_{M,i}^{-\phi}}{\Xi_{M,i}}\right) \tag{15}$$

The variable $\beta_i^{l(k)}$ denotes the aggregate share of labor of type l in the total production cost in region i, defined as

$$\beta_i^{l(k)} = \beta_k \zeta_k w_{k,i}^{-\phi}/\Xi_{k,i} + \beta_k(1-\zeta_k) \tag{16}$$

Here, $w_{k,i}^{-\phi}/\Xi_{k,i}$ represents the labor share in producing intermediate inputs for task k in region i. Although the production function assumes a Cobb-Douglas form, the overall labor share is no longer constant and will depend on manufacturing wages and other factors.

Cost Distribution. We now consider the cost distribution for firm j in region i, with task-specific costs as shown in (13). The marginal cost depends on task efficiency as per (6). The expected number of firms from location i that can deliver to destination n at a cost not exceeding c is expressed in the following equation, derived in Appendix E.2:

$$\mu_{ni}(c) = T_i \Xi_i \mathbb{W}_i d_{ni}^{-\theta} c^{\theta} \tag{17}$$

where Ξ_i is an aggregation of the endogenous technology parameters $\Xi_{k,i}$ defined in (14), reflecting the efficiency gains from outsourcing. The variable $\mathbb{W}_i$ is an aggregation of labor costs. These are defined by the following equations:

$$\Xi_i \equiv \prod_{k\in\{S,M\}} (\Xi_{k,i})^{\theta\zeta_k\beta_k/\phi}, \quad \mathbb{W}_i \equiv \prod_{k\in\{S,M\}} w_{k,i}^{-\theta(1-\zeta_k)\beta_k} \tag{18}$$

[25] The detailed derivation is provided in Appendix E.1.

[26] It is important to note that the comparative statics on matching efficiency assume fixed wages and do not account for general equilibrium effects, which are fully addressed in the quantitative analysis.

Aggregating across all sourcing cities i, the measure of potential sellers in region n that can deliver a unit of goods at a cost below c is derived by the following equation:

$$\mu_n(c) = \sum_i \mu_{ni}(c) = \mathbb{Y}_n c^\theta \tag{19}$$

where the technology parameter $\mathbb{Y}_n$ is defined by $\mathbb{Y}_n \equiv \sum_i T_i \Xi_i \mathbb{W}_i d_{ni}^{-\theta}$. The expression for $\mu_{ni}(c)$ in (17) aligns with the specification in (9). From this definition, we see that the overall capacity of the region i depends on the exogenous technology endowment T_i, trade costs d_{ni}, wages $w_{k,i}$, and matching efficiency $\lambda_{k,in}$. By combining (14) and (18), we can determine the vector Υ_i by solving the fixed point of the following system of equations, in a manner similar to that employed by Eaton et al. (2016):

$$\Upsilon_i = T_i \mathbb{W}_i \prod_{k \in \{S,M\}} \left[\sum_n \frac{\theta}{\phi} \lambda_{k,in} \Upsilon_n^{\phi/\theta} d_{in}^{-\phi} + w_{k,i}^{-\phi} \right]^{\theta \zeta_k \beta_k / \phi} \tag{20}$$

In Appendix E.3, we demonstrate that Υ_i can be computed using an iterative procedure under our assumptions. Consequently, we can calculate the probability that a potential seller delivering to region n at a unit cost below c is from region i:

$$\pi_{ni} = \frac{\Upsilon_i d_{ni}^{-\theta}}{\sum_j \Upsilon_j d_{nj}^{-\theta}} \tag{21}$$

Assuming a continuum of producers, π_{ni} also denotes the share of purchases in destination n sourced from location i. In particular, when firms are prohibited from outsourcing manufacturing tasks, with $\lambda_{k,i} = 0$ for all k, and there is no requirement for within-task assembly workers, with $\zeta_k = 1$ for all k, the above trade share is consistent with the results of Eaton and Kortum (2002) and Eaton et al. (2011).[27]

Impact of HSR on the Demand for Skills. The above assumptions about technology are consistent with an aggregate production function for region i, which takes the form:

$$Q_i = L_{S,i}^{\beta_S} \left\{ \left[\left(\psi \left(L_{1M,i} \right)^{\frac{\phi}{\phi+1}} + (1-\psi) \left(I_{M,i} \right)^{\frac{\phi}{\phi+1}} \right)^{\frac{\phi+1}{\phi}} \right]^{\zeta_M} \left[L_{2M,i} \right]^{1-\zeta_M} \right\}^{\beta_M} \tag{22}$$

[27] In the scenario where $\lambda_{k,i} = 0$ for all k, and $\zeta_k = 1$ for all k, we derive $\mu_n = \sum_i T_i \left(\bar{w}_i d_{ni} \right)^{-\theta} c^\theta$, where $\bar{w}_i$ is the average wage in region i, defined as $\bar{w}_i \equiv \prod_{k \in S,M} w_{k,i}^{\beta_k}$. Consequently, the trade share of region i in market n is given by $\pi_{ni} = T_i \left(\bar{w}_i d_{ni} \right)^{-\theta} / \sum_j T_j \left(\bar{w}_j d_{nj} \right)^{-\theta}$.

where ψ is a constant defined as $\psi \equiv 1/\left[1+\Gamma(1+1/\phi)^{\phi/(1+\phi)}\right]$. The other variables are defined as follows: $L_{S,i}$ denotes skilled labor for service tasks, $L_{1M,i}$ represents unskilled labor for outsourced manufacturing tasks, $L_{2M,i}$ indicates unskilled labor for non-outsourced manufacturing assembly, and $I_{M,i}$ refers to the intermediates used in manufacturing.[28] The production function indicates that intermediate inputs and unskilled labor are substitutes in manufacturing, with their elasticity of substitution governed by $1+\phi$ ($\phi > 0$). Even with enhanced outsourcing due to HSR connections, a positive amount of unskilled labor, at least $\beta_M(1-\zeta_M)$, is always required for final output. This ensures a minimum share of unskilled labor is consistently employed, regardless of the outsourcing attractiveness.

Connecting to HSR improves firm-to-firm interactions and lowers the average cost of outsourcing intermediate manufacturing tasks, $\bar{p}_{M,i}$, given by

$$\bar{p}_{M,i} = v_{M,i}^{-1/\phi}\Gamma\left(1+\frac{1}{\phi}\right) \tag{23}$$

This cost reduction boosts total production, leading to a clear increase in demand for skilled labor. The effect on unskilled labor, however, is more nuanced. On one hand, cheaper intermediates reduce the need for unskilled workers in intermediate production ($L_{1M,i}$). On the other, lower production costs raise aggregate output, increasing demand for unskilled labor in final assembly ($L_{2M,i}$). The net impact depends on which force dominates.

4.1.2 Consumers

Workers are risk-neutral and have linear utility over a consumption index: $U_{odi} = C_{odi}$, where C_{odi} is the consumption bundle for worker i, born in region o and employed in region d. Consumption depends on service goods ($C_{S,odi}$), manufacturing goods ($C_{M,odi}$), and an idiosyncratic preference shock z_{odi}, which captures individual-specific reasons for living in a particular region. We assume that consumption of each good is destination-specific, i.e., $C_{k,odi} = C_{k,di}\ \forall k \in \{S, M\}$, and the composite good follows a Cobb-Douglas form.

$$C_{odi} = \kappa z_{odi} C_{S,di}^{\alpha_S} C_{M,di}^{\alpha_M} \tag{24}$$

where $\kappa \equiv \prod_{k\in\{S,M\}} \alpha_k^{-\alpha_k} \times a_k^{-1}$ is a constant, α_k denotes the Cobb-Douglas share of need k, with $\alpha_k > 0$ and $\alpha_M + \alpha_S = 1$, and a_k is also a constant to be explained latter in Appendix E.5. On the consumer side, our framework departs from Eaton et al. (2016) in three important ways: (i) consumers must purchase from firms to satisfy their needs, (ii) consumer-to-firm matching is distinct from firm-to-firm interactions, and (iii) consumers can

[28] The proof of the equivalence between the production side of the model and the aggregate production function is provided in Appendix E.4.

migrate across regions subject to frictions. These features are essential for analyzing HSR's impact through firm networks in the Chinese context.[29]

Consumer–firm transactions face matching frictions. Let the arrival rate at which a firm in region d charging price p meets a consumer with need k be

$$\tilde{e}_{k,d}(p) = \tilde{\lambda}_{k,d}\mu_d(p)^{-\tilde{\gamma}} \tag{25}$$

where $\tilde{\lambda}_{k,d}$ captures the efficiency of matching for need k in region d, $\mu_d(p)$ is the measure of active firms at price p (see (19)), and $\tilde{\gamma}$ reflects how lower-priced firms crowd out others in the matching process. Aggregating over all firms, the number of price quotes a consumer receives for need k below price p follows a Poisson distribution, with the Poisson parameter representing the expected number of matches:

$$\tilde{\rho}_{k,d}(p) = \int_0^p \tilde{e}_{k,d}(x)d\mu_d(x) = \frac{1}{1-\tilde{\gamma}}\tilde{\lambda}_{k,d}\mathbb{Y}_d^{1-\tilde{\gamma}}p^{\theta(1-\tilde{\gamma})} \tag{26}$$

We require $\tilde{\gamma} < 1$ to ensure that the expected number of price quotes increases with unit cost. The probability that a consumer does not encounter a firm offering a price lower than p is $\exp\left(-\tilde{\rho}_{k,d}(p)\right)$. Therefore, the price distribution for need k is expressed as:

$$\tilde{G}_k(p) = 1 - exp\left[-\tilde{v}_{k,d}p^{\theta(1-\tilde{\gamma})}\right] \tag{27}$$

where $\tilde{v}_{k,d} \equiv \frac{1}{1-\tilde{\gamma}}\tilde{\lambda}_{k,d}\mathbb{Y}_d^{1-\tilde{\gamma}}$ measures the ease with which a consumer can purchase a product at a low price. For consumers of type $l \in \{W, B\}$, the indirect utility function, considering prices for each need k (p_S and p_M), is defined as:

$$V_{odi}^l(p_S, p_M) = \frac{w_d^l}{a_S a_M p_S^{\alpha_S} p_M^{\alpha_M}} \tag{28}$$

where w_d^l is the wage of a consumer of type l in location d, defined as $w_d^B \equiv w_{M,d}$ for blue-collar and $w_d^W \equiv w_{S,d}$ for white-collar consumers. The parameter a_k removes task-specific utility effects. Given price randomness, after perceiving taste shocks z_{odi}, consumer i focuses only on the destination-specific component of indirect utility in d, denoted as $\nu_d^l \equiv E\left\{V_{odi}^l(p_S, p_M)\right\}$. The indirect utility is derived in the following equation:

$$\nu_d^l = B \times w_d^l \times \mathbb{Y}_d^{\frac{1}{\theta}} \tag{29}$$

[29] In particular, separating consumer and firm matching ensures that HSR affects only inter-firm linkages, enhancing model realism.

The first exogenous term in (29) captures how easily a consumer finds a firm to satisfy their demand, defined as $B \equiv \left[\prod_{k\in\{S,M\}} \tilde{\lambda}_k^{\alpha_k}\right]^{1/\theta(1-\tilde{\gamma})}$. This results from the assumption that $\tilde{\lambda}_{k,d}$ is common to all cities, i.e., $\tilde{\lambda}_{k,d} = \tilde{\lambda}_k$.[30] The second term, w_d^l, represents the income effect, indicating that cities with higher incomes provide greater utility for both types of workers. Additionally, $\mathbb{Y}_d$ encompasses all other factors influencing a region's amenities. All else being equal, higher levels of technology and greater matching probabilities between buyers and sellers lead to higher values of Υ_d, and consequently, higher $\mathbb{Y}_d$ and welfare levels. However, higher wages can reduce a region's attractiveness by lowering Υ_d and $\mathbb{Y}_d$, partially offsetting the income effect and decreasing overall welfare.

Migration Across Regions. Migration is modeled as a one-time decision made at birth. Following Ahlfeldt et al. (2015), we incorporate heterogeneity in workers' preferences for different locations. Upon entering the labor market, individuals draw idiosyncratic tastes for regions and choose where to live based on destination-specific indirect utility and migration costs. These costs, denoted by e_{od}^l, vary by skill type and origin-destination pair. Given their location preferences $\{z_{odi}|d = 1, 2, ..., N\}$, workers born in region o choose to live in region d to maximize welfare:

$$\max_{d\in\{1,2,..,N\}} \left\{ \frac{z_{odi}\nu_d^l}{e_{od}^l} \right\} \tag{30}$$

where $\nu_d^l = Bw_d^l \mathbb{Y}_d^{\frac{1}{\theta}}$ denote the amenity-adjusted expected real wage for a worker of type l, born in o and considering region d. Migration costs e_{od}^l capture how workers discount income from a destination, similar to iceberg trade costs. A worker i of type $l \in \{B, W\}$ chooses to migrate to region d if it offers the highest utility: $\nu_d^l z_{odi}/e_{od}^l \geq \nu_g^l z_{ogi}/e_{og}^l$, $\forall g \in \{1, 2, ..., N\}$. Following Ahlfeldt et al. (2015), the idiosyncratic taste vector z_{odi} is drawn from a Fréchet distribution with correlated regional preferences: $F(z_{1i}, z_{2i}, ..., z_{Ni}) = exp\left[-\left(\sum_d z_{di}^{-\epsilon_l}\right)^{1-\rho}\right]$ where ϵ_l governs taste dispersion for worker type l, and ρ captures the correlation of preferences across regions.[31] The resulting migration probabilities for workers of type l from origin o to destination d are derived in Appendix E.6:

$$\delta_{od}^l = \frac{(\nu_d^l/e_{od}^l)^{\epsilon_l}}{\sum_g (\nu_g^l/e_{og}^l)^{\epsilon_l}} \tag{31}$$

[30] The derivation is provided in Appendix E.5. The full expression of the first exogenous term is $B_d \equiv \left[\prod_{k\in\{S,M\}} \tilde{\lambda}_{k,d}^{\alpha_k}\right]^{1/\theta(1-\tilde{\gamma})}$. The simplifying assumption for this welfare term does not affect our main results and allows for a more streamlined expression.

[31] This specification follows Hsieh et al. (2019), Ahlfeldt et al. (2015), Bryan and Morten (2015), and Fan (2019). A lower value of ϵ_l implies more dispersed tastes. When $\rho = 0$, taste shocks are independent; when $\rho = 1$, they are perfectly correlated.

Denote L_d^l as the number of workers of type l working in d, and $\bar{L}_o^l$ as the number of workers of type l born in region o. The number of workers of type l moving from o to d is $L_{od}^l \equiv \delta_{od}^l \bar{L}_o^l$. Thus, the supply of labor of type l in region d is given by:

$$L_d^l = \sum_o L_{od}^l = \sum_o \delta_{od}^l \bar{L}_o^l \tag{32}$$

Welfare. Finally, the expected utility of a type l worker born in region o, denoted as $\bar{U}_o^l$, is derived in Appendix E.7:

$$\bar{U}_o^l = \left(M_o^l\right)^{\frac{1}{\epsilon_l}} \Gamma \left[1 - \frac{1}{(1-\rho)\epsilon_l}\right] \tag{33}$$

where $M_o^l \equiv \sum_g \left(\nu_g^l / e_{og}^l\right)^{\epsilon_l}$ measures the welfare of being born in location o. The better connected o is to other labor markets (lower e_{og}^l) and the more attractive nearby cities are (higher ν_g^l), the higher the utility for workers born in o.[32] Migration costs prevent utility equalization across regions, allowing for regional disparity analysis and policy impact assessment. The aggregate average welfare is:

$$W = \sum_{l \in \{B,W\}} \sum_{i=1}^{N} m_i^l \times \left(M_i^l\right)^{\frac{1}{\epsilon_l}} \Gamma \left[1 - \frac{1}{(1-\rho)\epsilon_l}\right] \tag{34}$$

where $m_i^l = \bar{L}_i^l / \left(\sum_{l \in \{B,W\}} \sum_{s=1}^{N} \bar{L}_s^l\right)$ is the original share of worker of type l in region i.

Finally, a competitive equilibrium is defined as a set of prices and allocations such that all agents—workers and firms—make optimal decisions and all markets clear. Workers of both skill types choose their location and consumption to maximize utility, considering wages, amenities, and migration costs. Firms determine output and sourcing to maximize profits given prices and input costs. Labor and goods markets clear in every region, ensuring that supply equals demand. These decisions jointly determine the spatial allocation of labor, expenditure, and output across the economy.[33] The detailed equilibrium conditions are

[32] The expected utility (33) doesn't depend on the destination d for workers from the same region, as their average welfare remains the same regardless of their location. Attractive destinations directly increase welfare by enhancing utility based on idiosyncratic taste, but they also attract workers with lower taste draws, balancing the average utility. With Fréchet-distributed taste shocks, these effects cancel out, making a worker's welfare depend solely on birthplace characteristics.

[33] Our Eaton–Kortum–style framework abstracts from explicit agglomeration benefits and congestion costs that may affect local welfare within a country. In principle, denser regions could experience productivity gains through knowledge spillovers, while congestion or higher living costs may offset part of these gains. However, these forces are not expected to materially alter our main quantitative implications. First, the calibration of regional matching efficiency indirectly incorporates aspects of both agglomeration and congestion—regions with thicker firm networks or larger markets naturally exhibit higher matching efficiency and lower effective

presented in Appendix E.8. To quantify the aggregate and distributional effects of HSR, we apply the exact hat algebra method to solve for relative changes in equilibrium, with the full system of equations provided in Appendix E.9.

