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Trade Costs, Entry Costs, and Regional Economic Growth in China

Zeyi Qian
Clark University

Kensuke Suzuki
Clark University and Nagoya University

Junfu Zhang
Clark University and IZA@LISER

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Abstract

This paper examines sectoral growth patterns across Chinese provinces during the country's economic takeoff in the early 2000s, following major policy reforms including trade liberalization, infrastructure expansion, business climate improvements, and relaxed rural-to-urban migration restrictions. We develop a multi-sector, multi-region spatial general equilibrium model with heterogeneous firms *á la* Melitz-Chaney to analyze how these reforms interacted to shape regional economic growth. We quantify the model for the Chinese economy and conduct counterfactuals to identify the key mechanisms driving regional development. We find that reductions in trade costs and lowered entry barriers facilitate firm entry and intensify competition. Together, these factors shape regional specialization and China's overall economic growth. Our decomposition exercises reveal that lowered business entry costs played a larger role than the reduction in trade costs in promoting the growth of real wages, especially in inland provinces. This operates through a selection effect, where more productive firms expand and force the least productive ones to exit, and through increased variety, which effectively lowers the price index.

JEL classification

F12, R12, L60

Keywords

regional economic growth, trade costs, entry costs, Melitz-Chaney model, China's manufacturing

Corresponding author

Junfu Zhang
JuZhang@clarku.edu

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1 Introduction

China's rapid economic transformation since the early 2000s is one of the most significant developments in modern economic history, reshaping global production and lifting hundreds of millions out of poverty. Economists have examined the drivers of this transformation from several perspectives, including institutional reforms and decentralization; capital accumulation and infrastructure investment; trade liberalization; greater labor mobility; and shifts in demographics, education, and technology. Yet one important dimension remains underexplored: the role of firms. Specifically, how the reallocation of economic activities within and across sectors and regions has shaped the regional growth is not well understood. This paper addresses that gap by placing firm sorting and selection at the center of the analysis, examining how the reshuffling of firms and resources across space and industries shaped regional development and aggregate productivity during China's economic takeoff.

We develop a unified quantitative framework to analyze regional economic growth and its underlying mechanisms. The model builds on the general equilibrium framework of trade with heterogeneous firms *a la* Melitz-Chaney (Melitz 2003, Chaney 2008), extending it to incorporate multiple sectors with input-output linkage (Caliendo and Parro 2015) and multiple regions within a country (Redding 2016, Ramondo et al. 2016). This structure allows us to measure the effects of changes in international and domestic trade costs, firm entry costs, and labor market frictions on economic activity. We quantify the model using detailed establishment-level data and inter-provincial input-output tables from 2002 to 2007, a period of significant economic reforms. We calibrate key structural parameters and fundamentals, including national manufacturing employment, inter-provincial trade costs, and sector- and region-specific entry costs.

We conduct counterfactual analysis by solving the model in relative changes using exact hat algebra (Dekle et al. 2008). Using 2002 as the base year, we introduce shocks to the model and simulate the economy under various counterfactual scenarios. First, we simulate the Chinese economy before the major reforms. Second, we assess the role of trade liberalization by adjusting international trade costs to their post-WTO accession levels and evaluate the effects of infrastructure development by setting domestic trade costs to their 2007 levels. Finally, we analyze the implications of an increasingly business-friendly environment by simulating the economy under the 2007 sunk entry costs for firms. Throughout these counterfactual exercises, we measure how changes in trade costs and entry costs reshape regional economic growth and welfare.

Our analysis yields several key insights into China's economic transformation. We find that reductions in trade costs and entry costs, though operating through different channels, both intensify competition. As a result, more productive firms grow and survive, while less productive firms exit, leading to higher average productivity and improved welfare (Hopenhayn

1992, Melitz 2003). These forces also drive greater regional specialization. Lower trade costs enable regions to specialize according to their comparative advantages and benefit from increasing returns to scale. At the same time, reduced entry costs encourage more firms to enter specific regions, enhancing specialization through targeted industrial policy. Increased specialization, in turn, promotes China's overall economic growth. Following Caliendo et al. (2023), we decompose real wage growth and find that increased variety, resulting from greater firm entry, accounts for the largest share of regional real wage gains, contributing a substantial 58% of the total increase.

Broadly speaking, this paper contributes to the rapidly growing literature that applies quantitative trade models to the study of regional economies within a country. This emerging field of quantitative spatial economics builds on the renewed interest in economic geography sparked by Krugman (1991) and is transforming how regional economics is conducted. See, for example, Redding and Rossi-Hansberg (2017), Redding (2024), and Allen and Arkolakis (2025) for comprehensive reviews. Much of this literature is built on various extensions of the Krugman (1980) model and the Eaton and Kortum (2002) model, likely due to their analytical tractability and numerical solvability. In contrast, the influential Melitz (2003) model, despite its central role in international trade theory, is rarely incorporated into quantitative spatial economics.[1] As a result, the implications of firm heterogeneity are much less explored in the regional context than in international trade.

This paper deviates from the prevailing tradition by embedding a system of regional economies within a standard Melitz-Chaney framework (Melitz 2003, Chaney 2008). Following this approach, firms are monopolistically competitive and draw heterogeneous productivities from Pareto distributions. Like recent spatial models, we adopt a multi-region, multi-sector structure with both internal and external trade costs and input-output linkages. This framework allows us to examine how the expansion of more productive firms and sectoral specialization contribute to regional economic growth and aggregate productivity. As discussed in Kucheryavyy et al. (2023), the multi-sector trade models with increasing returns to scale, including the Melitz model, may have corner equilibria in which industries shut down in some regions. We assure the interior solution by adopting the nested CES structure in aggregating varieties from different regions.

More specifically, our paper contributes to the literature that applies quantitative spatial models to study regional economies in China. Existing studies have focused on two main policy issues: *Hukou* reforms and reductions in migration costs (Fan 2019, Ma and Tang 2020, Fang and Huang 2022, Imbert et al. 2022, Liu and Ma 2023, Li et al. 2024, Zi 2025, Huang

[1] Indeed, none of the three review articles cited above mentions Melitz (2003). Baldwin and Okubo (2006) represent an early attempt to embed a Melitz model of monopolistic competition with heterogeneous firms into a new economic geography framework, although they did not bring the model to data. Ma and Tang (2020) quantitatively studied the local welfare effects of inter-city migration in China and used a single sector Melitz-type setup to model the production side.

et al. 2025, Wu and You 2025, Cai et al. 2025), and infrastructure improvements that lower internal trade costs (Fan et al. 2023, Ma and Tang 2024, Xu and Yang 2021, Che et al. 2024, Xu and Yang 2025). Tombe and Zhu (2019) incorporate these shocks, as well as reductions in international trade costs, into a multi-sector Eaton-Kortum framework, which allows them to quantify the relative contributions of each factor to productivity growth. Analyzing the period from 2002 to 2007, they find that reductions in internal trade and migration costs are more important than reductions in external trade costs.[2]

Like Tombe and Zhu (2019), we also find that internal trade costs played a greater role in China's growth than external trade costs. In addition, our use of the Melitz-Chaney framework allows us to quantify the effects of reductions in firm entry costs. We find that lowered entry costs contributed even more to productivity growth than trade costs, which is particularly true in inland regions. In this respect, our paper is closely related to Brandt et al. (2025), who show that business entry barriers explain most of the variation in economic growth across Chinese prefectures. While Brandt et al. (2025) focus primarily on identifying the factors behind regional variation in entry barriers, our study quantifies the relative importance of entry cost reductions compared to other structural shocks.