5 Model Calibration

Before conducting counterfactual policy experiments, we first calibrate the model to the 2011 equilibrium and then analyze the impact of the HSR network expansion from 2011 to 2017.[34] The goal is to quantify the aggregate and distributional effects of HSR connections on welfare and skill disparity. Our analysis includes 101 geographic units: the top 100 export cities in China in the initial year, which together accounted for 94.4% of China's total exports, and the rest of the world. This section outlines the steps taken to calibrate the key parameters across these economic units.

5.1 Initial Equilibrium Conditions

Quantifying the model requires several key inputs, including bilateral trade shares (π_{ni}) and intermediate input shares ($v_{M,ij}/v_{M,i}$) across Chinese cities and between them and the rest of the world, inter-city bilateral migration flows by skill level (L_{od}^W, L_{od}^B), city-specific outsourcing shares ($\bar{\omega}_{M,i}$), and finally, the value-added for each task ($w_{M,n}L_{M,n}, w_{S,n}L_{S,n}$).

Trade Flows. The bilateral trade shares for the top 100 export cities in 2011 are derived from Taobao, one of China's largest e-commerce platforms. We aggregate the trade flow based on the origin and destination cities of delivery from all transaction records on the platform.[35] Since the trade flows from Taobao represent only online transactions within this platform, we scale these flows using the ratio of domestic trade to total transactions on Taobao.[36] To identify trade in intermediate inputs, we employ an estimated city-sector

production costs. Second, congestion effects are partly internalized through the equilibrium structure: as local labor demand rises, higher wages feed into the regional price index, capturing the increase in living costs associated with urban congestion. Because our welfare analysis focuses on relative changes arising from HSR-induced improvements in firm-to-firm matching and outsourcing efficiency—rather than on the full set of urban externalities. We therefore adopt a parsimonious welfare formulation that keeps the analysis transparent while remaining consistent with the calibrated spatial equilibrium structure of the model.

[34] We chose 2011 and 2017 as the beginning and ending periods for our quantitative exercises because these are the earliest and latest years for which we have inter-city bilateral trade data.

[35] Taobao consists of a Business-to-Consumer (B2C) platform (Tmall.com) and a Consumer-to-Consumer (C2C) platform (Taobao.com). Our analysis combines all transactions from both platforms.

[36] According to our estimates, based on national input-output data from the National Bureau of Statistics of China and export data from the Chinese Statistical Yearbook, the total domestic trade volume for the top 100 export cities was 68.2 trillion CNY in 2011, while Taobao's total transaction volume for those cities was 0.23 trillion CNY. This yields a ratio of domestic trade to Taobao transactions of 294. Although Taobao e-commerce data accounts for only a fraction of total trade volume, it provides a reliable lens through which

level inter-city input-output table for 2012 in China, following the methodology developed by Zheng et al. (2022), as used in Zhong et al. (2024).

Trade between Chinese cities and the rest of the world (ROW) in 2011 is calculated using China Customs Data, which provides detailed city-level export and import records by 8-digit HS code. We classify goods using the Broad Economic Categories (BEC) to differentiate between final consumption goods and intermediate inputs, aggregating them at the city level. Trade volumes within the ROW (excluding China) are obtained from the BACI trade database of 2011 (Gaulier and Zignago, 2010), which details bilateral trade flows across 200 countries at the HS 6-digit level, also aggregated into consumption and intermediate categories.

Migration Flows. Bilateral migration flows are computed using the 2010 Population Census, which provides detailed information on respondents' registered (Hukou) residence and current residence at the county (or district) level, along with their skill level. In practice, individuals with a degree above college are classified as skilled workers. We aggregate the number of migrants by origin and destination at the bilateral city level, resulting in migration flows for skilled and unskilled workers. Population data for the rest of the world are sourced from the World Bank Open Data. We assume no migration flows between Chinese cities and the rest of the world.

Outsourcing Share. The outsourcing share is calibrated based on the production costs of intermediate inputs and labor for each city. This estimation uses firm-level data on labor compensation and intermediate input purchases from the 2011 Chinese Tax Survey. Focusing on manufacturing firms, we aggregate labor and intermediate input costs at the city level and compute the outsourcing share as the ratio of intermediate input costs to the total of labor and intermediate costs. This share is approximately 90% for manufacturing firms.[37]

to observe intercity trade patterns in China. The key insight is that while the platform does not capture the absolute level of trade flows, the relative shares across city pairs closely mirror the underlying structure of trade costs and market accessibility. These bilateral trade shares therefore serve as a meaningful proxy for spatial trade frictions, especially in settings where consistent micro-level transaction data are otherwise unavailable. Similar reasoning underlies the use of e-commerce or digital platform data in prior studies such as Lin (2019) and Couture et al. (2021), which demonstrate that online transaction networks can effectively approximate traditional trade linkages in the offline economy.

[37]For comparison, the outsourcing share among service-sector firms is only 8%. We classify the following sectors as services: wholesale and retail trade; transportation, storage, and postal services; accommodation and food services; information technology services; financial services; real estate; leasing and business services; scientific research and technical services; environmental management; resident services and repairs; education; health care; culture, sports, and entertainment; and public administration and social organizations.

Value-added by Task. The value added by manufacturing and service tasks is indirectly estimated, as the contributions of skilled and unskilled labor within a firm are not directly observable. This estimation relies on inter-city trade flow data and model parameters. The labor market clearing condition in equation (A.61) uniquely determines the value added for each task. Total production for region i is calculated by summing its trade flows, while the labor value-added share for each labor type l is computed using equation (16), incorporating the calibrated outsourcing share, Cobb-Douglas shares for service and manufacturing tasks, and the proportion of assembly workers in manufacturing.

Other Model Parameters. The Cobb-Douglas share for the service (manufacturing) task is based on the 2011 value-added share of services in China, estimated at 0.44 (0.56) by World Bank Open Data. We calibrate the share of assembly workers using data from the 2012 CFPS, which provides detailed work profiles of surveyed individuals, including their wages, employment sectors, and occupations classified under the International Standard Classification of Occupations (ISCO-88). We classify individuals in the manufacturing sector as assembly workers, specifically those with 3-digit ISCO codes: 723 (Machinery mechanics and fitters), 724 (Electrical and electronic equipment mechanics and fitters), 828 (Assemblers), and 829 (Other machine operators not elsewhere classified). We aggregate wages to calculate labor costs for both assembly workers and the broader manufacturing workforce, determining the assembly worker share as the proportion of total labor costs attributed to this group. Our estimates indicate that assembly workers account for 25% of manufacturing labor costs ($\zeta_M = 0.75$), while we assume their share in the service sector is zero ($\zeta_S = 1$).

Last, we adopt some parameters from established literature. In particular, we set the shape parameter of the Fréchet distribution for firm productivity (θ) to 4, aligning with the preferred estimate from Simonovska and Waugh (2014). The matching parameter (γ) is set at 0.34, based on estimates from Eaton et al. (2022), who provide a strong foundation for this choice. For the correlation parameter (ρ) and the dispersion parameters (ϵ_B and ϵ_W) of the Fréchet distribution for workers' migration preferences, we rely on estimates from Fan (2019). These parameters are calibrated to $\rho = 0.36$, $\epsilon_B = 3.9$, and $\epsilon_W = 4.3$, as detailed in their study. A summary of the parameters used is provided in Appendix Table A.5.

5.2 Efficiency Change from HSR Connection

As the model outlines, HSR connections boost a location's ability to outsource manufacturing tasks to other regions while also making it a more attractive destination for outsourcing from other locations. These effects are captured by changes in the parameters $\lambda_{M,ni}$ and Ξ_i whenever either i or n is connected to the HSR network. Since these param-

eter changes are not directly observable, we infer the impact of HSR connections on task efficiency by combining auxiliary model equations with reduced-form estimates.

Specification of Changes in Task Efficiency. We model the effect of HSR access on task efficiency Ξ_{it} using a transparent reduced form that corresponds to a log–linear approximation around the pre-connection equilibrium:

$$\ln \Xi_{it} = \beta \, Connect_{it} + \mu_i^{\Xi} + \delta_t^{\Xi} + \varepsilon_{it}^{\Xi}. \tag{35}$$

where μ_i^{Ξ} absorbs time-invariant city fundamentals (including the initial level $\mu_i^{\Xi} \equiv \ln \Xi_{it_0}$), and δ_t^{Ξ} captures common shocks. The coefficient β is interpreted as the average change in (log) task efficiency associated with HSR connection. The identifying assumption is that, conditional on city and time fixed effects, idiosyncratic shocks—including technology shifts across locations—are orthogonal to variation in $Connect_{it}$.[38]

Specification of Technological Change. To account for the technological changes that occur during the expansion of the HSR network, we assume that a city's overall technological progress is governed by the following law of motion:

$$\ln T_{it} = \delta_i^T + \delta_t^T + \eta Z_{it} + \epsilon_{it}^T \tag{36}$$

where δ_i^T captures time-invariant factors specific to each city, and δ_t^T represents time-varying shocks that are common across all cities. The vector Z_{it} includes city-level control variables, such as population and access to ICT facilities. The term ϵ_{it}^T accounts for random shocks that are unique to each city and vary over time.

Parameterization of Foreign Trade Costs. We parameterize the trade cost $d_{ROW,it}$ as follows:

$$\ln d_{ROW,it} = \delta_i^d + \delta_t^d + \xi \times Tariff_{it} + \epsilon_{it}^d \tag{37}$$

where δ_i^d accounts for time-invariant trade barriers, such as a city's geographical distance from global markets, and δ_t^d captures time-varying factors, including global economic conditions or shifts in international trade policies that impact all cities. The term $Tariff_{it}$ represents

[38] We view (35) as a practical, local log–linear approximation rather than a strong functional–form commitment. It provides a first–order representation of potentially non-linear links from access to efficiency, so inference does not hinge on global functional forms. Identification rests on within-city changes relative to economy-wide trends, with time-invariant fundamentals and common shocks absorbed by μ_i^{Ξ} and δ_t^{Ξ}. In extensions, $Connect_{it}$ can be replaced by exposure intensity (years since first connection) with the same interpretation per unit of exposure.

the tariff rate specific to city i in year t, while ϵ_{it}^d captures all other idiosyncratic shocks affecting a city's trade costs when exporting to foreign markets.

Consistency with Reduced Form Regression. Returning to the model, the total exports of city i at time t are expressed as $y_{it} = \pi_{ROW,it} \times X_{ROW,t}$, where $\pi_{ROW,it}$ represents the share of city i in the total expenditure of the ROW (i.e., $X_{ROW,t}$). According to (21), the logarithm of city exports can be written as:

$$\ln y_{it} = \ln \Xi_{it} + \ln T_{it} + \ln \mathbb{W}_{it} - \theta \ln d_{ROW,it} + \delta_t^X \tag{38}$$

where δ_t^X is a time trend term defined as $\delta_t^X \equiv \ln X_{ROW,t} - \ln \sum_j \Upsilon_{j,t} d_{ROW,jt}^{-\theta}$. The labor cost parameter $\mathbb{W}_{it}$ is given by $\ln \mathbb{W}_{it} \equiv \gamma_M \ln w_{M,it} + \gamma_S \ln w_{S,it}$, where $\gamma_k = -\theta(1-\zeta_k)\beta_k$ for $k \in \{M, S\}$. Hence, by combining equations (35) to (37), we can rewrite (38) as follows:

$$\ln y_{it} = \beta \times Connect_{it} + X_{it}'\Gamma + \delta_i + \delta_t + \epsilon_{it} \tag{39}$$

where $\delta_i = \ln \Xi_{it_0} + \delta_i^T - \theta\delta_i^d$ and $\delta_t = \delta_t^\Xi + \delta_t^T + \delta_t^X - \theta\delta_t^d$ captures the city- and time-fixed effect, respectively; the variable $X_{it} = \{Z_{it}, \ln \mathbb{W}_{it}, Tariff_{it}\}$ includes relevant covariates, and the error term $\epsilon_{it} = \epsilon_{it}^\Xi + \epsilon_{it}^d - \theta\epsilon_{it}^d$ is the white noise. The OLS reduced-form regression precisely reflects the model-implied estimation equation for HSR's impact. By matching the empirical specification in equation (1), we recover the change in task efficiency due to HSR connections as $\hat{\Xi}_i = \exp(\hat{\beta} \times Connect_i)$. We use the IV estimate of β, valued at 0.119, as reported in column (2) of Table 1.

5.3 Other Technology Shock

In addition to the gains in production efficiency from improved supplier access via the HSR network, other technological changes may also impact the overall production efficiency parameter. To account for these factors, we estimate the changes in the endogenous variable that reflects the location's overall capacity ($\hat{\Upsilon}_i$), capturing both the effects of HSR and any additional technological shocks.

Parameterization of Domestic Trade Costs. To do this, we first calibrate the bilateral domestic trade costs between Chinese cities. Our approach follows Fan (2019), using bilateral trade flow data aggregated from Taobao. We parameterize the trade cost from city i to city j as follows:

$$\ln d_{ij} = \sum_{k=1}^{3} \beta_k I_{ij}^k + \sum_{k=1}^{3} \beta_{k+3} \times I_{ij}^k \times \ln Dist_{ij} + \mu_{ij} \tag{40}$$

where I_{ij}^1, I_{ij}^2, and I_{ij}^3 classify whether cities i and j are in the same province, in different provinces with a shared boundary, or in different provinces without a shared boundary, respectively. These mutually exclusive dummy variables capture structural differences in trade barriers across regions. The variable $Dist_{ij}$ represents geographic trade barriers, measured as the great-circle distance between i and j.

Estimating Overall Efficiency Change with Fixed Effects. We take the trade share from (21), dividing π_{ij} by π_{ii} and taking the logarithm. Substituting the specification for bilateral domestic trade costs from (40) gives us the following equation:

$$\ln \frac{\pi_{ij}}{\pi_{ii}} = \sum_{k=1}^{3} \tilde{\beta}_k I_{ij}^k + \sum_{k=1}^{3} \tilde{\beta}_{k+3} \times I_{ij}^k \times \ln Dist_{ij} + \underbrace{\ln \Upsilon_j - \ln \Upsilon_i}_{\text{Fixed Effects}} + \epsilon_{ij} \tag{41}$$

We estimate the regression with origin ($\ln \Upsilon_j$) and destination ($\ln \Upsilon_i$) dummies to obtain annual fixed effects. We then recover $\hat{\Upsilon}_j$ as the ratio of the fixed effects for 2017 to those for 2011.[39]

6 Quantitative Results

With estimated parameters, we use the quantitative model as the laboratory to study the aggregate and distributional effects of HSR placement in a period between 2011 and 2017.[40] We first present results showing the performance of the model at predicting key data moments, then conduct various policy experiments.

6.1 Model Fit

We begin by assessing the model's ability to replicate key macroeconomic patterns. Appendix Figure A.5 compares model-predicted changes in key outcomes from 2011 to 2017—driven by overall efficiency changes ($\hat{\Upsilon}_i$)—with those observed in the data. Panel (a) plots predicted versus actual city-level export growth, with each point representing a city. The fitted line has a slope of 0.22 (t = 2.574), indicating a statistically significant correlation and suggesting the model captures meaningful variation in export performance. Panel (b) compares predicted changes in bilateral inter-city trade flows with Taobao data, yielding a slope of 0.61, showing a similarly strong correlation. Panel (c) examines changes

[39] Estimation results are provided in Appendix Table A.6, and Appendix Figure A.4 displays the distribution of $\hat{\Upsilon}_j$ across cities. These estimates reflect shifts in broader economic conditions, including technological advancements ($\hat{T}$) and improved outsourcing capabilities in manufacturing due to HSR connections ($\hat{\lambda}$).

[40] Using the estimated parameter change, $\hat{\Upsilon}_i$, which accounts for all possible shifts in technology and outsourcing capabilities driven by HSR, we solve for changes in other endogenous variables through the system of equations detailed in Appendix E.9.

in export skill content—measured as skilled workers per unit of export sales—while panel (d) evaluates shifts in cities' outsourcing shares. Overall, the model closely tracks actual changes in each case, reinforcing its ability to explain observed patterns in skilled labor demand and outsourcing behavior.

6.2 Aggregate Impact of HSR

Welfare Effect. Welfare gains from HSR are calculated by solving the system of equations in Appendix equation (A.62). To isolate the gains from HSR expansion, we compare China's equilibrium before and after HSR implementation, holding technological conditions constant between 2011 and 2017. Welfare is measured by compensating variation as a percentage of 2011 GDP, with findings shown in column (1) of Table 4. HSR connectivity yields a 3.4 percent increase in national welfare, though these gains are unevenly distributed across cities. Skilled labor benefits significantly, with a welfare increase of 5.09 percent, while unskilled labor faces a decline of 0.62 percent. The decline in unskilled workers' welfare arises from lower intermediate task costs due to HSR connectivity. Enhanced matching efficiency boosts task outsourcing and reduces demand for unskilled labor, harming their welfare.