There is an early literature on the rise of China's economy that emphasizes "Chinese-style federalism," which incentivized local leaders to improve the business environment and attract investment (see, e.g., Montinola et al. 1995, Li and Zhou 2005, Zhang 2011, and Deng et al. 2025). Our findings, along with those of Brandt et al. (2025), are consistent with this literature's central theme that improvements in the local business climate played a key role in explaining the "China miracle." However, this earlier literature does not directly engage with the more recent body of work on the contributions of reduced migration and trade costs. By analyzing all of these factors within a unified framework, our paper is the first to explicitly bridge the gap between these two strands of research.

The remainder of the paper is structured as follows: Section 2 presents motivating evidence. Section 3 introduces the model framework. Section 4 quantifies the model, and Section 5 performs counterfactual analysis. Finally, Section 6 concludes.

2 Motivating Evidence

2.1 Regional Development of China 2002-2007

Since the early 2000s, China's economic transformation has been marked by significant expansion in the number of firms and the differential growth of productivity across regions. A key turning point was the country's accession to the WTO in 2001, which accelerated its

[2]Other works have examined related topics using reduced-form approaches, including Au and Henderson (2006), Zheng and Kahn (2013), Faber (2014), Lu and Yu (2015), Brandt et al. (2017), Baum-Snow et al. (2017), Lin (2017), Qin (2017), Erten and Leight (2021), and Yuan and Ouyang (2025).

integration into the global economy. This integration had profound implications for trade and investment patterns across the country.

At the same time, China undertook extensive infrastructure development, particularly in high-speed rail and highway networks. Improved connectivity facilitated the movement of goods and services, allowing firms to expand their market reach. Between 2002 and 2007, international trade costs for non-agricultural sectors fell by 8%, while domestic trade costs declined by 11% (Tombe and Zhu 2019). These trade cost reductions intensified market competition, forcing less productive firms to exit and enabling more competitive firms to expand, reshaping the geographic distribution of manufacturing activity.

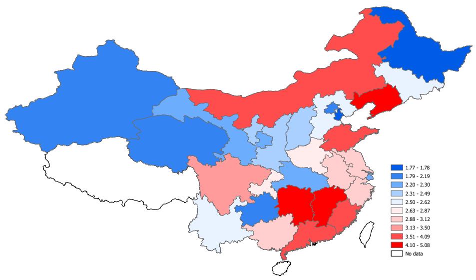
Another major driver of economic reallocation was the relaxation of the *Hukou* system, which historically restricted rural-to-urban migration. Recent reforms have eased these restrictions, allowing more rural workers to move to urban areas and fueling growth in manufacturing employment. The resulting increase in labor supply enabled firms to scale production, reduce costs, and compete more effectively in both domestic and international markets.

Equally important, though often underappreciated, is the role of regional development policies. In the early stages of economic reform, state-owned enterprises dominated the market, while private firms faced significant entry barriers due to strict regulations and limited access to resources. As reforms deepened and the business climate improved, these restrictions were gradually lifted, leading to a surge in private-sector participation. Local governments, operating within a system of "Chinese-style federalism," actively promoted economic growth by establishing development zones, offering tax incentives, and providing subsidies and cheap land. Development zones, in particular, offered streamlined administrative support and well-integrated infrastructure, creating a business-friendly environment that encouraged entrepreneurship and investment (Zhang 2011).

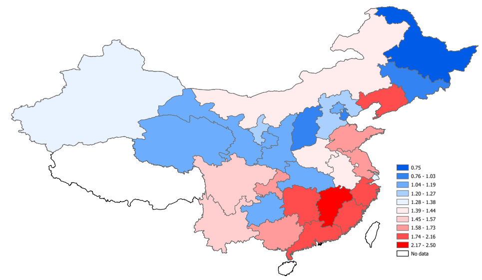
The combined effects of trade liberalization, infrastructure expansion, rural-to-urban migration, and regional development policies led to a notable reallocation of economic activity across regions. Coastal provinces experienced rapid growth, driven by foreign direct investment and the establishment of export-oriented manufacturing plants. By 2007, the six largest exporting provinces—Guangdong, Fujian, Jiangsu, Shanghai, Shandong, and Zhejiang—were all in coastal areas, collectively accounting for 79.7% of China's total exports. Panel A of Figure 1 shows the relative change in regional manufacturing GDP over the period from 2002 to 2007,[3] highlighting that the regions with the highest growth (indicated by red) were predominantly coastal, solidifying their role as key hubs in China's manufacturing landscape. This robust economic growth created a large number of new jobs, which in turn attracted more workers to these coastal areas, as shown in Panel B.

While much of the focus has been on coastal growth, inland regions have also experienced

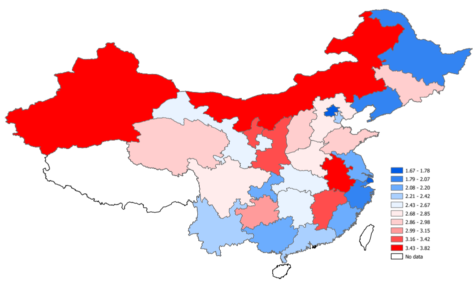
[3] For a generic variable x, the relative change from period t to t' is hereafter defined as $x_{t'}/x_t$.



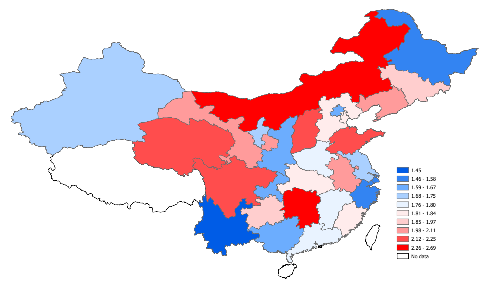
A: GDP



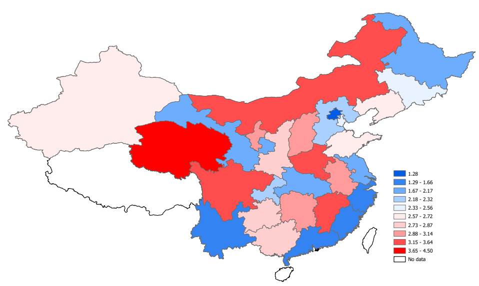
B: Employments



C: Number of Establishments



D: Average Wage



E: Average Productivity

Figure 1: Growth of Manufacturing by Region, 2002-2007

Note: We aggregated manufacturing firm-level data to calculate the number of establishments, GDP, average productivity, average wage, and employment for both 2002 and 2007. The map visualizes the 2007 figures relative to the 2002 baseline, with red shades representing higher values, highlighting regions with more significant growth.

significant industrial expansion. Since 2004, manufacturing output in these provinces has risen substantially (Zheng et al. 2014), driven by declining trade and entry costs, government-led initiatives such as the Western Development Program, and ongoing infrastructure improvements that enhanced market accessibility. Lower labor costs in these regions further motivated firms to establish operations there. Panel C of Figure 1 illustrates this shift, showing a growing concentration of manufacturing establishments in inland areas compared to coastal regions. While the absolute levels of economic output, wages, and productivity remain higher in coastal regions, Panels D and E clearly show that inland regions experienced faster growth in both wages and productivity, which significantly contributed to their overall economic development.[4]

2.2 Spatial Redistribution of Manufacturing 2002-2007

In addition to regional differences in economic growth, there are also sectoral differences in the spatial redistribution of industrial activities. For illustration, we draw attention to two high-profile companies. The first is the Angang Group. Headquartered in the city of Anshan, about 50 miles from the coast, its manufacturing facilities were initially clustered in the inland area. Over time, as the steel industry became increasingly reliant on inputs from foreign countries and output markets worldwide, Angang moved closer to the coast by acquiring and building new plants in coastal areas. Its new steel plant at Bayuquan was largely constructed on reclaimed land. In contrast, Foxconn, the multinational electronics manufacturer, first entered China in coastal provinces (Shenzhen in Guangdong Province and Kunshan in Jiangsu Province). Over time, as infrastructure improved in China, Foxconn set up one plant after another in inland provinces, paying only slightly higher transportation costs while saving significantly on wages by locating closer to sources of migrant workers.[5]

To measure this redistribution more systematically, we compute the Ellison and Glaeser (1997) index for each sector and examine its changes over time. The index is defined as follows:

$$G^j = \sum_n \left(\frac{Y_n^j}{Y_C^j} - \frac{Y_n}{Y_C} \right)^2$$

where Y_n^j denotes the GDP of sector j in region n, Y_C^j represents the GDP of sector j in the whole country, Y_n represents the total GDP of region n, and Y_C is the total GDP of the whole country. A higher value of this index indicates that a sector's GDP is more heavily concentrated in certain regions rather than being evenly spread nationwide.

Table 1 compares sectoral concentration levels between 2002 and 2007. Most sectors became more geographically concentrated, while only one showed greater dispersion. Electronics, Food,

[4]In Appendix B, we demonstrate through a quantile regression analysis that the productivity distribution of firms in inland regions experienced a greater rightward shift compared to those in coastal regions.

[5]See the illustration in Appendix C.

Table 1: Sectoral Concentration Index

	Food	**Chemicals**	**Metals**	**Machinery**	**Electronics**	**Others**
2002	0.0029	0.0013	0.0039	0.0086	0.0183	0.0074
2007	0.0048	0.0017	0.0040	0.0055	0.0265	0.0087
Δ	0.0019	0.0004	0.0001	-0.0031	0.0082	0.0013
$\%\Delta$	63.91%	31.93%	1.21%	-36.77%	44.44%	17.48 %

Note: We consolidate the manufacturing industries into six sectors (5 specific sectors+1 other sector) and use *Chinese Industrial Enterprise Database* to calculate the outcomes, which will be discussed in detail in the calibration section. In Appendix D, we provide another way to measure regional specialization by the Herfindahl-Hirschman Index.

and Chemicals, for example, experienced a marked rise in concentration, reflecting production that clustered more tightly in specific regional hubs. The Metals sector's index rose by only 1.21%, indicating a relatively stable distribution over the period. By contrast, the Machinery sector was the sole case of declining concentration, with its index falling by 37%, suggesting that production spread more widely across the country.

These patterns highlight substantial regional differences in economic growth and sectoral variation in the spatial distribution of manufacturing activity in China, underscoring the importance of understanding how trade liberalization, infrastructure development, improvements in the local business climate, and labor mobility interact to shape the country's manufacturing landscape.

3 Quantitative Model

To gain deeper insights into regional manufacturing growth, we develop a multi-region, multi-sector Melitz–Chaney model with heterogeneous firms (Melitz 2003, Chaney 2008). The model incorporates interregional trade, sectoral input–output linkages (Caliendo and Parro 2015), labor mobility (Redding 2016), and both domestic and international trade frictions. We use the model to examine the effects of a reduction in trade costs, lower firm entry barriers, and increased total employment, thereby clarifying the key drivers of local productivity growth and the redistribution of manufacturing activity across regions in China.

3.1 Environment

We consider a world consisting of China and the rest of the world (RoW). China is divided into N regions, indexed by subscripts m or n $(= 1, 2, \ldots, N)$, while the RoW is denoted by subscript 0. For convenience, the term "region" refers to both Chinese regions and the RoW. Each region's economy consists of J manufacturing sectors, indexed by superscripts i or j $(= 1, 2, \ldots, J)$, and an agricultural sector, indexed by superscript 0. When needed, we use $k \in \{M, A\}$ to distinguish manufacturing sectors (M) in urban areas from the agricultural sector (A) in rural areas. Labor and land are primary factors of production, and land is only used for agricultural production. Total endowment of labor in both China and the RoW is fixed, and each region is endowed with a fixed amount of land. Within China, workers are mobile across regions and sectors, but each has idiosyncratic preferences for particular (n, k) region-sector combinations.

3.2 Worker Preferences

There is an ex-ante identical continuum of consumers indexed by ω. The mass of workers in China and the RoW is fixed and represented by L_C and L_0, respectively.

A worker ω residing in the urban (working in manufacturing) or rural (working in agricultural) area k of region n has a utility defined as:

$$u_n^k(\omega) = \ln(C_n(\omega)) + \ln\left(B_n^k\right) + \eta\varepsilon_n^k(\omega), \tag{1}$$

where $C_n(\omega)$ is goods consumption index, B_n^k is a local amenity, and ε_n^k is an idiosyncratic preference shock. The parameter η scales the variance of the shock. The preference shock captures heterogeneous tastes for living in urban or rural areas of each region in China. Following Diamond (2016) and Caliendo et al. (2019), we assume that $\varepsilon_n^k(\omega)$ is independently drawn across Chinese regions and workers from a Gumbel distribution with CDF $F(\epsilon) = \exp(-\exp(-\varepsilon - \tilde{\gamma}))$, where $\tilde{\gamma}$ is the Euler-Mascheroni constant.

Since the RoW consists of a single region, we normalize $B_0^k = 1$. The goods consumption index C_n is defined as a Cobb-Douglas bundle of sectoral final goods C_n^j:

$$C_n(\omega) = \prod_{j=0}^{J}\left(\frac{C_n^j(\omega)}{\alpha^j}\right)^{\alpha^j} \quad \text{with } \alpha^j \in (0,1) \text{ and } \sum_{j=0}^{J}\alpha^j = 1, \tag{2}$$

where $C_n^j(\omega)$ is worker ω's consumption of final good j in region n and α^j is the expenditure share on final good j. From (1) and (2), we obtain the indirect utility of consumer ω residing in region n:

$$v_n^k(\omega) = \ln\left(B_n^k \frac{e_n^k(\omega)}{P_n}\right) + \eta\varepsilon_n^k(\omega)$$

where $e_n^k(\omega)$ is the worker's expenditure on final goods and P_n is the consumer price index dual to (2):

$$P_n = \prod_{j=0}^{J}\left(P_n^j\right)^{\alpha^j}, \tag{3}$$

where P_n^j is the price of sectoral final good j in region n.