Table 4: Welfare Impact of HSR Connection (2011-2017)

Specification	(1) HSR ($\hat{\lambda}$)	(2) HSR + Technological Change ($\hat{\lambda}$+$\hat{T}$)	(3) HSR Contribution: (1)/(2)
Unskilled Worker	-0.62%	9.20%	-6.78%
Skilled Worker	5.09%	14.12%	36.02%
Whole Population	3.40%	12.67%	26.82%

Notes: The table illustrates the percentage changes in welfare attributable to HSR connectivity ($\hat{\lambda}$) and the broader effects of improvements in economic conditions, including both technological advancements ($\hat{T}$) and improved outsourcing capabilities from HSR ($\hat{\lambda}$). Column (3) highlights the contribution of enhanced matching efficiency due to HSR, relative to the broader economic shifts.

Column (2) of Table 4 presents the welfare change accounting for technological advancements ($\hat{T}$) and enhanced outsourcing from HSR ($\hat{\lambda}$). The total welfare gain is estimated at 12.67 percent, with skilled labor benefiting more significantly at 14.12 percent compared to 9.2 percent for unskilled labor. Column (3) quantifies HSR's contribution to the overall welfare changes noted in column (2). HSR accounts for about 26.82% of the total welfare gain overall from 2011 to 2017, with a more significant impact on skilled workers, who see around 36% of the welfare increase attributed to HSR. Conversely, unskilled workers experience a negative welfare change relative to overall economic improvements.

Impact on Matching Efficiency. We also estimate changes in firm-to-firm matching efficiency across cities, assuming that bilateral efficiency can be expressed as the product of

unilateral terms: $\lambda_{M,ni} = \lambda_{M,n} \times \lambda_{M,i}$. While these estimates are not required to compute welfare effects, this parameterization offers a transparent way to recover changes in matching efficiency ($\hat{\lambda}$), as detailed in Appendix E.10. Appendix Figure A.6 maps the results, while Appendix Figure A.7 shows histograms comparing cities with and without HSR access by 2017. In non-HSR cities, the average $\hat{\lambda}$ remains near 1, implying no meaningful change. By contrast, HSR-connected cities exhibit a significant increase, with an average $\hat{\lambda}$ of 1.23. A t-test confirms this difference is statistically significant (T = –55).

The improved matching efficiency between buyers and suppliers facilitated by HSR connections reduces the cost of outsourcing intermediate inputs, making outsourcing a more attractive option for firms compared to hiring local unskilled workers. Appendix Table A.7 summarizes the reduction in intermediate input costs resulting from the introduction of HSR.[41] Overall, the HSR connection lowers the cost of intermediate inputs, equivalent to a 9.28 percent reduction in iceberg trade costs. Appendix Figure A.8 shows that the savings are most pronounced in coastal cities, consistent with their higher productivity, denser supplier networks, and network externalities from proximity to other connected hubs.

Impact on Technology, Intra- and International Trade. To what extent does improved matching efficiency contribute to a city's overall technological efficiency? We explore this question using a variance decomposition approach to evaluate HSR's impact on regional technology, city exports, and inter-city trade within China. We follow the method of Eaton et al. (2004), regressing each outcome variable under a counterfactual scenario with only matching efficiency changes against the corresponding outcomes under a scenario that incorporates all changes in economic fundamentals. This enables us to isolate and quantify the specific contribution of improved supplier-buyer connections relative to broader economic trends, which are reported in Appendix Table A.8. According to our estimates, HSR explains 44% of the technological changes across cities from 2011 to 2017 and 56% of the variations in city exports. However, HSR accounts for a relatively smaller proportion—25%—of the total variation in domestic trade flows among Chinese cities.[42] Nonetheless, the significant proportions explained by HSR in other areas highlight its transformative role in shaping China's economic landscape.

[41] We calculate the average unit cost of intermediate inputs sourced from region i derived in Appendix E.4, which is proportional to $v_{M,i}^{-1/\phi}$.

[42] The smaller impact on domestic trade could be attributed to the fact that domestic trade patterns are influenced by a broader set of factors, such as existing logistics networks, regional trade policies, and varying levels of industrial specialization across cities.

6.3 Distributional Impact of HSR

Skill-biased Impact of HSR Connections. The benefits of HSR connectivity are unevenly distributed across regions. Figure 2a shows the geographic variation in welfare changes, with warm tones indicating gains and cool tones reflecting losses. Provincial capitals capture the largest benefits—Beijing leads, followed by Wuhan, Changsha, and Shenyang. While some unconnected cities gain modestly through spillovers, several regions—including parts of Shandong, Hebei, Henan, and Xinjiang—see net welfare declines.

To unpack the distributional effects, Figures 2b and 2c present welfare changes by skill group. Gains are concentrated among skilled workers, while unskilled workers see limited improvements and, in some east coast regions, even losses. This divergence is reflected in the rising skill premium, shown in Figure 2d and detailed in Appendix Table A.7. On average, skilled workers gain 4.51% in welfare, while unskilled workers experience a 0.67% loss, resulting in an average skill premium increase of 5.01%. By lowering coordination costs, HSR makes domestic outsourcing easier, shifting routine, labor-intensive tasks to lower-cost locations. Core cities therefore tilt toward skill-intensive activities, increasing the demand for skilled labor and widening the wage gap between skilled and unskilled workers.

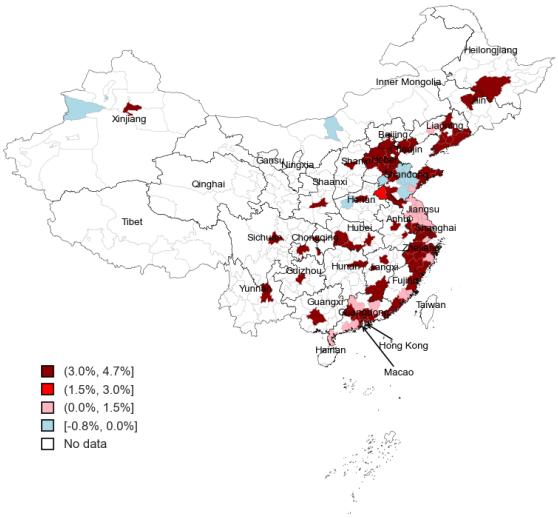
Overall Inequality. The skill-biased impact of HSR has significantly intensified regional inequality, with the overall Theil index rising by 1.5%, largely due to the uneven spatial distribution of skilled labor. To quantify this effect, we decompose the Theil index into within-city and between-city components, as well as within-skill and between-skill components. Panel (a) of Table 5 shows that 57.4% of the total increase in inequality following HSR integration is attributable to between-city disparities. Panel (b) further decomposes the changes by skill type and confirms that between-city variation remains the dominant source of rising inequality, with within-skill differences accounting for 56% of the overall increase. These patterns suggest that HSR infrastructure disproportionately benefits regions with greater concentrations of skilled labor, exacerbating inequality both across cities and within the workforce.

6.4 The Role of Domestic Trade and Migration Costs

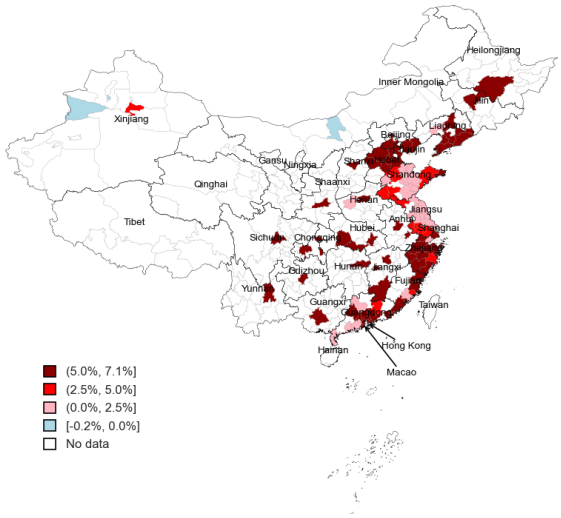
Thus far, we've shown that HSR improves welfare but widens the income gap between skilled and unskilled workers. We now investigate how domestic migration and trade costs shape HSR's impact on welfare and inequality. This analysis seeks to inform policies that sustain HSR's benefits while addressing its unequal effects.

Figure 2: Changes in Welfare by Skill Type and in Skill Premium across Chinese Cities

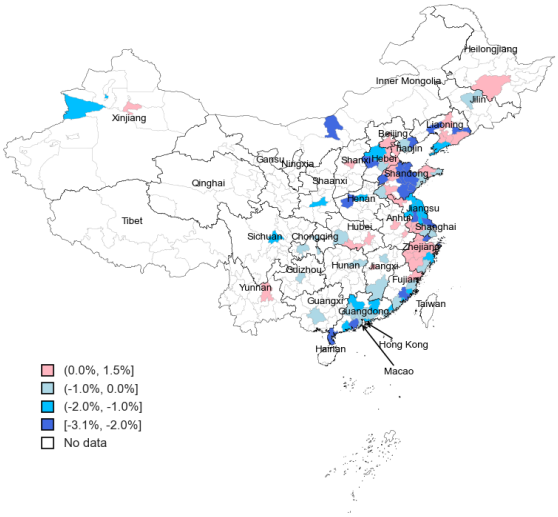
(a) Overall Welfare Change



(b) Welfare Change for Skilled Workers



(c) Welfare Change for Unskilled Workers



(d) Change in Skill Premium

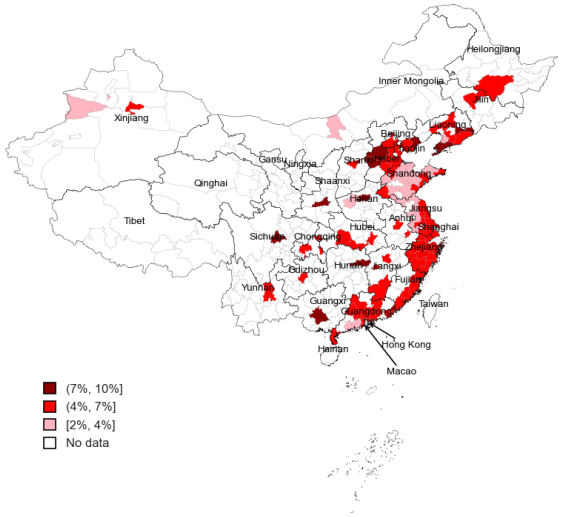


Table 5: Impact of HSR on Inequality

Part (a): Inequality across Cities	Within-city Theil	Between-city Theil	Overall Theil Index
NO HSR Connection	0.390	1.272	1.662
HSR Connection	0.400	1.286	1.686
Percentage Change in Inequality	2.7%	1.1%	1.5%
Relative Contribution to Theil Index Change	42.6%	57.4%	100.0%
Part (b): Inequality by Skill Type	**Within-skill Theil**	**Between-skill Theil**	**Overall Theil Index**
NO HSR Connection	1.278	0.383	1.662
HSR Connection	1.292	0.394	1.686
Percentage Change in Inequality	1.1%	2.8%	1.5%
Relative Contribution to Theil Index Change	55.4%	44.6%	100.0%

Notes: Part (a) presents the decomposition of the Theil index into within-city and between-city components for economies with and without HSR connections. Part (b) repeats this decomposition, but across different worker skill types.

Labor Mobility. We first assess how HSR's effects vary with labor mobility, holding all other model parameters fixed. Migration costs are scaled from 0.7 to 1.3 relative to their calibrated baseline. Panel (a) of Appendix Figure A.10 shows that higher migration costs lead to greater wage dispersion across regions. This, in turn, strengthens firms' incentives to outsource tasks to low-wage areas rich in unskilled labor, boosting local demand and welfare for unskilled workers. Conversely, when labor is more mobile, wage differentials shrink and outsourcing incentives weaken, dampening unskilled workers' relative gains. Panel (b) illustrates how inequality responds. As outsourcing intensifies under higher migration frictions, unskilled wages rise in low-cost regions, narrowing within-city inequality. However, this also sharpens inequality between cities, as welfare gains become concentrated in areas with more unskilled labor. Nationally, welfare exhibits a U-shaped pattern: unskilled workers benefit more when wage gaps are larger, while skilled workers benefit when regional differences are smaller and outsourcing is less pronounced.[43]

Domestic Trade Costs. We next examine how trade frictions interact with HSR's effects. Varying trade costs between 0.7 and 1.3, Panels (c) and (d) of Appendix Figure A.10 show that the welfare impact of HSR rises with trade costs. When shipping costs are high, HSR delivers larger cost savings by improving matching efficiency and encouraging supplier entry—especially in settings where outsourcing is initially limited.[44] As trade costs rise, outsourcing intensifies, shifting production toward tasks that rely more on skilled labor. This

[43]Panel (a) of Appendix Figure A.11 illustrates how higher migration barriers increase outsourcing from skill-intensive to labor-abundant cities.

[44]Panel (b) of Appendix Figure A.11 shows that the share of outsourcing rises with trade costs, reflecting HSR's amplified impact when frictions are high.

raises the relative demand for skilled workers while limiting opportunities for the unskilled, leading to diverging welfare outcomes: gains for the skilled, losses for the unskilled. The result is a rise in overall inequality, driven primarily by within-city differences across skill groups, as captured by the increasing Theil index.

6.5 Towards Optimal Placement of HSR Hubs

While our results show that HSR investments generated sizable gains—raising compensating variation by 3.4 percent of 2011 GDP—it remains unclear whether the network reflects an efficient allocation of hubs. Without detailed segment-level cost data, designing a globally optimal network is difficult. Still, our framework reveals potential inefficiencies by asking: given the number of stations built between 2011 and 2017, which cities should have been prioritized to maximize welfare?

We solve a social planner's problem that selects 71 out of the top 100 export cities, consistent with our quantitative sample, to receive HSR access in order to maximize aggregate welfare. Each connected city is assumed to experience a 12.7 percent boost in task efficiency, based on our baseline estimates, and the welfare effects are computed using the general equilibrium framework outlined in section E.9. We implement the optimization using the Simulated Annealing algorithm (Henderson et al., 2003), and as a robustness check, we also apply a greedy algorithm that iteratively adds the most beneficial city at each step (Cormen et al., 2022). Full computational details are provided in Appendix E.11. Both methods converge to the same optimal network configuration, which delivers a welfare gain of 3.78 percent, which is 0.38 percentage points higher than the gain under the actual HSR network.

Figure A.9 compares the actual HSR network with the welfare-maximizing design. Cities fall into four groups: connected in both (dark red), unconnected in both (dark blue), newly connected under the optimum (light red), and disconnected under the optimum (light blue). The map shows that the welfare-maximizing network would reallocate connectivity across space, implying a different geographic pattern of access than the realized system. In particular, it suggests expanding HSR access in coastal provinces such as Jiangsu and Shandong, where high firm productivity and a dense skilled labor force amplify the benefits of improved connectivity. Conversely, it recommends reducing HSR coverage in parts of Hebei province—despite their current inclusion in the network—reflecting a divergence between political or regional development goals and welfare-based priorities.[45] Furthermore, of the 18 cities that would gain HSR access under the welfare-maximizing configuration, 15 are missing from the least-cost network constructed in Appendix D. The gap highlights that

[45]This discrepancy likely reflects the influence of administrative and political objectives—particularly the coordinated development strategy of the Jing-Jin-Ji region—which may prioritize regional balance and integration over purely efficiency-driven placement.

connecting these cities would raise aggregate welfare, but they were likely bypassed because construction costs were too high. The same pattern supports the least-cost-path instrument, suggesting that HSR placement is shaped by plausibly exogenous construction costs rather than local economic potential. Overall, we find that the actual HSR network performs remarkably well—achieving approximately 90 percent of the welfare gain under the optimal configuration, conditional on the same number of hubs.

7 Conclusion

Improved firm-to-firm matching can accelerate the outsourcing of manufacturing tasks, shifting labor demand toward skilled workers. This paper examines how high-speed rail—a modern infrastructure investment that enhances business travel—reshapes firm-to-firm connections and, in turn, drives both aggregate and distributional changes across Chinese cities.

Our first contribution is to show that HSR improves production networks by enabling more frequent and efficient interactions between firms, reshaping firm boundaries, and driving production efficiency gains, a pattern consistent with Bernard and Moxnes (2018). What is novel in our findings, however, is that this improvement not only bolsters a city's export performance but also significantly transforms trade patterns, as reflected in a notable increase in the skill content of exports. These changes in trade dynamics are accompanied by substantial shifts in the relative demand for different types of labor—an effect not previously documented in the literature. The effects are long-lasting. Connected cities see faster wage growth, greater R&D intensity, and a growing skill premium. These outcomes point to a structural shift in local labor markets toward higher skill intensity, reinforcing the link between infrastructure and human capital demand.

To move beyond reduced-form evidence, we develop a spatial general equilibrium model with frictional trade, labor mobility, and endogenous outsourcing. The model captures both the displacement of unskilled labor through outsourcing and the offsetting gains from output expansion. A key innovation is the use of city-to-city transaction data from the Taobao platform, which provides a high-resolution view of China's domestic trade flows and production geography. Quantitatively, improved firm linkages through HSR are equivalent to a 9.28 percent reduction in trade costs and account for more than a quarter of total welfare gains in the aggregate. These gains are unevenly distributed: coastal cities benefit more because they are more skill- abundant, widening regional inequality. We also find that the existing HSR network still delivers nearly 90 percent of the welfare gains attainable under an optimal hub configuration. The welfare-maximizing design favors dynamic coastal regions over politically prioritized areas around Beijing, revealing a trade-off between economic efficiency and policy-driven infrastructure placement.

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A Table Appendix

Table A.1: Descriptive Statistics

Variable	Unit	Num. Obs.	Mean	Std	Min	Max
Panel (a): City-level						
City exports (Log)	CNY	1,816	23.09	1.89	15.33	28.38
Skill content in exports	100%	1,816	0.08	0.11	0.01	0.99
Wage rates in manufacturing sector (Log)	CNY	1,732	12.98	0.45	11.63	14.87
Wage rates in service sector (Log)	CNY	1,732	12.73	0.49	10.66	14.27
Population (Log)	-	1,736	15.24	0.65	12.18	17.34
Number of internet users (Log)	-	1,716	13.51	0.87	10.76	16.55
Tariff rate	100%	1,816	1.06	0.03	1.00	1.51
Panel (b): Firm-level						
Input Materials (Log)	CNY	3,428,840	6.59	3.68	0.00	20.69
Foreign Inputs (Log)	CNY	196,926	8.15	2.89	-1.11	19.80
Sourcing distance (Log)	Km	703	6.04	1.35	2.88	8.09
Wage rate (Log)	CNY	3,788,085	3.29	1.03	-11.49	13.39
R&D expenses (Log)	CNY	195,509	7.35	2.47	-1.11	16.84
Capital labor ratio (Log)	-	3,692,657	3.41	2.23	-11.62	19.38
Employment (Log)	-	4,193,199	3.36	1.73	0.00	33.43

Notes: All variables are presented in logarithmic form, with the exception of skill content and tariff rates.

Table A.2: Robustness: Placebo Test Using Processing Exports

Dependent Variable:	Ordinary Exports			Processing Exports		
	(1) TWFE	(2) IV	(3) CSDID	(4) TWFE	(5) IV	(6) CSDID
$Connect_{it}$	0.048*	0.111*	0.114**	0.001	0.258	-0.111
	(0.025)	(0.061)	(0.044)	(0.114)	(0.272)	(0.272)
Observations	1,709	1,709	1,709	1,709	1,709	1,709
R-squared	0.982	-	-	0.877	-	-
City FE	Y	Y	-	Y	Y	-
Year FE	Y	Y	-	Y	Y	-
Group-Year FE	Y	Y	-	Y	Y	-
City Controls	Y	Y	Y	Y	Y	Y

Notes: The table reports the results of a placebo test using processing exports. Columns (1)–(3) show the impact of HSR connections on ordinary exports, while columns (4)–(6) present the corresponding estimates for processing exports. Columns (1) and (4) use the two-way fixed effects model. Columns (2) and (5) instrument HSR connections using the least-cost path spanning tree. Columns (3) and (6) report estimates based on the CSDID method proposed by Callaway and Sant'Anna (2021). Cities are grouped by population size: Group 1 includes cities with fewer than 1 million residents; Group 2 includes those with populations between 1 and 10 million; and Group 3 includes cities with more than 10 million residents. City-level control variables include average annual wages in the manufacturing and services sectors, tariff rates, population size, and internet coverage. Robust standard errors are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Robustness: Big-City Exclusion, Transport-Mode Controls, and Treatment Intensity

	(a): Exclude Major Cities		(b): (a) + Transport Mode Controls		(c): (a) + Years Since HSR Connection	
Dependent Variable:	(1) Export	(2) Skill Content	(3) Export	(4) Skill Content	(5) Export	(6) Skill Content
$Connect_{it}$	0.109*	0.156**	0.132**	0.172**	0.020*	0.036***
	(0.064)	(0.074)	(0.063)	(0.074)	(0.012)	(0.013)
Observations	1,440	1,440	1,440	1,440	1,440	1,440
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Group-Year FE	Y	Y	Y	Y	Y	Y
City Controls	Y	Y	Y	Y	Y	Y

Notes: The table re-estimates the baseline IV specification on a restricted sample that excludes all provincial capitals, the four centrally administered municipalities (Beijing, Shanghai, Chongqing, Tianjin), and any city with a 2011 population above ten million to mitigate big-city agglomeration concerns. Panel (a), columns (1)–(2) report effects on total exports and the skill content of exports. Panel (b), columns (3)–(4) build on panel (a) by adding city–year controls for other transport modes—air passenger traffic and highway passenger *and* freight traffic—from the *China Statistical Yearbook*. Panel (c), columns (5)–(6) build on panel (a) by replacing the staggered connection dummy $Connect_{it}$ with a continuous exposure measure, *Years Since HSR Connection*, defined as the cumulative number of years since a city's first HSR link (coded 0 prior to connection); coefficients are interpreted as average annual marginal effects. All specifications include city fixed effects, year fixed effects, and group–year fixed effects. City controls include manufacturing and services wages, tariff rates, total population, and internet coverage. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Impact of HSR on Firm Sourcing and Talent Utilization: Adding Firm Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Firms sourcing pattern					
Dependent Variable:	Travel Expenses	Input Materials	Foreign Inputs	Sourcing Distance	Wage	R&D Share
$Connect_{it}$	0.001*	0.003***	-0.001***	0.719**	0.016***	0.005**
	(0.000)	(0.001)	(0.000)	(0.277)	(0.002)	(0.002)
Observations	2,340,310	2,340,310	2,340,310	181	2,340,310	120,227
R-squared	0.566	0.548	0.583	0.899	0.641	0.790
Firm-level Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Group-Year FE	Y	Y	Y	Y	Y	Y

Notes: The table reports the estimates of the impact of HSR connection on firm outcomes with firm-level controls including employment and capital per workers. Columns (1)–(3) examine business mobility expenditure, domestic intermediate purchases, and foreign intermediate purchases—each measured as a share of operating costs and transformed using log(x+1) transformation. Column (4) evaluates the effect on the weighted average sourcing distance to a firm's top five suppliers. Columns (5)–(6) report the effects on the firm's average wage and on R&D expenditure as a share of operating costs. All regressions incorporate fixed effects for firms, years, and group-years. Cities are categorized into three groups according to their population levels: those with populations below 1 million are labeled as 1, those with populations between 1 million and 10 million are labeled as 2, and cities with populations exceeding 10 million are denoted as 3. Other controls include employment and capital per employment at the firm level. Robust standard errors are clustered at the firm level and reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Summary of Key Parameter Calibration in the Model

Parameter	Description	Source / Target	Value
π_{ni}	Trade in final goods	Taobao, Chinese Customs Data, BACI Trade	
$v_{M,ij}/v_{M,i}$	Trade in intermediate inputs	Inter-City Input-Output (IO) Table	
L_{od}^W, L_{od}^B	Migration flows	Chinese Population Census	
$\bar{\omega}_{M,i}$	Outsourcing share	China Tax Survey	
$w_{M,i}L_{M,i}$, $w_{S,i}L_{S,i}$	Value-added	Market Clearing Conditions	
β_M, β_S	Cobb-Douglas cost share	World Bank Open Data	0.56, 0.44
$1-\zeta_M$, $1-\zeta_S$	Assembly worker share	China Family Panel Studies (CFPS)	0.25, 0
θ	Elasticity of trade	Simonovska and Waugh (2014)	4
γ	Matching parameter	Eaton et al. (2022)	0.34
ρ	Correlation parameter	Fan (2019)	0.36
ϵ_B, ϵ_W	Taste dispersion	Fan (2019)	3.9, 4.3

Table A.6: Estimation Results of Trade Costs in 2011 and 2017

Dependent Variable: $\ln \pi_{ij} - \ln \pi_{ii}$	(1) Year 2011	(2) Year 2017
I_{ij}^1 (Same Province)	4.734***	2.959***
	(0.455)	(0.321)
I_{ij}^2 (Different Provinces, Common Border)	12.156**	4.955**
	(4.736)	(2.182)
I_{ij}^3 (Different Provinces, No Common Border)	1.936***	3.306***
	(0.171)	(0.122)
I_{ij}^1 (Same Province) $\times \ln Dist_{ij}$	-0.579***	-0.357***
	(0.038)	(0.026)
I_{ij}^2 (Different Provinces, Common Border) $\times \ln Dist_{ij}$	-1.242***	-0.538***
	(0.406)	(0.185)
I_{ij}^3 (Different Provinces, No Common Border) $\times \ln Dist_{ij}$	-0.377***	-0.387***
	(0.012)	(0.009)
Observations	9,897	9,900
R-Squared	0.969	0.973

Notes: This table reports the estimates of trade costs. Robust standard errors are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: Summary Statistics: Effects of HSR on Input Prices, Welfare, and Skill Premium

	(1) Mean	(2) SD	(3) Min	(4) Median	(5) Max
Intermediate Input Costs	-9.28%	5.85%	-15.21%	-12.48%	1.57%
Unskilled Welfare	-0.67%	1.20%	-3.08%	-0.49%	1.50%
Skilled Welfare	4.51%	2.04%	-0.20%	5.38%	7.15%
Skill Premium	5.01%	1.87%	1.02%	4.93%	9.66%

Notes: The table reports summary statistics for percentage changes in intermediate input prices across cities resulting from HSR connections. It also presents summary statistics for percentage changes in welfare for both unskilled and skilled workers, as well as changes in the skill premium, measured as the wage difference between skilled and unskilled labor.

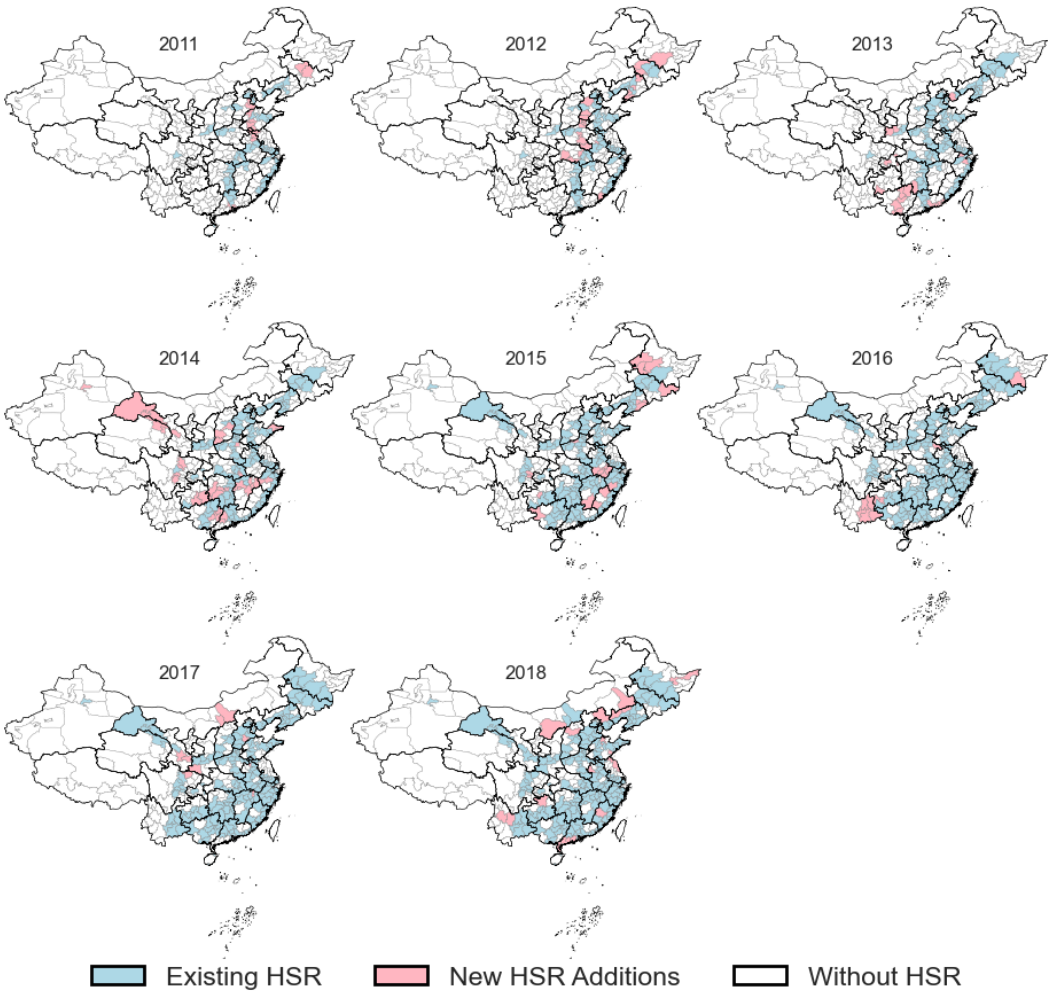
Table A.8: Impact of HSR on Technology, Domestic, and International Trade

	Variations Explained by HSR
Change in Overall Technology	44%
Change in City Exports	56%
Change in Inter-City Trade	25%

Notes: The table presents the percentage of total variance in technology change ($\hat{\Upsilon}_i$), city exports, and inter-city trade explained by HSR connections, as predicted by the model from 2011 to 2017.

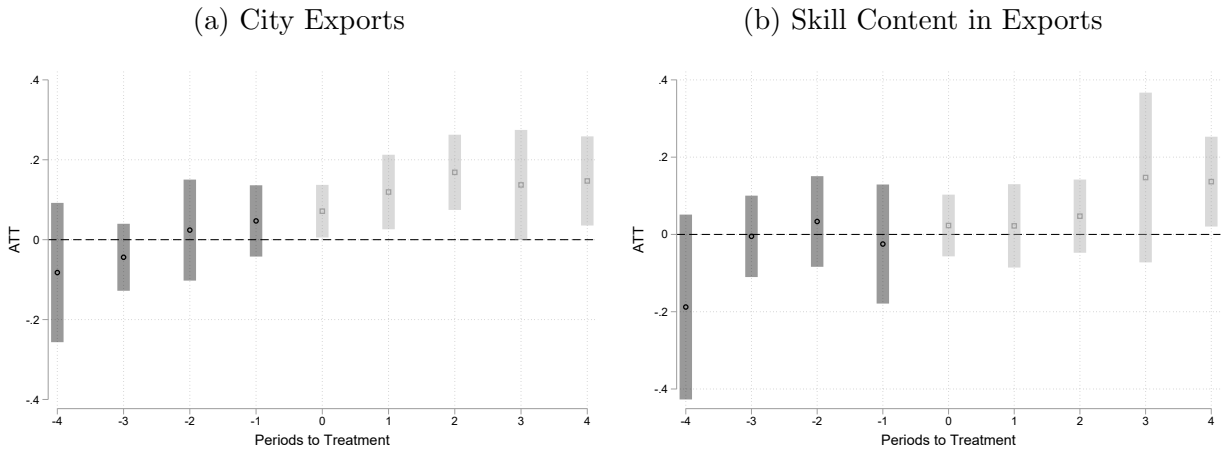
B Figure Appendix

Figure A.1: Evolution of HSR Expansion from 2011 to 2018



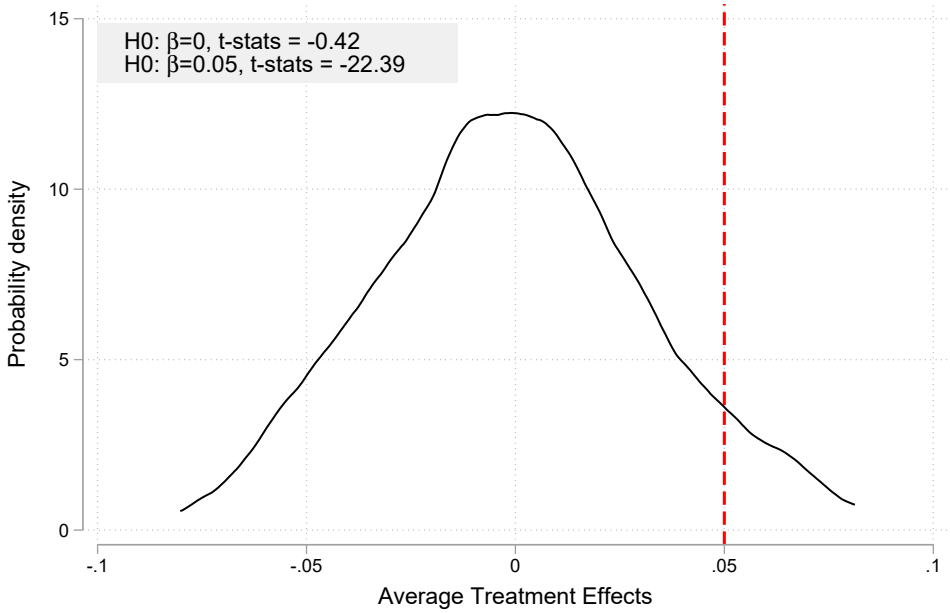
Notes: The figure illustrates the evolution of prefectures connected to the HSR network from 2011 to 2018. Areas in blue represent prefectures that were connected prior to the current year, while areas in red denote prefectures connected during the current year.

Figure A.2: CSDID Event Study: Impact of HSR Connections Over Time



Notes: The figure presents point estimates and 95% confidence intervals for both pre-treatment and post-treatment periods, using the CSDID method developed by Callaway and Sant'Anna (2021). The dependent variables are city-level exports and the skill content of exports, respectively.