After observing the realization of idiosyncratic preference shocks, workers choose the region-area pair that maximizes their utility:

$$\max_{n \in \{1,\ldots,N\},\ k \in \{A,M\}} v_n^k(\omega).$$

3.3 Production Side

On the production side, the model distinguishes between the agriculture and manufacturing sectors. In each region, a perfectly competitive representative producer supplies a non-tradable agricultural good. In contrast, each manufacturing sector is populated by a continuum of heterogeneous firms producing differentiated varieties sold in monopolistically competitive markets across regions.

Agriculture

A representative producer in region n produces an agricultural good according to the Cobb-Douglas technology defined over inputs of labor L_n^A and land D_n:

$$Q_n^A = \mathcal{A}_n^A \left(\frac{L_n^A}{\beta^A}\right)^{\beta^A} \left(\frac{D_n}{1-\beta^A}\right)^{1-\beta^A},$$

where $\mathcal{A}_n^A$ denotes exogenous agricultural productivity, and β^A is the labor share in total cost of production. Solving the cost minimization problem given factor prices yields the unit cost function:

$$P_n^A = \frac{\left(w_n^A\right)^{\beta^A} \left(\tilde{r}_n\right)^{1-\beta^A}}{\mathcal{A}_n^A},$$

where w_n^A is the wage for agricultural workers, and $\tilde{r}_n$ is the rental rate of land.

Manufacturing

Intermediate Good Producers

Each manufacturing sector features a continuum of firms, each producing a distinct variety. Output is costly traded across space and sold in monopolistically competitive markets. Firms are heterogeneous in their core productivity *à la* Melitz (2003). Let φ_n^j be the productivity of a firm in sector j located in region n. As each firm is distinguished by productivity and produces a unique variety, we use φ_n^j to index firm and variety. A firm with productivity φ_n^j in sector j and region n has a Cobb-Douglas production function defined over labor input

$\ell_n^j(\varphi_n^j)$ and composite intermediate inputs $m_n^j(\varphi_n^j)$:

$$q_n^j(\varphi_n^j) = \varphi_n^j \left(\frac{\ell_n^j(\varphi_n^j)}{\beta^j}\right)^{\beta^j} \left(\frac{m_n^j(\varphi_n^j)}{1-\beta^j}\right)^{1-\beta^j},$$

where β^j is the cost share of labor input in total production cost. Following the formulation of sectoral input-output linkages by Caliendo and Parro (2015), we assume that firms use sectoral final goods (defined below) from all sectors as intermediate inputs, such that

$$m_n^j(\varphi_n^j) = \prod_{i\in\{1,2,\ldots,J\}} \left(\frac{m_n^{ji}(\varphi_n^j)}{\gamma^{ji}}\right)^{\gamma^{ji}}, \tag{4}$$

where $m_n^{ji}(\varphi_n^j)$ is the quantity of final good i used to produce variety φ_n^j and γ^{ji} is the associated intermediate input share.

Solving the cost minimization problem of a firm gives the marginal cost of production as $c_n^j(\varphi_n^j) = c_n^j/\varphi_n^j$, where c_n^j is the cost of input bundle defined as:

$$c_n^j = \left(w_n^M\right)^{\beta^j} \left(\Xi_n^j\right)^{1-\beta^j},$$

where w_n^M is manufacturing wage, and Ξ_n^j is the price index of composite intermediate inputs dual to (4):

$$\Xi_n^j = \prod_{i\in\{1,2,\ldots,J\}} \left(P_n^i\right)^{\gamma^{ji}},$$

where P_n^i is the price index of final good i.

A firm in sector j based in region n needs to incur two types of costs to serve the market in region m. The first cost is the variable iceberg trade costs, and the second is a fixed cost, which will be introduced below. To ship one unit of sector j good from n to m, a firm needs to ship τ_{mn}^j units of the goods. $\tau_{mn}^j \geq 1$ and we assume $\tau_{nn}^j = 1$ for all m, n and the triangular inequality holds. The marginal cost of serving goods from n to m is given by:

$$c_{mn}^j(\varphi_n^j) = \tau_{mn}^j \frac{c_n^j}{\varphi_n^j}.$$

Final Good Producers

In each sector and region, there is a final good producer that purchases and aggregates all of the varieties sold to the market. To avoid a corner equilibrium where industries do not produce at all in some regions, we follow Kucheryavyy et al. (2023) and adopt a three-tier nested CES structure as an aggregator. Let Q_n^j be the quantity of sectoral final good j sold in region n. The upper-tier of the aggregator is defined over goods sourced from China and RoW:

$$Q_n^j = \left(\left(\tilde{Q}_{nC}^j \right)^{\frac{\rho^j - 1}{\rho^j}} + \left(\tilde{Q}_{n0}^j \right)^{\frac{\rho^j - 1}{\rho^j}} \right)^{\frac{\rho^j}{\rho^j - 1}}. \tag{5}$$

where $\tilde{Q}_{n0}^j$ is the composite of RoW-sourced varieties. $\tilde{Q}_{nC}^j$ is the composite of varieties sourced from different Chinese regions in sector j defined by the middle-tier CES aggregator:

$$\tilde{Q}_{nC}^j = \left(\sum_{m \in \{1,2,\ldots,N\}} \left(Q_{nm}^j \right)^{\frac{\epsilon^j - 1}{\epsilon^j}} \right)^{\frac{\epsilon^j}{\epsilon^j - 1}},$$

Finally, Q_{nm}^j is the composite of varieties produced by firms in a Chinese region m and sold in region n, which is defined by the lower-tier aggregator:

$$Q_{nm}^j = \left(\int_{\phi \in \Omega_{nm}^j} \left(q_{nm}^j(\phi) \right)^{\frac{\sigma^j - 1}{\sigma^j}} d\phi \right)^{\frac{\sigma^j}{\sigma^j - 1}},$$

where $q_{nm}^j(\phi)$ is the quantity of variety ϕ produced in region m and sold in region n. σ^j denotes the elasticity of substitution across varieties produced within a region (lower-tier CES elasticity), ϵ^j represents the elasticity of substitution across goods produced in different regions in China (middle-tier CES elasticity), and ρ^j is the elasticity of substitution between domestic and foreign-produced goods (upper-tier CES elasticity). Ω_{nm}^j is the set of varieties produced in m and sold in n, which is determined in equilibrium.