Figure A.3: Distribution of Estimated Coefficients in the Falsification Test



Notes: The figure shows the probability density of the estimated coefficients from 200 simulations randomly assigning HSR connection to cities. The vertical line presenting the estimate of column (5) in Table 1.

Figure A.4: Estimation Result of Technology Shock across Cities

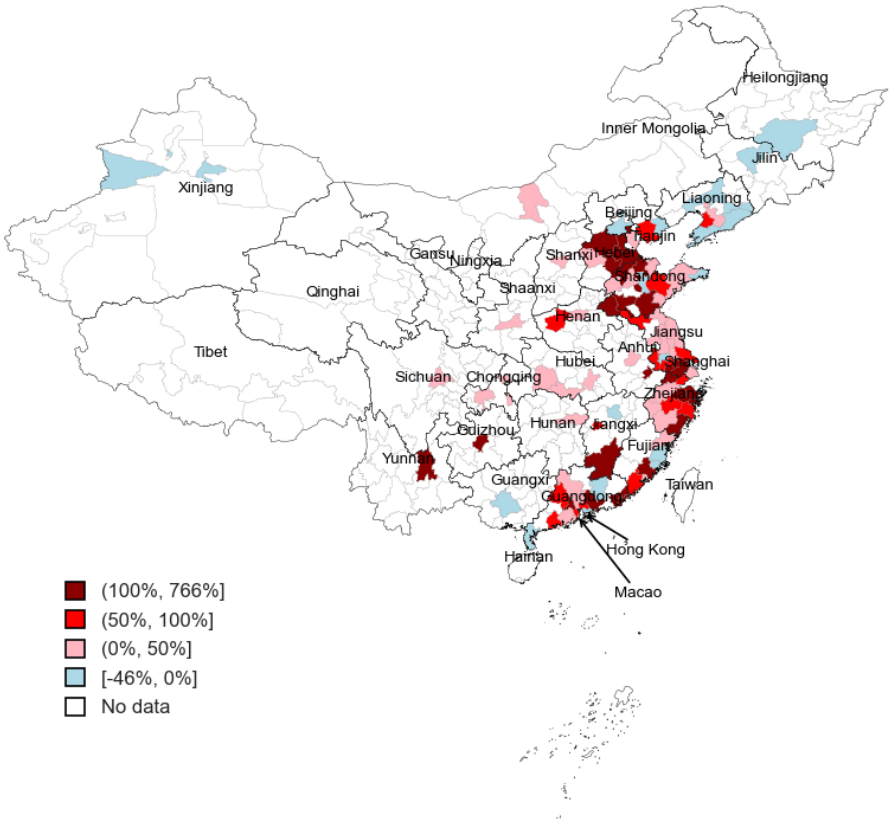
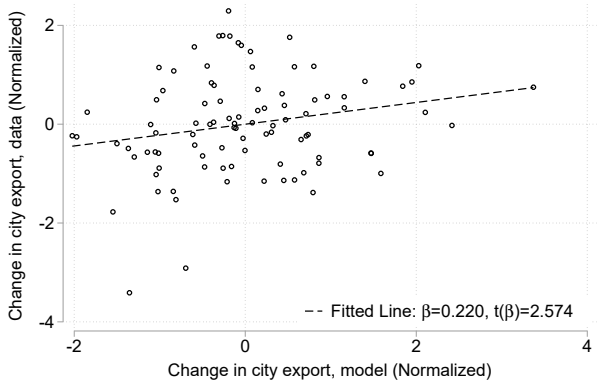
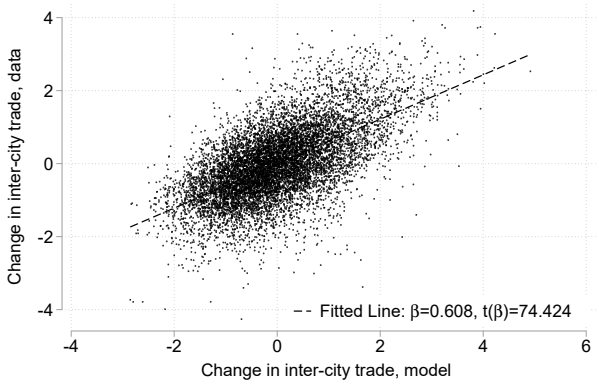


Figure A.5: Goodness of Fit Between Model Predictions and Data (2011-2017)

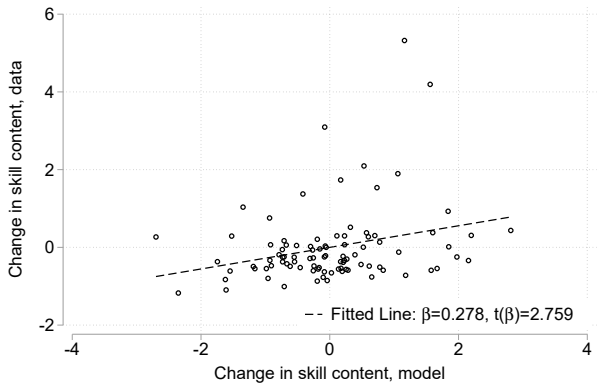
(a) City exports



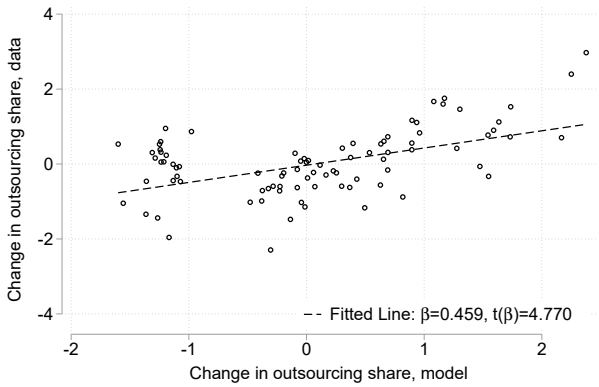
(b) Bilateral city trade



(c) City's skill content in exports



(d) City's outsourcing share



Notes: The figure presents the goodness of fit between model-predicted and actual changes in four key city-level outcomes from 2011 to 2017. Panel (a) compares changes in total city exports. Panel (b) focuses on changes in bilateral city-to-city trade flows. Panel (c) examines changes in skill content of exports, measured by the number of skilled workers per unit of export sales. Panel (d) analyzes changes in cities' outsourcing shares. In each panel, a fitted line is included, along with the corresponding beta coefficient and t-statistic, to highlight the model's predictive performance. To ensure comparability across variables, both axes in each scatter plot are normalized by subtracting the mean and dividing by the standard deviation.

Figure A.6: Changes in Matching Efficiency Across Cities

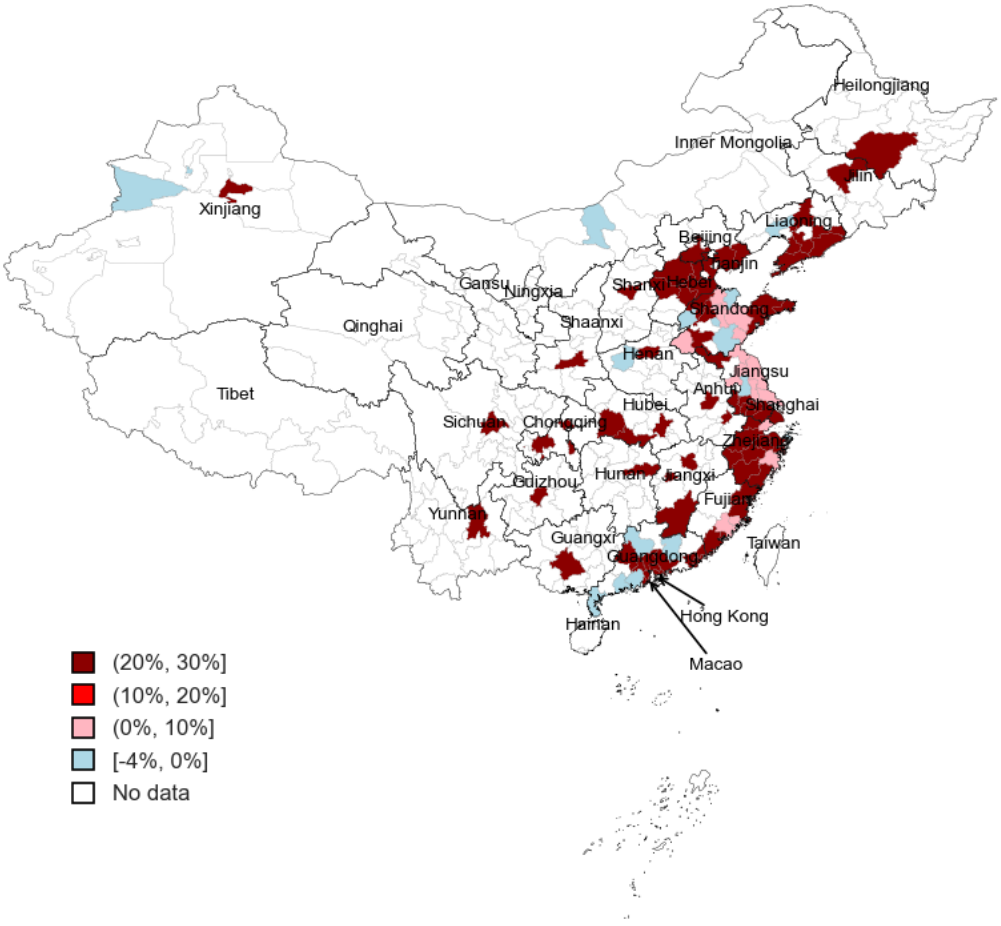


Figure A.7: Distribution of Matching Efficiency Change across Cities

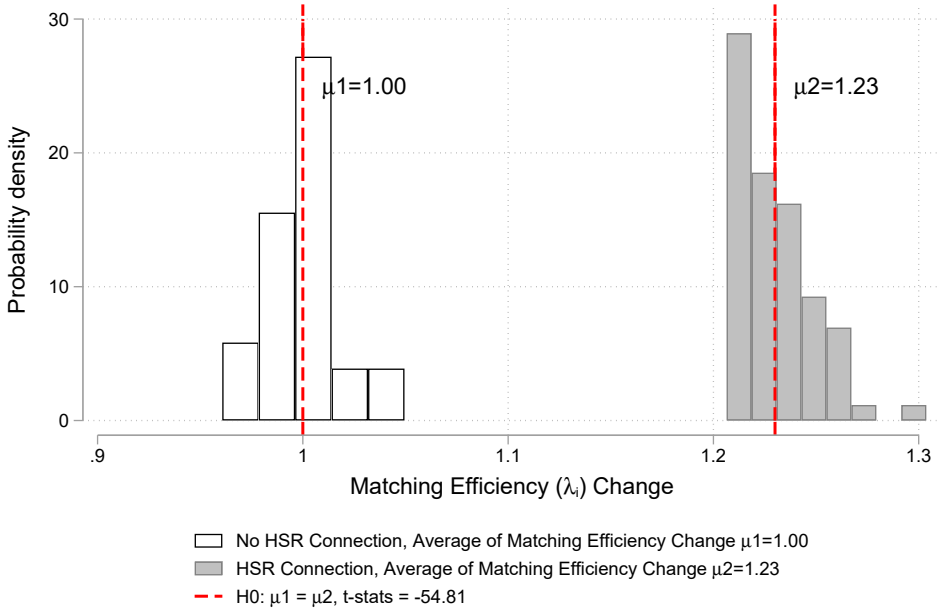


Figure A.8: Changes of Intermediate Inputs Price across Cities

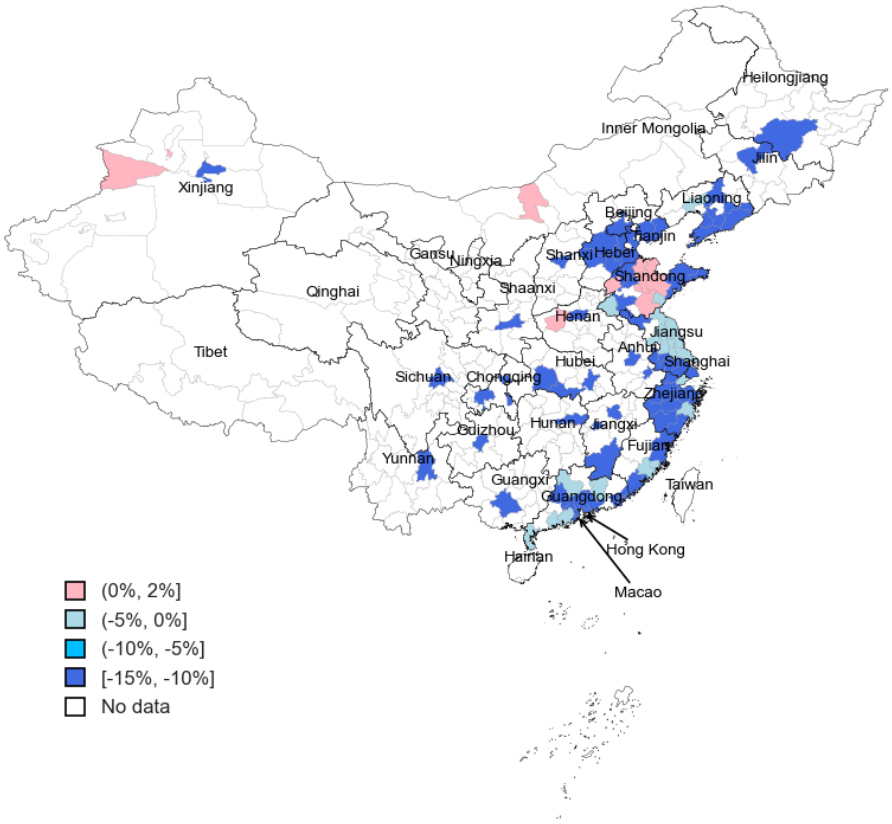
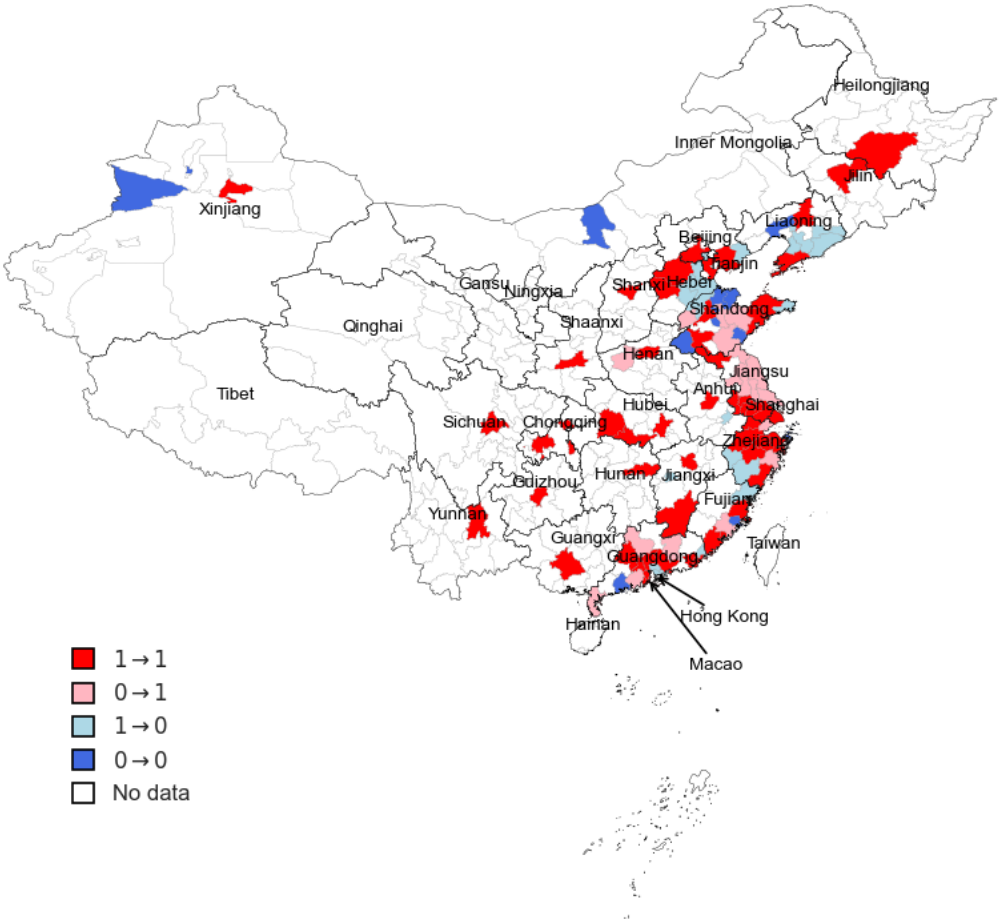


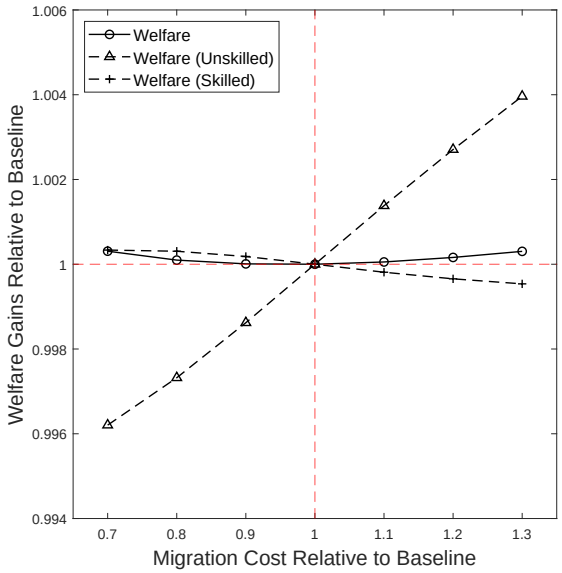
Figure A.9: Changes in HSR Connectivity Under the Welfare-Maximizing Configuration



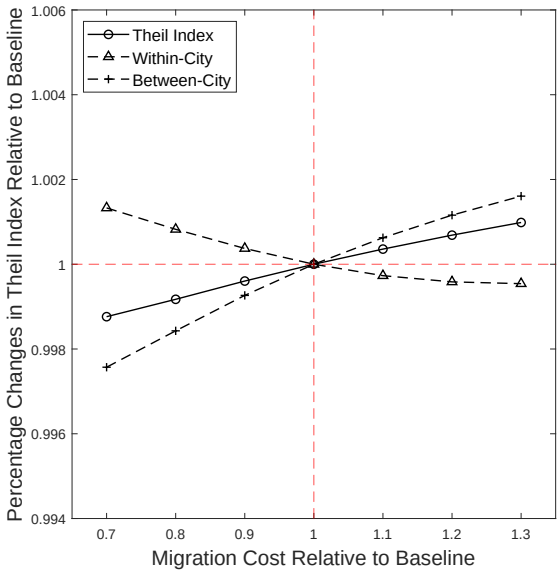
Notes: The figure compares each city's HSR connection status under the actual network and the optimal, welfare-maximizing configuration. Cities are grouped into four categories based on whether they retain, gain, or lose HSR access. Dark red ($1 \to 1$) and dark blue ($0 \to 0$) indicate cities that remain connected or unconnected in both networks. Light red ($0 \to 1$) marks cities that would gain HSR access under the optimal configuration, while light blue ($1 \to 0$) shows those that would lose it.