Solving a firm's profit maximization problem, we get the firm's pricing rule,

$$p_{nm}^j(\varphi_m^j) = \mu^j c_{nm}^j(\varphi_m^j), \tag{6}$$

where $\mu^j = \frac{\sigma^j}{\sigma^j - 1}$ is the markup for sector j (Dixit and Stiglitz 1977). Price index of the sectoral final good dual to (5) is given by:

$$P_n^j = \left(\left(\tilde{P}_{nC}^j \right)^{1-\rho^j} + \left(\tilde{P}_{n0}^j \right)^{1-\rho^j} \right)^{\frac{1}{1-\rho^j}}, \tag{7}$$

where the price index for China-sourced varieties $\tilde{P}_{nC}^j$ is given by

$$\tilde{P}_{nC}^j = \left(\sum_{m \in \{1,2,\ldots,N\}} (\zeta_{nm}^j)^{1-\epsilon^j} \right)^{\frac{1}{1-\epsilon^j}},$$

where

$$\zeta^j_{nm} = \left(\int_{\phi \in \Omega^j_{nm}} \left(p^j_{nm}(\phi) \right)^{1-\sigma^j} d\phi \right)^{\frac{1}{1-\sigma^j}}, \tag{8}$$

for $n \in \{0, 1, ..., N\}$ and $m \neq 0$. For the RoW-sourced varieties, $\tilde{P}^j_{n0}$ is defined as:

$$\tilde{P}^j_{n0} = \left(\int_{\phi \in \Omega^j_{n0}} \left(p^j_{n0}(\phi) \right)^{1-\sigma^j} d\phi \right)^{\frac{1}{1-\sigma^j}}.$$

The nested CES structure of the final good aggregator implies that the expenditure share on goods sourced from China in the total spending on sectoral final good in region n is given by:

$$g^j_{nC} = \frac{\left(\tilde{P}^j_{nC} \right)^{1-\rho^j}}{\left(P^j_n \right)^{1-\rho^j}}, \tag{9}$$

Similarly, we can show that the expenditure share on goods sourced from a Chinese region m in total spending on China-sourced goods is

$$\lambda^j_{nm} = \frac{\left(\zeta^j_{nm} \right)^{1-\epsilon^j}}{\left(\tilde{P}^j_{nC} \right)^{1-\epsilon^j}}. \tag{10}$$

Sunk Entry Costs and Fixed Costs to Serve Each Market

As in Melitz (2003), firms entering sector j in region m must pay an upfront sunk entry cost f^{jE}_m, measured in local labor, before drawing their productivity. This cost represents the initial investment required to start the business, such as feasibility studies, business registration, and compliance with local regulations. It is a one-time expense, independent of future production or sales, and reflects the overall business environment. These costs act as barriers to entry.

After drawing the productivity by paying the sunk entry cost, firms in sector j and region m need to pay a fixed cost f^j_{nm} to serve in market n, again denominated in local labor. This may include costs for market research and the establishment of distribution networks. We assume that there is a fixed cost to serve in the local market, but this is presumably lower than the ones of serving other regions, i.e., $f^j_{nm} \geq f^j_{mm}$. Furthermore, the fixed cost to serve the foreign market should be higher than the ones of serving domestic markets, i.e., $f^j_{nm} \leq f^j_{0m}$, resulting in a productivity sorting of firms to export.

Let $r_{nm}(\varphi^j_m) \equiv q^j_{nm}(\varphi^j_m) p^j_{nm}(\varphi^j_m)$ be the revenue of firm φ^j_m from selling to region n. It follows from (6) that the firm's operating profit gross of fixed cost is a constant fraction of revenue:

$$\varpi^j_{nm}(\varphi^j_m) = r^j_{nm}(\varphi^j_m) - q^j_{nm}(\varphi^j_m)c^j_{nm}(\varphi^j_m) = \frac{1}{\sigma^j} r^j_{nm}(\varphi^j_m).$$

Since $\varpi_{nm}(\varphi^j_n)$ is monotonically increasing in productivity φ^j_m, there is a unique productivity cutoff ϕ^j_{nm}, which represents the productivity of the least productive firm that can cover the fixed cost of serving from m to n. The cutoff productivity is defined by:

$$\varpi^j_{nm}(\phi^j_{nm}) = f^j_{nm} w^M_m. \tag{11}$$

3.4 Aggregation and General Equilibrium

Price Indices and Goods Market Clearing

Following Chaney (2008), we assume that ex-ante identical entrants draw productivity from a Pareto distribution with the cumulative distribution function $G^j_n(\phi) = 1 - \left(\tilde{b}^j_n/\phi\right)^{\theta^j}$ where $\varphi^j_n \geq \tilde{b}^j_n$. Its density function is denoted by $g^j_n(\phi) = \frac{d}{d\phi}G^j_n(\phi)$. The shape parameter θ^j differs across sectors. The location parameter $\tilde{b}^j_n$ is region- and sector-specific, capturing the heterogeneity in fundamental sectoral productivity across regions.

Sales of firm φ^j_m based in region m selling to region n can be expressed as:

$$r^j_{nm}(\varphi^j_m) = \begin{cases} X^j_{nC}\left(\frac{p^j_{nm}(\varphi^j_m)}{\zeta^j_{nm}}\right)^{1-\sigma^j}\left(\frac{\zeta^j_{nm}}{\tilde{P}^j_{nC}}\right)^{1-\epsilon^j}, & \text{for } m \neq 0 \\ X^j_{n0}\left(\frac{p^j_{nm}(\varphi^j_m)}{\tilde{P}^j_{n0}}\right)^{1-\sigma^j}, & \text{for } m = 0 \end{cases} \tag{12}$$

where X^j_{nC} is the total expenditure on China-sourced sector-j goods in region n and X^j_{n0} is the total expenditure on the ROW-sourced sector-j goods. From the zero cutoff profit condition in (11), the cutoff productivity above which firms serve the market in region n from region m is given by,

$$\phi^j_{nm} = \begin{cases} \left(\frac{\sigma^j w^M_m f^j_{nm}(\mu^j c^j_{nm})^{\sigma^j-1}}{X^j_{nC}\left(\zeta^j_{nm}\right)^{\sigma^j-\epsilon^j}\left(\tilde{P}^j_{nC}\right)^{\epsilon^j-1}}\right)^{\frac{1}{\sigma^j-1}}, & \text{for } m \neq 0 \\ \left(\frac{\sigma^j w^M_0 f^j_{n0}(\mu^j c^j_{n0})^{\sigma^j-1}}{X^j_{n0}\left(\tilde{P}^j_{n0}\right)^{\sigma^j-1}}\right)^{\frac{1}{\sigma^j-1}}. & \text{for } m = 0 \end{cases} \tag{13}$$

In our model, competition affects the selection of firms through the change in productivity cutoff ϕ^j_{nm}, which determines which firms can profitably serve a market. Wage w^M_m, fixed costs f^j_{nm}, and production costs c^j_{nm} raise the cutoff productivity required for firms to serve. In addition, higher expenditures and a lower price index in region n lower the cutoff. These factors drive a competitive selection effect, where only firms with higher productivity can survive and compete, while less productive firms are forced to exit the market.

Using the cutoff productivity obtained in (13), we define the average productivity of sector-j firms selling goods from m to n as

$$\overline{\phi}^j_{mn} = \left(\frac{1}{1 - G^j_n(\phi^j_{mn})} \int_{\phi^j_{mn}} (\phi)^{\sigma^j - 1} \, dG^j(\phi) \right)^{\frac{1}{\sigma^j - 1}} = \left(\frac{\theta^j}{\theta^j + 1 - \sigma^j} \right)^{\frac{1}{\sigma^j - 1}} \phi^j_{mn}. \tag{14}$$

Furthermore, the mass of firms selling from m to n is given by

$$T^j_{nm} = (1 - G^j_n(\phi^j_{nm}))T^j_m = \left(\frac{\tilde{b}^j_m}{\phi^j_{nm}} \right)^{\theta^j} T^j_m. \tag{15}$$

where T^j_n is the mass of entrants who draw the productivity. The mass of entrants is determined by the free-entry condition discussed below.

Combining equations (6), (8), (14), and (15), we can solve for the price index of goods sourced from the Chinese region m and sold in the region n as

$$\zeta^j_{nm} = \frac{\mu^j \left(T^j_{nm} \right)^{\frac{1}{1-\sigma^j}} c^j_{nm}}{\overline{\phi}^j_{nm}} \quad \text{for } m \neq 0, \tag{16}$$

and the price index of goods sourced from the RoW and sold in region n as

$$\tilde{P}^j_{n0} = \frac{\mu^j \left(T^j_{n0} \right)^{\frac{1}{1-\sigma^j}} c^j_{n0}}{\overline{\phi}^j_{n0}}.$$

Total spending on final goods j in region n is the sum of expenditure by workers as final consumption (E^j_n) and by firms as an intermediate input (M^j_n):

$$X^j_n = E^j_n + M^j_n. \tag{17}$$

Total spending on sector-j good is decomposed into spending on China-sourced goods and RoW-sourced goods. Spending on China-sourced goods is given by:

$$X^j_{nC} = g^j_{nC} X^j_n,$$

where g^j_C is the expenditure share on China-sourced goods in total spending on final goods defined by (9). X^j_{n0} is defined analogously.

Then the bilateral trade flow, i.e., the total spending on goods sourced from m and sold in

n can be expressed as:

$$X_{nm}^j = \begin{cases} \lambda_{nm}^j X_{nC}^j, & \text{for } m \neq 0 \\ X_{n0}^j. & \text{for } m = 0 \end{cases} \tag{18}$$

Let Y_n^j be the total sales (gross output) of firms based in region n. Total sales are the sum of total spending on the goods over all destination regions:[6]

$$Y_n^j = \sum_{m=0,1,\ldots,N} X_{mn}^j. \tag{19}$$

Spending by firms in region n on sectoral good j as an intermediate input can be expressed using the total sales Y_n^j:

$$M_n^j = \sum_{i \in \{1,2,\ldots,6\}} \frac{Y_n^i}{\mu^i}(1-\beta^i)\gamma^{ij}. \tag{20}$$

For the agricultural sector, output is non-tradable. Therefore, the total sales in region n is equal to the total spending, i.e.,

$$X_n^A = Y_n^A,$$

where $X_n^A = E_n^A$ is the total spending on agricultural goods as final goods and Y_n^A is the total sales.

Free Entry of Firms

Following Melitz (2003), we assume that the mass of entrants T_n^j is determined such that the ex-ante expected profit is zero, i.e.,

$$\mathbb{E}\left[\sum_{n=0}^{N}\left(\varpi_{nm}(\varphi_m^j) - f_{nm}^j w_m^j\right)\right] = f_m^{jE} w_m^M,$$

where the expectation is taken over the productivity. This suggests that, in equilibrium, the aggregate profit of all firms in region m will be zero. To derive the free entry condition determining the mass of entrants T_m^j, we first show that the total spending on fixed costs by

[6]Equation (19) can be seen as a goods market clearing condition where the left-hand side is supply and the right-hand side is demand. Total sales are the sum of factor rewards and intermediate input costs, multiplied by the constant markup. With Cobb-Douglas technology, $Y_n^j = \mu^j \frac{w_n^M L_n^j}{\beta^j}$ where L_n^j is the total demand for labor in sector j.

all firms serving from region m to n, F^j_{nm}, is a constant fraction of the aggregate sales, i.e.,

$$F^j_{nm} = T^j_{nm} w^M_m f^j_{nm} = \frac{\theta^j + 1 - \sigma^j}{\sigma^j \theta^j} X^j_{nm}. \tag{21}$$

Since the operating profit of the firm is a constant share of revenue, by combining the result from (21), we can show that the total profit of firms producing in region m, net of fixed cost payment, is also a constant share of total sales, i.e.,

$$\Pi^j_m = \sum_{n \in \{0,1,2,\ldots,N\}} \left(\frac{1}{\sigma^j} X^j_{nm} - F^j_{nm} \right) = \left(\frac{\sigma^j - 1}{\sigma^j \theta^j} \right) Y^j_m.$$

Free entry of firms in equilibrium implies that the total profit of firms in the region m (net of fixed costs) is equal to the payment for the sunk entry cost: $\left(\frac{\sigma^j - 1}{\sigma^j \theta^j} \right) Y^j_m = T^j_m w_m f^{jE}_m$. This gives the mass of entrants entering region m in sector j,

$$T^j_m = \frac{\left(\frac{\sigma^j - 1}{\sigma^j \theta^j} \right) Y^j_m}{w^M_m f^{jE}_m}. \tag{22}$$

Thus, the mass of entrants T^j_m is inversely proportional to sunk entry costs f^{jE}_m, meaning that higher sunk entry costs lead to fewer entrants.

Labor and Land Market Clearing

We now outline the aggregate results for labor sorting. Unlike other quantitative spatial studies that explicitly incorporate migration costs across regions in China (e.g., Fan 2019, Tombe and Zhu 2019, and Zi 2025), we do not consider the bilateral migration, following Redding (2016). Despite the absence of the bilateral migration restrictions, our model captures the sluggish response of labor sorting to the aggregate variables by a lower location choice elasticity (higher η).[7] This assumption helps ease the computational burden inherent in a Melitz–Chaney type model. Given the real wage and amenity, by taking advantage of Gumbel distributed preference shocks, we can derive the analytical expression for the choice probability for region $n \in \{1, 2, .., N\}$ and sector $k \in \{A, M\}$:

$$\psi^k_n = \frac{\left(B^k_n \frac{w^k_n}{P_n} \right)^{1/\eta}}{\sum_k \sum_m \left(B^k_m \frac{w^k_m}{P_m} \right)^{1/\eta}}, \tag{23}$$

[7] As detailed below, we calibrated a location choice elasticity of 0.5 from Caliendo et al. (2021), in contrast to 1.5 in Tombe and Zhu (2019) and over 4 in Fan (2019).

where $1/\eta$ is location choice elasticity as in Caliendo et al. (2019). By the law of large numbers, the mass of workers residing in region n and area k in China is

$$L_n^k = \psi_n^k L_C,$$

where L_C is the mass of workers in China, which is exogenously given in the model.