Figure A.10: The Role of Labor Mobility and Domestic Trade Costs in HSR's Impact

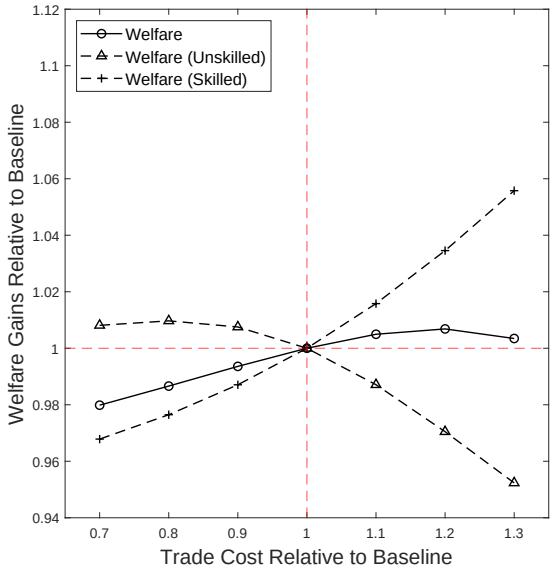
(a) Welfare Effect by Labor Mobility



(b) Inequality Effect by Labor Mobility



(c) Welfare Effect by Domestic Trade Costs



(d) Inequality Effect by Domestic Trade Costs

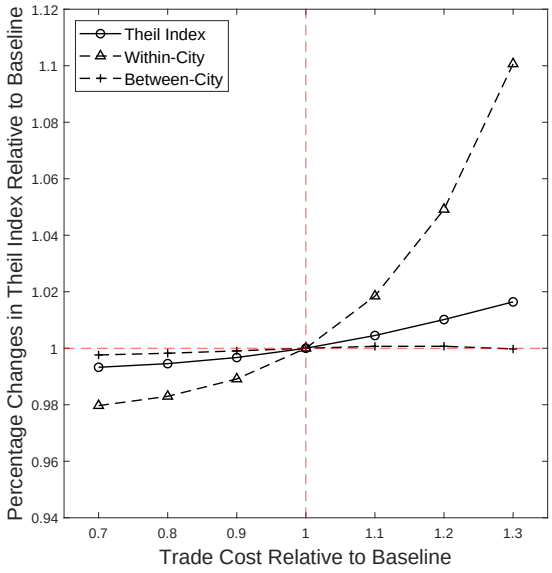
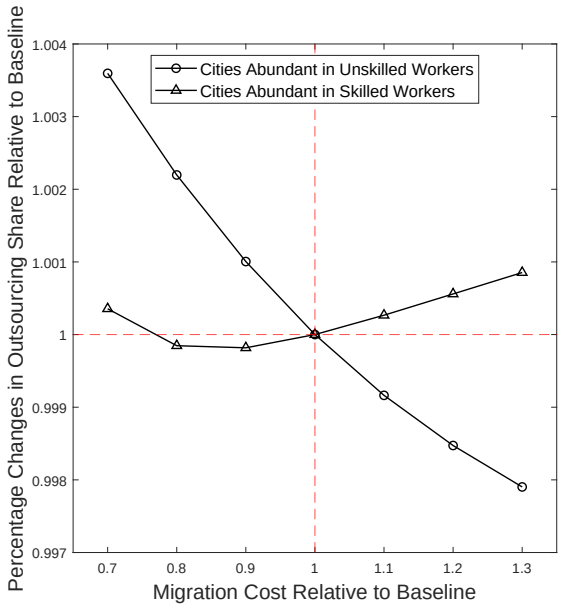
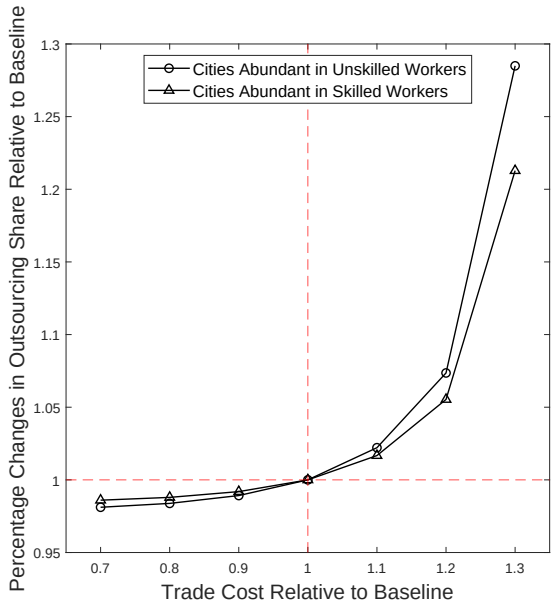


Figure A.11: The Role of Labor Mobility and Domestic Trade Costs in Outsourcing

(a) Impact of Labor Mobility



(b) Impact of Domestic Trade Costs



C Data Appendix

C.1 Skill Premium

The skill premium refers to the wage differential between skilled and unskilled workers. To estimate the skill premium, we employ the data from the CFPS, a nationally representative, biennial longitudinal survey of Chinese communities, families, and individuals, initiated in 2010 by the Institute of Social Science Survey at Peking University. The specification adopted is provided as:

$$\ln w_i = \beta_0 + \beta_1 College_i + \beta_2 Age_i + \beta_3 Age_i^2 + \gamma X_i + u_i \tag{A.1}$$

where w_i represents the wage of individual i, $College_i$ is a binary variable indicating whether individual i has completed tertiary education beyond high school, and Age_i is used as a proxy for work experience. The vector X_i includes control variables for marital status, gender, ethnicity, and sector of employment. This model is estimated separately for each city and year. The coefficient β_1 on the education dummy variable quantifies the wage premium for skilled workers, reflecting the additional earnings they receive compared to their unskilled counterparts within the same city and year.

C.2 Firm Data

Chinese tax survey: The firm-level data in this study is primarily sourced from the enterprise income tax records maintained by the Chinese State Administration of Tax (SAT), which functions similarly to the Internal Revenue Service (IRS) in the United States. The SAT collects and audits tax payments and maintains comprehensive firm-level records. These records include various firm characteristics and financial statement details, such as tax identification numbers, locations, industry classifications, employment numbers, cash flow statements, balance sheets, and income statements. For this analysis, we utilize data spanning from 2011 to 2016, covering variables such as registration location, capital, employment, labor compensation, business travel expenses, Research and Development (R&D) expenses, materials purchased, exports and imports, and operational sales and costs.

WIND financial data: The second dataset employed in our firm analysis is from WIND, a leading provider of financial data on Chinese firms. This dataset includes detailed purchasing information from the top five suppliers for each listed firm. It is important to note that these suppliers are not necessarily listed firms themselves. To create a comprehensive dataset, we combined the firm characteristics from the Chinese Tax Survey with the purchasing data

from WIND. This integration has yielded a detailed firm-level dataset that encompasses both buyer and seller information spanning from 2011 to 2016.

Measure for sourcing distance: To calculate the sourcing distance for each listed firm based on the purchasing data, we first determine the geographical distances ($Dist_{ni}$) between each listed firm (n) and its suppliers (i), , based on their city locations in the matched sample. The sourcing distance for a firm is then calculated as the weighted average of the distances to its top five suppliers, with the weights being the purchase amounts (Q_{ni}) from each supplier. This is expressed as $SourcingDistance_n = \sum_{i=1}^{5} Dist_{ni} \times \frac{Q_{ni}}{\sum_{k=1}^{5} Q_{nk}}$. This procedure yields 650 firm-year observations with valid estimates of sourcing distance.

Measurement of additional firm variables: Additionally, we assess other relevant firm variables such as wage, R&D expenses, materials cost, and firm imports. Wages are estimated by dividing total labor costs by the number of employees. The shares of R&D expenses, materials, and imports are then calculated as proportions of total operational costs, using data from the tax survey dataset.

D Least-Cost HSR Network

The section describes the method of constructing the least-cost path networks of HSR that is used as the instrument variables for being connected to HSR in reality. The construction method follows Faber (2014) and we differ in that the objectives of HSR is to link all the provincial capitals on a single network, as stated in the official report. The involved data, such as land usage, land cover, and elevation, are obtained from Institute of Geographic Sciences and Natural Resources Research Chinese Academy of Sciences.

First, we adopt the construction–cost function in Faber (2014):[46]

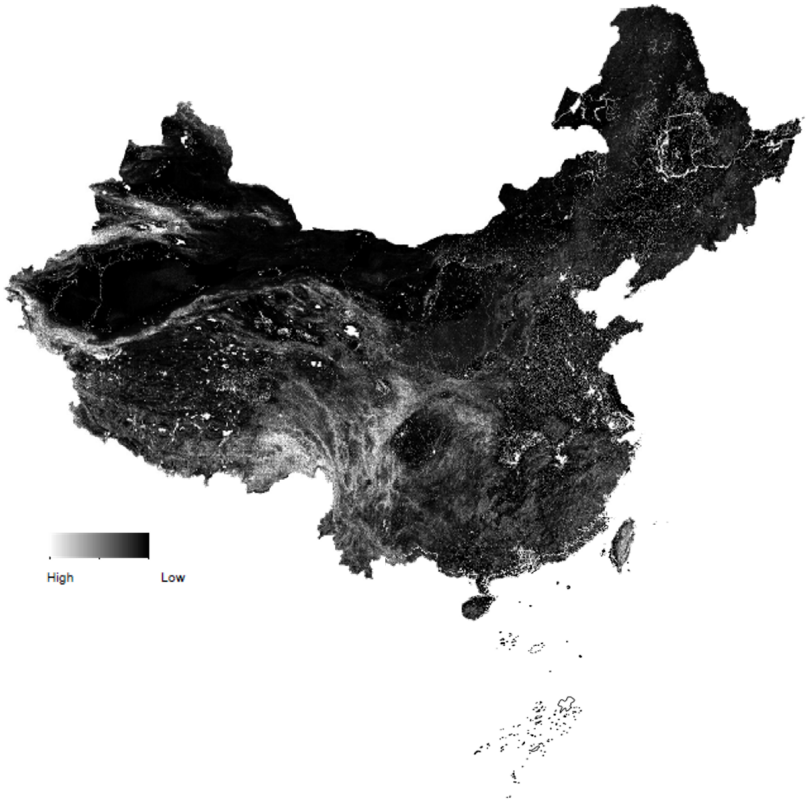
$$c_i = 1 + Slope_i + 25 \times Built_i + 25 \times Water_i + 25 \times Wetland_i,$$

where c_i is the incurred cost if the HSR crosses a pixel of land i, $Slope_i$ stands for the average slope gradient of land i, $Built_i$ is a dummy variable that equals one if land i is covered by any industrial, mining and residential building, $Water_i$ and $Wetland_i$ indicates whether the pixel is covered by water or wetland. This simple cost function implies that the high costs are associated crossing built structures, water area as well as long and steep

[46] Although Faber (2014) develop the cost model for highways, the main cost drivers—terrain grade, bridges and tunnels, right-of-way acquisition, and urban density—also govern HSR construction. Hence the functional form provides a reasonable proxy for HSR costs. We further verify robustness to alternative cost weights and specifications.

routes. We use the satellite sensing data on elevation, land cover and land use to compute the cost (c_i) for each pixel. We harmonize the elevation, land-cover, and land-use rasters to a common $1\,\text{km} \times 1\,\text{km}$ grid by reclassifying and resampling each layer. Figure A.12 displays the resulting construction–cost surface. Shades map relative crossing costs: lighter tones denote higher-cost barriers, while darker tones indicate lower-cost corridors.

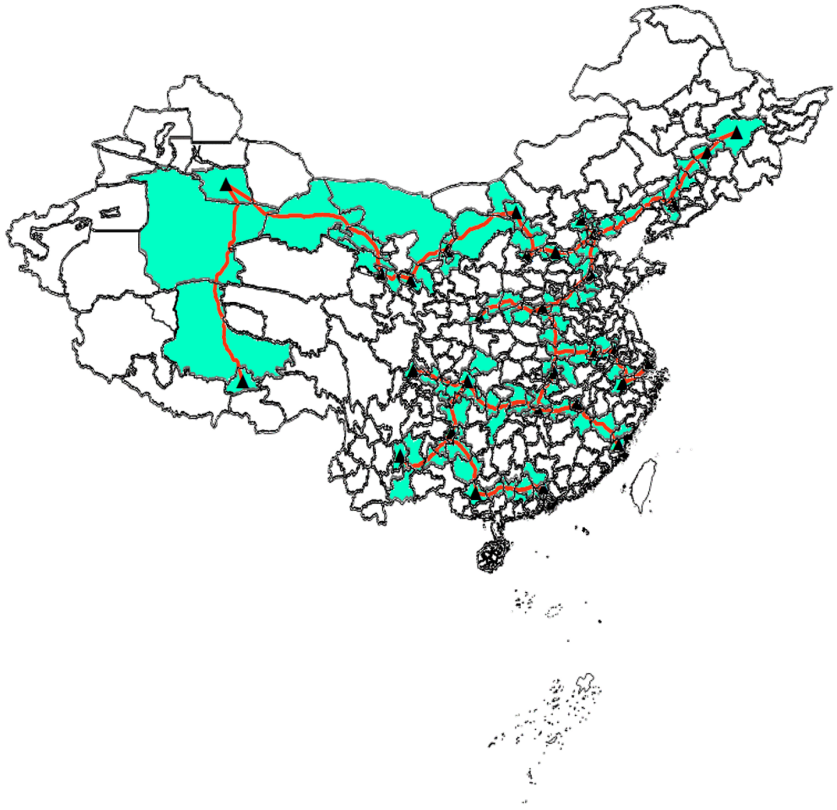
Figure A.12: The Estimated Construction Cost of HSR in China



After obtaining the constructing cost raster as the input, we then proceed to construct the least cost HSR paths between the 30 capital cities.[47] This generates 435 ($\frac{30*29}{2}$) possible bilateral paths between all pairs of the targeted city nodes. We then compute the aggregate construction cost for each candidate bilateral path and use it as the edge weight in Prim's minimum spanning tree. Figure A.13 depicts the resulting LCP HSR network.

[47]The 30 *capital cities* cover 21 provinces excluding Hainan and Taiwan, 5 autonomous regions as well as 4 municipalities.