We assume that wage is the only source of income for workers, which yields the total expenditure in region n on final goods as:

$$E_n = L_n^M w_n^M + L_n^A w_n^A,$$

and sectoral spending is given by

$$E_n^j = \alpha^j E_n.$$

The labor market clearing condition for manufacturing sectors requires that

$$L_n^M w_n^M = \sum_{j \in \{1,2,\ldots,6\}} \left(\beta^j \frac{Y_n^j}{\mu^j} + \frac{1}{\sigma^j} Y_n^j \right), \tag{24}$$

where the left-hand side is labor supply in terms of value, and the right-hand side is the labor demand, which is the sum of demand for labor as variable costs and as fixed and sunk entry costs. The labor market clearing condition for the agricultural sector is

$$L_n^A w_n^A = \beta^A Y_n^A, \tag{25}$$

where the total value of what is produced, sold, and spent on agricultural goods is all equal.

Finally, the land market clearing condition follows from (25). Since agricultural production is the sole use of land, total expenditure on land in agriculture equals the value of regional land endowment:

$$D_n \tilde{r}_n = \left(1 - \beta^A\right) Y_n^A.$$

Welfare

Following Caliendo et al. (2019), welfare is represented by the rescaled expected utility of a worker. Given the Gumbel-distributed preference shocks, this rescaled expected utility can be derived as follows,

$$W_C = e^{\overline{u}} = \left(\sum_n \sum_k \left(B_n^k \frac{w_n^k}{P_n} \right)^{1/\eta} \right)^{\eta},$$

where $\frac{w_n^k}{P_n}$ represents the real wage. A higher real wage indicates that workers can purchase more goods with their income, leading to an increase in welfare. Consequently, regions with higher real wages contribute more significantly to overall welfare.

General Equilibrium

A general equilibrium of the model is a vector of wages $\{w_n^k\}$, price indices $\{\tilde{P}_{n0}^j\}$ and $\{\tilde{P}_{nC}^j\}$, total sales $\{Y_n^j\}$, mass of entrants $\{T_n^j\}$, and labor allocations $\{L_n^k\}$, that satisfy the following equilibrium conditions: (i) *utility maximization by each household*, which yields price index (3); (ii) *profit maximization by each firm*, implying (6) and (7); (iii) *zero profit of the marginal firm as a result of free entry*, which determines the cutoff productivity and mass of entrants in (13) and (22); (iv) *goods markets clearing for every sector in each region*, as in (17)-(20); and (v) *labor market clearing for every sector in each region*, given by (24).

3.5 Equilibrium in Relative Changes

Solving an equilibrium of the model in levels requires calibration of all parameters, including structural parameters (such as Pareto shape and elasticities of substitutions) and all fundamentals (such as Pareto location, trade costs, sunk entry costs, and fixed costs). In the next section, we measure changes in the key fundamentals that underlie economic reforms and takeoff in China in the 2000s, i.e., expansion of total employment and reductions in trade costs and sunk entry costs. Yet, calibration of the Pareto scale parameters and bilateral fixed costs is particularly challenging due to the data limitations.[8] Therefore, we employ the exact hat algebra method following Dekle et al. (2008), which solves the model in relative change, conditioning on the base-year equilibrium outcomes. The underlying assumption of the method is that there is a vector of fundamentals that rationalizes the base-year outcomes (i.e., what we observe in the data). Then, for a given set of shocks to the fundamentals (e.g., a reduction in trade costs), we characterize the equilibrium relative to the base year outcomes.

Specifically, for a generic variable x, we define the "hat" notation as $\hat{x} = \frac{x'}{x}$, where x is the variable in the baseline equilibrium and x' is the one in the counterfactual equilibrium. Then a general equilibrium in relative changes is defined formally as follows.

Definition *For given structural parameters,* θ^j, $\tilde{b}_n^j$, σ^j, ϵ^j, η, α^j, β^j, γ^{ji}, *and* ρ^j, *and for given fundamentals in relative changes,* $\{\hat{L}_C\}$, $\{\hat{L}_0\}$, $\{\hat{D}_n\}$, $\{\hat{\tau}_{nm}^j\}$, $\{\hat{B}_n^j\}$, $\{\hat{f}_{nm}^j\}$, $\{\hat{f}_n^{Ej}\}$, *and* $\{\hat{A}_n^A\}$, *a general equilibrium in relative changes is given by a vector of* $\{\hat{w}_n^k\}$, $\{\hat{\tilde{P}}_{n0}^j\}$, $\{\hat{\tilde{P}}_{nC}^j\}$, $\{\hat{Y}_n^j\}$, $\{\hat{L}_n^k\}$, $\{\hat{T}_n^j\}$, *and* $\{\hat{\phi}_{mn}^j\}$.

[8]In Appendix F, we solve the model in levels by feeding all the calibrated fundamentals (see the next section for the details) other than the Pareto location and fixed costs, and compare the model-implied outcomes with the data counterparts. The model fits the data better for the regional outcomes, such as regional output and employment, but fails to capture the sectoral heterogeneity. This calls for the equilibrium characterization in relative changes.

Appendix G shows all of the equilibrium conditions in relative change and the solution algorithm.

3.6 Decomposition

Before we move on to the quantification, we use the equilibrium conditions to decompose the change in two key aggregate variables: real wages and average productivity. This decomposition guides us to empirically identify the driver of the changes in the two key aggregate variables.

Real Wages

We start by decomposing the change in real wages for the manufacturing sector. For the sake of analytical convenience, we first define the Cobb-Douglas price index for manufacturing goods as:

$$P_n^M = \prod_{j=1}^{J} \left(P_n^j\right)^{\tilde{\alpha}^j},$$

where $\tilde{\alpha}^j = \alpha^j/(1-\alpha^0)$ is expenditure share on sector-j final good in total spending on manufacturing goods. We then let $\tilde{v}_n^M = w^M/P_n^M$ be the manufacturing real wage, which we decompose as follows:

$$\begin{aligned}
\frac{d\tilde{v}_n^M}{\tilde{v}_n^M} =& \frac{dw_n^M}{w_n^M} - \sum_j \tilde{\alpha}^j \frac{dP_n^j}{P_n^j} \\
=& \frac{dw_n^M}{w_n^M} \quad \cdots\cdots \textbf{Term 1} \\
&+ \sum_j \frac{\tilde{\alpha}^j}{\theta^j}\Bigg[\underbrace{\left(\frac{\theta^j}{\sigma^j-1}-1\right)}_{\text{Selection}}\left(\underbrace{\frac{dX_n^j}{X_n^j}}_{\text{Scale}} - \underbrace{\frac{d\left(w_n^M f_{nn}^j\right)}{w_n^M f_{nn}^j}}_{\text{Fixed costs}}\right) + \underbrace{\frac{dT_n^j}{T_n^j}}_{\text{Firm entry}}\Bigg] \quad \cdots\cdots \textbf{Term 2} \\
&+ \sum_j \frac{\tilde{\alpha}^j}{\theta^j}\Bigg[\underbrace{\left(\frac{\theta^j}{\sigma^j-1}-\frac{\theta^j}{\epsilon^j-1}-1\right)}_{\text{Armington across regions}}\frac{d\lambda_{nn}^j}{\lambda_{nn}^j} + \underbrace{\left(\frac{\theta^j}{\sigma^j-1}-\frac{\theta^j}{\rho^j-1}-1\right)}_{\text{Armington across countries}}\frac{dg_{nC}^j}{g_{nC}^j}\Bigg] \quad \cdots\cdots \textbf{Term 3} \\
&- \sum_j \tilde{\alpha}^j\Bigg[\underbrace{\beta^j\frac{dw_n^M}{w_n^M}}_{\text{Labor costs}} + \underbrace{\left(1-\beta^j\right)\sum_i \gamma^{ji}\frac{dP_n^i}{P_n^i}}_{\text{Intermediate goods costs}}\Bigg], \quad \cdots\cdots \textbf{Term 4}
\end{aligned} \tag{26}$$

where we treat the direct change in nominal wage as residual in Term 1. The change in wages is primarily driven by inter-industry resource reallocation from less productive to more productive firms, which we discuss in detail below. For further details of the derivation of (26), see Appendix E.