Figure A.13: The Least Cost Path Spanning Tree Network



E Theoretical Appendix

E.1 Deriving the Probability of Outsourcing

The probability that firm j in region i is not able to encounter any suppliers with price lower than c for task k is $\prod_n exp(-\rho_{k,in}(c))$ by Poisson distribution. The cost distribution of outsourcing the task, given parameter restriction $\gamma = (\theta - \phi)/\theta$, is expressed as

$$G^o_{k,i}(c) = 1 - exp(-v_{k,i}c^\phi) \tag{A.2}$$

where $v_{k,i} \equiv \sum_n \frac{\theta}{\phi}\lambda_{k,in}\Upsilon_n^{\phi/\theta}d_{in}^{-\phi}$. The probability that labor cost $(w_{k,i}/q_{k,i}(j))$ is no less than c is $F(w_{k,i}/c)$, and the cost distribution of hiring labor is thus

$$G^l_{k,i}(c) = 1 - exp(-w_{k,i}^{-\phi}c^\phi) \tag{A.3}$$

If the cost of using labor to fulfill task k is p, then the probability that hiring labor costs less than outsourcing is equal to $1 - G^o_{k,i}(p)$. Then we integrate this for all possible p under density $dG^l_{k,i}(p)$ to obtain

$$\int_0^{+\infty}(1 - G^o_{k,i}(p))dG^l_{k,i}(p) = \int_0^{+\infty} exp(-v_{k,i}p^\phi)dG^l_{k,i}(p) \tag{A.4}$$

$$= -w_{k,i}^{-\phi}\int_0^{+\infty}\phi p^{\phi-1}exp\left[-(v_{k,i} + w_{k,i}^{-\phi})p^\phi\right]dp \tag{A.5}$$

$$= \frac{w_{k,i}^{-\phi}}{\Xi_{k,i}} \tag{A.6}$$

where $\Xi_{k,i} = v_{k,i} + w_{k,i}^{-\phi}$. The probability of fulfilling task k by outsourcing is then $v_{k,i}/\Xi_{k,i}$.

E.2 Derivation of Cost Distribution $\mu_{ni}(c)$

$$\mu_{ni}(c) = E\left\{\mu_i^Z\left(\frac{d_{ni}}{c}\prod_{k\in\{S,M\}}\frac{(c_{k,i}(j)^{\zeta_k}w_{k,i}^{1-\zeta_k})^{\beta_k}}{b_k}\right\}\right. \tag{A.7}$$

$$= T_i d_{ni}^{-\theta} c^{\theta}\prod_{k\in\{S,M\}}\int_0^{+\infty} b_k^{\theta}c_k^{-\theta\zeta_k\beta_k}w_{k,i}^{-\theta(1-\zeta_k)\beta_k}dG_{k,i}(c_k) \tag{A.8}$$

$$= T_i d_{ni}^{-\theta} c^{\theta}\prod_{k\in\{S,M\}} b_k^{\theta}w_{k,i}^{-\theta(1-\zeta_k)\beta_k}\Xi_{k,i}^{\theta\zeta_k\beta_k/\phi}\int_0^{+\infty} x^{-\theta\zeta_k\beta_k/\phi}exp(-x)dx \tag{A.9}$$

$$= T_i d_{ni}^{-\theta} c^{\theta}\prod_{k\in\{S,M\}} b_k^{\theta}w_{k,i}^{-\theta(1-\zeta_k)\beta_k}\Xi_{k,i}^{\theta\zeta_k\beta_k/\phi}\Gamma(1-\frac{\theta\zeta_k\beta_k}{\phi}) \tag{A.10}$$

$$= T_i\Xi_i\mathbb{W}_i d_{ni}^{-\theta}c^{\theta} \tag{A.11}$$

where we define $x_k \equiv \Xi_{k,i}c_k^{\phi}$ in the third equality. The last equality is derived by assuming $b_k = \Gamma(1-\frac{\theta\zeta_k\beta_k}{\phi})^{-\frac{1}{\theta}}$, which require $\theta\zeta_k\beta_k/\phi < 1$ in order to make $\mu_{ni}(c)$ meaningful. Furthermore, we define $\Xi_i \equiv \prod_{k\in\{S,M\}}(\Xi_{k,i})^{\theta\zeta_k\beta_k/\phi}$ and define $\mathbb{W}_i \equiv \prod_{k\in\{S,M\}} w_{k,i}^{-\theta(1-\zeta_k)\beta_k}$ to obtain the last equality.

E.3 Algorithm of Computing Υ

Υ is denoted as the vector of $N\times 1$, whose i-th element is defined as (20). We denote the function form of (20) as $\Upsilon = f(\Upsilon)$. To show there is a fixed point, we transform the fixed point problem in form of $\ln\Upsilon = F(\ln\Upsilon)$,where $F(x) \equiv \ln f(exp(x))$. There exists a unique fixed point of F if it is a contraction. $F_i(x)$, the i-th element of vector $F(x)$ is derived as:

$$F_i(x) = \ln\left\{T_i\mathbb{W}_i\prod_{k\in\{S,M\}}\left[\sum_n\frac{\theta}{\phi}\lambda_{k,in}exp(\frac{\phi}{\theta}x_n)d_{in}^{-\phi}+w_{k,i}^{-\phi}\right]^{\theta\zeta_k\beta_k/\phi}\right\} \tag{A.12}$$

$$= \ln\left\{T_i\mathbb{W}_i w_{S,i}^{-\theta\zeta_S\beta_S}\left[\sum_n\frac{\theta}{\phi}\lambda_{M,in}exp(\frac{\phi}{\theta}x_n)d_{in}^{-\phi}+w_{M,i}^{-\phi}\right]^{\theta\zeta_M\beta_M/\phi}\right\} \tag{A.13}$$

where the second equality comes from the assumption that the service task cannot be outsourced, $\lambda_{S,i} = 0$.

To apply Blackwell's contraction mapping theory, we need to verify both monotonicity and discounting properties for $F(x)$ to confirm the sufficient conditions. For monotonicity, let x and y satisfy that $x \le y$, as all the exogenous parameters are positive then

$$F_i(x) = \ln\left\{ T_i \mathbb{W}_i w_{S,i}^{-\theta\zeta_S\beta_S} \left[\sum_n \frac{\theta}{\phi} \lambda_{M,in} exp(\frac{\phi}{\theta} x_n) d_{in}^{-\phi} + w_{M,i}^{-\phi} \right]^{\theta\zeta_M\beta_M/\phi} \right\} \tag{A.14}$$

$$\leq \ln\left\{ T_i \mathbb{W}_i w_{S,i}^{-\theta\zeta_S\beta_S} \left[\sum_n \frac{\theta}{\phi} \lambda_{M,in} exp(\frac{\phi}{\theta} y_n) d_{in}^{-\phi} + w_{M,i}^{-\phi} \right]^{\theta\zeta_M\beta_M/\phi} \right\} \tag{A.15}$$

$$= F_i(y) \tag{A.16}$$

For discounting, for $\forall a > 0$

$$F_i(x+a) = \ln\left\{ T_i \mathbb{W}_i w_{S,i}^{-\theta\zeta_S\beta_S} \left[\sum_n \frac{\theta}{\phi} \lambda_{M,in} exp(\frac{\phi}{\theta} x_n + \frac{\phi}{\theta} a) d_{in}^{-\phi} + w_{M,i}^{-\phi} \right]^{\theta\zeta_M\beta_M/\phi} \right\} \tag{A.17}$$

$$\leq \ln\left\{ T_i \mathbb{W}_i w_{S,i}^{-\theta\zeta_S\beta_S} \left[\sum_n \frac{\theta}{\phi} \lambda_{M,in} exp(\frac{\phi}{\theta} x_n + \frac{\phi}{\theta} a) d_{in}^{-\phi} + w_{M,i}^{-\phi} exp(\frac{\phi}{\theta} a) \right]^{\theta\zeta_M\beta_M/\phi} \right\} \tag{A.18}$$

$$= \ln\left\{ T_i \mathbb{W}_i w_{S,i}^{-\theta\zeta_S\beta_S} \left[\sum_n \frac{\theta}{\phi} \lambda_{M,in} exp(\frac{\phi}{\theta} x_n) d_{in}^{-\phi} + w_{M,i}^{-\phi} \right]^{\theta\zeta_M\beta_M/\phi} exp(\zeta_M\beta_M a) \right\} \tag{A.19}$$

$$= F_i(x) + \zeta_M\beta_M a \tag{A.20}$$

where the inequality comes from that $exp(\frac{\phi}{\theta}a) > 1$. As $\beta_M < 1$ and $\zeta_M \leq 1$, discounting is verified.

Therefore, we are able to compute the fixed point ($\ln \Gamma$) by iterating on:

$$\ln \Upsilon_{t+1} = F(\ln \Upsilon_t)$$

with the initial value of $\ln \Upsilon_0 = 0$. After we obtain $\ln \Upsilon$, we are able to calculate Υ. The result directly implies that each element of $\ln \Upsilon$ increases with technology parameter T_i anywhere, decreases with any task-specific labor cost $w_{k,i}$ in any region, and increases with the task-specific arrival rate of price quotes $\lambda_{k,ni}$ in any region, though the comparative statics only capture the partial effect and do not predict the general equilibrium outcomes.

E.4 Aggregate Production Function

The proof follows Eaton et al. (2016). We only focus on the manufacturing tasks, since service tasks uses the skilled workers only. The cost distribution of outsourcing the task, given parameter restriction $\gamma = (\theta - \phi)/\theta$, is expressed as

$$G^o_{M,i}(c) = 1 - exp(-v_{M,i}c^{\phi}) \tag{A.21}$$

where $v_{M,i} \equiv \sum_n \frac{\theta}{\phi}\lambda_{M,in}\Upsilon_n^{\phi/\theta}d_{in}^{-\phi}$. The average unit cost of using intermediate input sourced from region i is

$$\begin{aligned}
\bar{p}_{M,i} &= \int_0^{+\infty} p dG^o_{M,i}(p) && \text{(A.22)}\\
&= \int_0^{+\infty} \phi \times v_{M,i}p^{\phi} \times exp\left(-v_{M,i}p^{\phi}\right) dp && \text{(A.23)}\\
&= \int_0^{+\infty} \left(\frac{x}{v_{M,i}}\right)^{1/\phi} \times exp(-x)dx && \text{(A.24)}\\
&= v_{M,i}^{-1/\phi}\Gamma\left(1 + \frac{1}{\phi}\right) && \text{(A.25)}
\end{aligned}$$

The aggregate labor share in the production of task M can be rewritten as (by written $v_{M,i}$ as function of average price $\bar{p}_{M,i}$):

$$\begin{aligned}
\beta_i^{l(M)} &= \beta_M \times \frac{w_{M,i}^{-\phi}}{v_{M,i} + w_{M,i}^{-\phi}} && \text{(A.26)}\\
&= \beta_M \times \frac{w_{M,i}^{-\phi}}{\left[\bar{p}_{M,i}/\Gamma\left(1 + \frac{1}{\phi}\right)\right]^{-\phi} + w_{M,i}^{-\phi}} && \text{(A.27)}
\end{aligned}$$

We now turn to the production function shown in equation (22). For each manufacturing task in region i, the representative firm could hire unskilled labor $L_{M,i}$ at blue-collar wage rate w_i^B, and purchase the composite intermediate task $I_{M,i}$ at the average price $\bar{p}_{M,i}$. The first order condition of cost minimization of manufacturing task yields:

$$\frac{w_{M,i}L_{M,i}}{\bar{p}_{M,i}I_{M,i}} = \Gamma\left(1+\frac{1}{\phi}\right)^{-\phi} \times \left(\frac{w_{M,i}}{\bar{p}_{M,i}}\right)^{-\phi} \tag{A.28}$$

$$= \frac{w_{M,i}^{-\phi}}{\left[\bar{p}_{M,i}/\Gamma\left(1+\frac{1}{\phi}\right)\right]^{-\phi}} \tag{A.29}$$

Then it is straightforward that the labor share generated by the aggregate production function is same with the one implied by the assumptions on technology in model.

E.5 Derivation of Expected Indirect Utility

Given taste shocks z_{odi}, the expected indirect utility is expressed as

$$\nu_d^l = E\left\{V_{odi}^l(p_S, p_M)\right\} \tag{A.30}$$

$$= \int\int \frac{w_d^l}{a_S a_M p_S^{\alpha_S} p_M^{\alpha_M}} d\tilde{G}(p_S) d\tilde{G}(p_M) \tag{A.31}$$

$$= w_d^l \prod_{k\in\{S,M\}} a_k^{-1} \int_0^{+\infty} p_k^{-\alpha_k} d\tilde{G}(p_k) \tag{A.32}$$

$$= w_d^l \prod_{k\in\{S,M\}} a_k^{-1} \int_0^{+\infty} p_k^{-\alpha_k} \tilde{v}_{k,d}\theta(1-\tilde{\gamma}) p_k^{\theta(1-\tilde{\gamma})-1} exp\left[-\tilde{v}_{k,d} p_k^{\theta(1-\tilde{\gamma})}\right] dp_k \tag{A.33}$$

$$= w_d^l \prod_{k\in\{S,M\}} a_k^{-1} \tilde{v}_{k,d}^{\frac{\alpha_k}{\theta(1-\tilde{\gamma})}} \Gamma\left(1-\frac{\alpha_k}{\theta(1-\tilde{\gamma})}\right) \tag{A.34}$$

$$= B_d \times w_d^l \times \mathbb{Y}_d^{\frac{1}{\theta}} \tag{A.35}$$

where the third equality comes from the assumption that the prices p_S and p_M are independently drawn. Here B_d is defined as

$$B_d \equiv \left[\prod_{k\in\{S,M\}} \tilde{\lambda}_{k,d}^{\alpha_k}\right]^{\frac{1}{\theta(1-\tilde{\gamma})}} \tag{A.36}$$

and a_k is cautiously chosen as

$$a_k = (1-\tilde{\gamma})^{-\frac{\alpha_k}{\theta(1-\tilde{\gamma})}} \times \Gamma\left(1-\frac{\alpha_k}{\theta(1-\tilde{\gamma})}\right) \tag{A.37}$$

to eliminate the effect of need k on utility. We also require $\alpha_k < \theta(1-\tilde{\gamma})$ to make the Gamma function well-defined.

E.6 Derivation of Migration Share

The migration share from o to d of workers of type l is expressed as:

$$\delta_{od}^{l} = \mathbf{Pr}(\frac{\nu_{d}^{l} z_{di}}{e_{od}^{l}} \geq \frac{\nu_{g}^{l} z_{gi}}{e_{og}^{l}},\ \forall g) \tag{A.38}$$

$$= \mathbf{Pr}(z_{gi} \leq \frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} z_{di},\ \forall g) \tag{A.39}$$

$$= \int_{0}^{+\infty} \left[\int ... \int_{z_{gi} \leq \frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} z_{di}, \forall g \neq d} \frac{\partial^{n} F(\mathbf{z}_{-d}, z_{d})}{\partial z_{1} \partial z_{2} ... \partial z_{N}} d\mathbf{z}_{-d} \right] dz_{d} \tag{A.40}$$

$$= \int_{0}^{+\infty} \left\{ \int ... \int_{z_{gi} \leq \frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} z_{di}, \forall g \neq d,j} \left[\int_{0}^{\frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{j}^{l}/e_{oj}^{l}}} \left(d \underbrace{\frac{\partial^{n-1} F(\mathbf{z}_{-d-j}, z_{j}, z_{d})}{\partial z_{1} \partial z_{2} ... \partial z_{g} ... \partial z_{N}}}_{g \neq d,j} / dz_{j} \right) dz_{j} \right] d\mathbf{z}_{-d-j} \right\} dz_{d} \tag{A.41}$$

$$= \int_{0}^{+\infty} \left\{ \int ... \int_{z_{gi} \leq \frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} z_{di}, \forall g \neq d,j} \left[\frac{\partial^{n-1} F(\mathbf{z}_{-d-j}, \frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{j}^{l}/e_{oj}^{l}} z_{di}, z_{d})}{\underbrace{\partial z_{1} \partial z_{2} ... \partial z_{g} ... \partial z_{N}}_{g \neq d,j}} \right] d\mathbf{z}_{-d-j} \right\} dz_{d} \tag{A.42}$$

$$= .....$$

$$= \int_{0}^{+\infty} \frac{\partial F(\frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{1}^{l}/e_{o1}^{l}} z_{di}, ..., \frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{N}^{l}/e_{oN}^{l}} z_{di})}{\partial z_{d}} dz_{d} \tag{A.43}$$

where $\mathbf{z}_{-d}$ denotes the vector of $\{z_{gi}\}$ which does not include z_{di}, and the same notation meaning for $\mathbf{z}_{-d-j}$. Given the formula of F, it follows that

$$\delta_{od}^{l} = \int_{0}^{+\infty} \left[\sum_{g} \left(\frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} \right)^{-\epsilon_{l}} z_{di}^{-\epsilon_{l}} \right]^{-\rho} (1-\rho) \epsilon_{l} z_{di}^{-\epsilon_{l}-1} exp \left\{ -z_{di}^{-\epsilon_{l}(1-\rho)} \times \left[\sum_{g} \left(\frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} \right)^{-\epsilon_{l}} \right]^{1-\rho} \right\} dz_{di} \tag{A.44}$$

$$= \int_{0}^{+\infty} \frac{1}{\sum_{g} \left(\frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} \right)^{-\epsilon_{l}}} \times dexp \left\{ -z_{di}^{-\epsilon_{l}(1-\rho)} \times \left[\sum_{g} \left(\frac{\nu_{d}^{l}/e_{od}^{l}}{\nu_{g}^{l}/e_{og}^{l}} \right)^{-\epsilon_{l}} \right]^{1-\rho} \right\} \tag{A.45}$$

$$= \frac{\left(\nu_{d}^{l}/e_{od}^{l}\right)^{\epsilon_{l}}}{\sum_{g} \left(\nu_{g}^{l}/e_{og}^{l}\right)^{\epsilon_{l}}} \tag{A.46}$$

E.7 Derivation of Expected Utility

The joint probability of utility for worker of type l from city o is denoted by vector $\mathbf{u}_o^l = \{u_{od}^l | d = 1, 2, ...N\}$ where $u_{od}^l \equiv \frac{z_{di}\nu_d^l}{e_{od}^l}$. Then the joint distribution of utility is derived as

$$U_o^l(\mathbf{u}_o^l) = \mathbf{Pr}\left(u_{o1}^l \leq u_1, ..., u_{oN}^l \leq u_N\right) \tag{A.47}$$

$$= \mathbf{Pr}\left(..., z_{di} \leq \frac{e_{od}^l u_d}{\nu_d^l}, ...\right) \tag{A.48}$$

$$= exp\left\{-\left[\sum_d \left(\frac{e_{od}^l u_d}{\nu_d^l}\right)^{-\epsilon_l}\right]^{1-\rho}\right\} \tag{A.49}$$

Therefore, the distribution of $u_o^l \equiv \max_{d\in\{1,2,..,N\}}\left\{\frac{z_{di}\nu_d^l}{e_{od}^l}\right\}$, which is denoted as $\mathbb{U}_o^l(u)$:

$$\mathbb{U}_o^l(u) = \mathbf{Pr}\left(u_o^l \leq u\right) \tag{A.50}$$

$$= \mathbf{Pr}\left(u_{od}^l \leq u,\ \forall d\right) \tag{A.51}$$

$$= U_o^l(u, u, ..., u) \tag{A.52}$$

$$= exp\left\{-\left[\sum_d \left(\frac{e_{od}^l u}{\nu_d^l}\right)^{-\epsilon_l}\right]^{1-\rho}\right\} \tag{A.53}$$

$$= exp\left\{-\left[\sum_d \left(\frac{e_{od}^l}{\nu_d^l}\right)^{-\epsilon_l}\right]^{1-\rho} u^{-(1-\rho)\epsilon_l}\right\} \tag{A.54}$$

$$= exp\left[-\left(M_o^l\right)^{1-\rho} u^{-(1-\rho)\epsilon_l}\right] \tag{A.55}$$

where $M_o^l \equiv \sum_d \left(\frac{e_{od}^l}{\nu_d^l}\right)^{-\epsilon_l}$. Then the expected utility born in city o is then

$$\bar{U}_o^l = \int_0^{+\infty} u d\mathbb{U}_o^l(u) \tag{A.56}$$

$$= \int_0^{+\infty} \left(M_o^l\right)^{1-\rho}(1-\rho)\epsilon_l u^{-(1-\rho)\epsilon_l} exp\left[-\left(M_o^l\right)^{1-\rho} u^{-(1-\rho)\epsilon_l}\right] du \tag{A.57}$$

$$= \left(M_o^l\right)^{\frac{1}{\epsilon_l}} \int_0^{+\infty} x^{-\frac{1}{(1-\rho)\epsilon_l}} exp\left(-x\right) dx \tag{A.58}$$

$$= \left(M_o^l\right)^{\frac{1}{\epsilon_l}} \Gamma\left[1 - \frac{1}{(1-\rho)\epsilon_l}\right] \tag{A.59}$$

where the derivation of the third equality uses the transformation $x = \left(M_o^l\right)^{1-\rho} u^{-(1-\rho)\epsilon_l}$ and the last equality comes from the definition of Gamma function.

E.8 Definition of Equilibrium

Goods Market. The aggregate production in location i includes the total revenue from selling consumption goods and the revenue from supplying intermediate inputs globally. With balanced trade, the total expenditure on final goods equals labor income, as there is no profit in this model. For region i, we have:

$$Y_i = \sum_{n=1}^{N} \pi_{ni} \left[X_n^c + \Phi_n^I Y_n \right], \quad X_n^c = \sum_{l \in \{B,W\}} w_n^l L_n^l \tag{A.60}$$

where $\Phi_n^I \equiv 1 - \beta_n^L$ represents the share of intermediate inputs in final production, and β_n^L denotes the overall labor share of production costs as defined in (15).

Labor Market. With balanced trade, the final expenditure X_i^C in region i is given by (A.60), and the equilibrium for labor of type $l \in \{B, W\}$ in region i implies:

$$w_i^l L_i^l = \beta_i^l Y_i \tag{A.61}$$

where β_i^l represents the production cost share of labor type l in region i, as given in (16), and L_i^l is the endogenous supply of workers of type l in region i, provided in (32). These equations for each labor type l in region i determine the wage w_i^l.

Equilibrium. The competitive equilibrium is reached when workers' migration and consumption decisions, firms' production choices, and the clearing of labor and goods markets are all optimal and consistent with endogenous labor supply and expenditure patterns. This equilibrium is formally defined as a set of prices and allocations such that the following conditions are satisfied:

1. *The migration decisions for workers of both types are optimal, i.e.,* (30) *and* (31) *are satisfied.*
2. *The distribution of labor* L_i^l*, and the final consumption expenditure* X_i^C *are consistent with the endogenous supply of workers, i.e.,* (32) *and* (A.60)*.*
3. *The decisions about firm's production are optimal.*
4. *The decisions about worker's consumption are optimal.*

5. *Labor markets and goods markets clear, i.e.,* (A.60) *and* (A.61).

E.9 Relative Change in Equilibrium

To quantify the aggregate and distributional effects of HSR, we further apply the exact hat algebra method (Allen et al., 2020). This approach models the impact of changes in exogenous variables, such as bilateral matching efficiency (from $\lambda_{M,ni}$ to $\lambda'_{M,ni}$). A variable with a hat, $\hat{x}$, represents its relative change, defined as $\hat{x} = x'/x$.

Assuming no change in $\hat{d}_{ni}$, $\hat{e}_{od}$, and $\hat{T}_i$, i.e., $\hat{d}_{ni} = \hat{e}_{od} = \hat{T}_i = 1$, we can solve 15 simultaneous equations given the matching efficiency shock ($\hat{\lambda}_{M,ni}$) through equations (A.63) to (A.77) and determine the impact of HSR connections on various variables including $\{\hat{w}_{M,i}$, $\hat{w}_{S,i}$, $\hat{\Xi}_i$, $\hat{\Xi}_{M,i}$, $\hat{\Upsilon}_i$, $\hat{\mathbb{Y}}_i$, $\hat{v}_{M,i}$, $\hat{\pi}_{ni}$, $\hat{\delta}^B_{od}$, $\hat{\delta}^W_{od}$, $\hat{L}_{M,i}$, $\hat{L}_{S,i}$, Y'_i, $\Phi^{I\prime}_n$, $X^{c\prime}_i\}$. Therefore, the relative change in aggregate average welfare is derived by the following expression:

$$\hat{W} = \sum_{l\in\{B,W\}} \sum_{i=1}^{N} \tilde{\omega}^l_i \times \hat{\tilde{U}}^l_o \tag{A.62}$$

where the change in the expected utility of a type l worker born in o, denoted as $\hat{\tilde{U}}^l_o$, and the original welfare share of a worker of type l in region i, denoted as $\tilde{\omega}^l_i$, are defined by:

$$\hat{\tilde{U}}^l_o = \left(\sum_g \delta^l_{og}(\hat{w}^l_g \hat{\mathbb{Y}}^{1/\theta}_g / \hat{e}^l_{og})^{\epsilon_l}\right)^{\frac{1}{\epsilon_l}}, \quad \tilde{\omega}^l_i = \frac{m^l_i \times \left(M^l_i\right)^{\frac{1}{\epsilon_l}} \times \Gamma\left[1 - \frac{1}{(1-\rho)\epsilon_l}\right]}{\sum_{l'\in\{B,W\}} \sum_{i'=1}^{N} m^{l'}_{i'} \times \left(M^{l'}_{i'}\right)^{\frac{1}{\epsilon_{l'}}} \times \Gamma\left[1 - \frac{1}{(1-\rho)\epsilon_{l'}}\right]}$$

Since changes in matching efficiency are not directly observable, we estimate changes in task efficiency ($\hat{\Xi}_i$) and use these to compute the relative changes in equilibrium due to HSR connections and recover changes in matching efficiency at the same time. Specifically, given $\hat{\Xi}_i$ and that $\hat{d}_{ni} = \hat{e}_{od} = \hat{T}_i = 1$, we solve equations (A.63) to (A.77) to obtain $\{\hat{w}_{M,i}$, $\hat{w}_{S,i}$, $\hat{\lambda}_{ni}$, $\hat{\Xi}_{M,i}$, $\hat{\Upsilon}_i$, $\hat{\mathbb{Y}}_i$, $\hat{v}_{M,i}$, $\hat{\pi}_{ni}$, $\hat{\delta}^B_{od}$, $\hat{\delta}^W_{od}$, $\hat{L}_{M,i}$, $\hat{L}_{S,i}$, Y'_i, $\Phi^{I\prime}_n$, $X^{c\prime}_i\}$.

Furthermore, we assess changes in broader technology ($\hat{\Upsilon}_i$), which allows us to compute the relative shifts in equilibrium due to both HSR connections and other technological advancements. This exercise assumes that $\hat{d}_{ni} = \hat{e}_{od} = 1$ and solve for $\{\hat{w}_{M,i}$, $\hat{w}_{S,i}$, $\hat{\mathbb{Y}}_i$, $\hat{\pi}_{ni}$, $\hat{\delta}^B_{od}$, $\hat{\delta}^W_{od}$, $\hat{L}_{M,i}$, $\hat{L}_{S,i}$, Y'_i, $\Phi^{I\prime}_n$, $X^{c\prime}_i\}$ through equations (A.67) to (A.77).

$$\hat{v}_{M,i} = \sum_j \frac{v_{M,ij}}{v_{M,i}} \hat{\lambda}_{M,ij} \hat{\Upsilon}_j^{\phi/\theta} \hat{d}_{ij}^{-\phi} \tag{A.63}$$

$$\hat{\Xi}_{M,i} = \bar{\omega}_{M,i} \hat{v}_{M,i} + (1 - \bar{\omega}_{M,i}) \hat{w}_{M,i}^{-\phi} \tag{A.64}$$

$$\hat{\Xi}_i = \hat{\Xi}_{M,i}^{\theta\zeta_M\beta_M/\phi} \hat{w}_{S,i}^{-\theta\zeta_S\beta_S} \tag{A.65}$$

$$\hat{\Upsilon}_i = \hat{T}_i \hat{w}_{M,i}^{-\theta(1-\zeta_M)\beta_M} \hat{\Xi}_{M,i}^{\theta\zeta_M\beta_M/\phi} \hat{w}_{S,i}^{-\theta\beta_S} \tag{A.66}$$

$$\hat{\mathbb{Y}}_n = \sum_j \pi_{nj} \hat{\Upsilon}_j \hat{d}_{nj}^{-\theta} \tag{A.67}$$

$$\hat{\pi}_{ni} = (\hat{\Upsilon}_i \hat{d}_{ni}^{-\theta}) / \hat{\mathbb{Y}}_n \tag{A.68}$$

$$\hat{\delta}_{od}^B = \frac{(\hat{w}_{M,d} \hat{\mathbb{Y}}_d^{1/\theta} / \hat{e}_{od}^B)^{\epsilon_B}}{\sum_g \delta_{og}^B (\hat{w}_{M,g} \hat{\mathbb{Y}}_g^{1/\theta} / \hat{e}_{og}^B)^{\epsilon_B}} \tag{A.69}$$

$$\hat{\delta}_{od}^W = \frac{(\hat{w}_{S,d} \hat{\mathbb{Y}}_d^{1/\theta} / \hat{e}_{od}^W)^{\epsilon_W}}{\sum_g \delta_{og}^W (\hat{w}_{S,g} \hat{\mathbb{Y}}_g^{1/\theta} / \hat{e}_{og}^W)^{\epsilon_W}} \tag{A.70}$$

$$\hat{L}_{M,d} = \sum_o \hat{\delta}_{od}^B \frac{\delta_{od}^B \bar{L}_o^B}{L_{M,d}} \tag{A.71}$$

$$\hat{L}_{S,d} = \sum_o \hat{\delta}_{od}^W \frac{\delta_{od}^W \bar{L}_o^W}{L_{S,d}} \tag{A.72}$$

$$Y_i' = \sum_{n=1}^N \pi_{ni} \hat{\pi}_{ni} \left[X_n^{c\prime} + \Phi_n^{I\prime} Y_n' \right] \tag{A.73}$$

$$\Phi_n^{I\prime} = 1 - \beta_S - \beta_M(1 - \zeta_M) - \beta_M \zeta_M (1 - \bar{\omega}_{M,n}) \frac{\hat{w}_{M,n}^{-\phi}}{\hat{\Xi}_{M,n}} \tag{A.74}$$

$$X_n^{c\prime} = w_{M,n} L_{M,n} \hat{w}_{M,n} \hat{L}_{M,n} + w_{S,n} L_{S,n} \hat{w}_{S,n} \hat{L}_{S,n} \tag{A.75}$$

$$w_{M,i} L_{M,i} \hat{w}_{M,i} \hat{L}_{M,i} = \left[\beta_M \zeta_M (1 - \bar{\omega}_{M,i}) \frac{\hat{w}_{M,i}^{-\phi}}{\hat{\Xi}_{M,i}} + \beta_M (1 - \zeta_M) \right] Y_i' \tag{A.76}$$

$$w_{S,i} L_{S,i} \hat{w}_{S,i} \hat{L}_{S,i} = \beta_S Y_i' \tag{A.77}$$

E.10 Estimating the Change in Matching Efficiency

We decompose the bilateral matching efficiency as the interaction of unilateral matching efficiencies of origin-destination city pairs ($\lambda_{M,ni} = \lambda_{M,n} \times \lambda_{M,i}$). Then, equation (A.63) can be rewritten as

$$\hat{v}_{M,i} = \hat{\lambda}_{M,i} \sum_j \frac{v_{M,ij}}{v_{M,i}} \hat{\lambda}_{M,j} \hat{\Upsilon}_j^{\phi/\theta} \hat{d}_{ij}^{-\phi} \tag{A.78}$$

To solve for $\hat{\lambda}_{M,i}$, we define function $F(x)$ from $\mathbb{R}_+^N$ to $\mathbb{R}^N$ as:

$$F(x_i) = x_i \sum_j \frac{v_{M,ij}}{v_{M,i}} x_j \hat{\Upsilon}_j^{\phi/\theta} \hat{d}_{ij}^{-\phi} - \hat{v}_{M,i} \tag{A.79}$$

Let's denote the derivative of $F(x)$ with respect to x_i as $F'(x_i)$, which we calculate as the following equation:

$$F'(x_i) = \sum_j \frac{v_{M,ij}}{v_{M,i}} x_j \hat{\Upsilon}_j^{\phi/\theta} \hat{d}_{ij}^{-\phi} + x_i \frac{v_{M,ii}}{v_{M,i}} \hat{\Upsilon}_i^{\phi/\theta} \hat{d}_{ii}^{-\phi} \tag{A.80}$$

Since $F'(x_i) > 0$, $F(x)$ is a monotonically increasing function. Given that $F(x = 0) < 0$ and $\liminf F(x) > 0$, there exists a unique solution for $\hat{\lambda}_{M,i}$ such that $F(\hat{\lambda}_{M,i}) = 0$ for all i.

E.11 Algorithm for Optimal HSR Placement

Social planner's problem. To maximize welfare, we consider a social planner whose objective is to select 71 out of the top 100 export cities in order to maximize aggregate welfare gains. Under each counterfactual HSR placement, every connected city is assumed to receive an exogenous increase in task efficiency, captured by $\hat{\Xi}_i = \exp(0.119) = 1.127$. The resulting welfare gains are then evaluated using the general equilibrium framework described in Appendix E.9.

Simulated Annealing algorithm. We first apply the Simulated Annealing algorithm (Henderson et al., 2003) to search for the optimal HSR placement that maximizes welfare. The algorithm begins with an initial configuration that replicates the actual HSR network, represented as a binary column vector of length 100, with 71 ones (connected cities) and 29 zeros (unconnected cities). The algorithm proceeds iteratively, with a maximum of 50,000 iterations. At each step, a new candidate solution is generated by randomly selecting one connected city and one unconnected city and swapping their statuses (i.e., exchanging a 0 and a 1 in the vector). This ensures that the constraint of exactly 71 connected cities is always satisfied. The new solution is evaluated and accepted according to the standard simulated annealing acceptance rule. If the new configuration yields higher welfare, it is accepted unconditionally. Otherwise, it is accepted with a probability proportional to $\exp\left(\frac{y_{\text{new}} - y_{\text{current}}}{T}\right)$, where T is the current temperature and y denotes the welfare gain, the objective being maximized. The temperature T decreases gradually over time following the cooling schedule: $T = T_0 \cdot \alpha^t$, where $T_0 = 1$ is the initial temperature, $\alpha = 0.99$ is the cooling rate, and t is the iteration count. By occasionally accepting inferior solutions, this approach helps the algorithm escape local optima and more thoroughly explore the solution space.

Greedy algorithm. We also implement a greedy algorithm that sequentially selects the locally optimal city at each step to approximate the global solution (Cormen et al., 2022). Specifically, we start with a zero column vector of length 100, indicating that no cities are initially connected. We then iteratively select the city whose inclusion—i.e., changing its corresponding entry from 0 to 1—yields the largest increase in welfare. Given the set of cities already selected, we continue to add one city at a time by choosing the unconnected city that maximizes welfare conditional on the existing configuration. This process is repeated until 71 cities are selected for HSR connection.