Term 2–4 in (26) decomposes the change in price indices through three distinct channels. Term 2 captures Ethier's (1982) "love-of-variety" effects.[9] Higher total spending and lower fixed costs will lower the cutoff productivity according to (13), which will expand the extensive margins of varieties, lowering the prices. The extent to which the extensive margins expand in response to the marginal change in cutoff productivity hinges on the productivity dispersion, θ^j, i.e., the higher θ^j is, the larger the response in the extensive margin. The gains from more varieties depend on the elasticity of substitution, σ^j, i.e., the lower the elasticity is, the less substitutable varieties are, leading to the greater gains. On top of these two effects, the larger mass of firms mechanically lowers the price indices through (16).

Term 3 captures the gains from trade effects. As discussed in Arkolakis et al. (2012), in a wide class of quantitative trade models, including Melitz-Chaney, the gains from trade are captured by the sufficient statistics of "own trade share." In our framework, there are two own trade shares, λ^j_{nn} for inter-provincial trade and λ^j_{nC} for international trade, with corresponding trade elasticities of $1/(\epsilon^j - 1)$ and $1/(\rho^j - 1)$. The larger the response of own trade shares, the larger the gains from trade.

Term 4 captures the impacts on prices through the cost of production. Higher wages and input prices will raise the price indices. We will use this decomposition result in the counterfactuals below.

Average Productivity

In the real-wage decomposition above, the change in nominal wages remained as a residual, focusing on the different channels affecting prices. We now proceed to decompose the change in wage, which is primarily driven by productivity. In the Melitz-Chaney framework, the average productivity of the industry is defined for each destination market. Given that the fixed cost of serving the local market is presumably lower than that of serving other markets, i.e., $f^j_{nn} < f^j_{mn}$ for all $m \neq n$, the productivity of sector j in region n is well captured by the average productivity of firms serving in their own local market, which is a function of ϕ^j_{nn}. Change in the average productivity can be decomposed as:

$$\frac{d\overline{\phi}^j_{nn}}{\overline{\phi}^j_{nn}} = \frac{1}{\theta^j} \underbrace{\left[\underbrace{\frac{dY^j_n}{Y^j_n}}_{\text{Total sales}} - \underbrace{\frac{d(f^{jE}_n w^M_n)}{f^{jE}_n w^M_n}}_{\text{Sunk entry costs}} \right]}_{\text{Firm entry: } dT^j_n/T^j_n} + \frac{1}{\theta^j} \underbrace{\frac{d(w^M_n f^j_{nn})}{w^M_n f^j_{nn}}}_{\text{Fixed costs}} + \underbrace{\frac{d\tilde{b}^j_n}{\tilde{b}^j_n}}_{\text{Pareto location}} - \frac{1}{\theta^j} \underbrace{\frac{dX^j_{nn}}{X^j_{nn}}}_{\text{Local spending}}, \quad (27)$$

[9] Caliendo et al. (2023) call this as "selection effect."

The first term captures the effect through the firm entry. The higher total sales and lower sunk entry costs expand the mass of entrants, intensifying the competition among firms and raising the cutoff productivity. The second term shows that higher fixed costs make less productive firms unprofitable in serving the home market, driving up the cutoff productivity. The last term shows that higher spending on local products allows firms to spread fixed costs over greater sales, leading to less productive firms surviving, i.e., a lower cutoff productivity.

After clarifying the source of the changes in the average productivity of the sector, which is defined for each destination market, we use (12) and (18) to establish that regional labor productivity is a weighted aggregation of sector-level average productivity within that region, and its changes are thus closely tied to the average productivity. The decomposition of regional labor productivity is as follows:

$$\frac{d\left(\frac{Y_m}{L_m^M}\right)}{\frac{Y_m}{L_m^M}} = \underbrace{\sum_j \sum_n s_{nm}^j \left(\underbrace{\frac{dT_{nm}^j}{T_{nm}^j}}_{\text{Active Firms}} + \underbrace{\frac{dr_{nm}^j(\overline{\phi}_{nm}^j)}{r_{nm}^j(\overline{\phi}_{nm}^j)}}_{\text{Firm revenue}} \right)}_{\text{Total sales: } \frac{dY_m}{Y_m}} - \underbrace{\frac{dL_m^M}{L_m^M}}_{\text{Labor}}, \tag{28}$$

where $s_{nm}^j = \frac{X_{nm}^j}{Y_m} = \frac{T_{nm}^j r_{nm}^j(\overline{\phi}_{nm}^j)}{Y_m}$ is the share of sales from sector j region m to region n. The regional labor productivity growth is fundamentally driven by two counteracting forces stemming from the total sales and labor input components. The first term captures the weighted aggregate of growth. The average productivity, as discussed in (27), boosts firms' average revenue. It increases the region's total sales, leading to an increase in labor productivity. The second term represents the changes in labor input in a region, the denominator of the labor productivity. A larger workforce reduces the output per worker, resulting in a decline in measured labor productivity.

This decomposition allows us to determine, among three components, which factor contributes most to the productivity growth across regions in response to the shock we give in the counterfactuals.

4 Calibration

We bring the model to the data for the Chinese economy and the RoW. Our analysis covers 29 Chinese provinces (listed in Table A1) and seven sectors (one agricultural and six manufacturing sectors listed in Table A2).[10] The sectoral classification follows the inter-regional input-output tables, which we discuss in detail below.

[10]Due to data limitations, we excluded Hainan Island and Tibet from our study.

4.1 Data

We use the *Chinese Industrial Enterprises Database* (CIED) from 2002–2007 to calibrate structural parameters and compute the base year (2002) equilibrium outcomes. This dataset covers over 180,000 manufacturing establishments per year in mainland China with sales exceeding 5 million Chinese Yuan (approximately 680 thousand US dollars), a threshold that applies only to privately owned firms. The database provides key establishment information, including location, industry, ownership type, and number of workers, as well as revenue and production costs. Despite the threshold for sales to be surveyed by the CIDE, the dataset accounts for around 91.1% of revenue from principal activity and 68.65% of total manufacturing employment in China (according to the comparable annual report of the first national economic census in 2004), allowing us to calibrate the key structural parameters of the model.

We also take advantage of the novel data on *Chinese Enterprise Registration Data* (CERD) from 2002–2007, which covers the universe of registered establishments in China, regardless of their sales, to proxy the mass of entrants (potential entrepreneurs) and to back out the sunk entry costs. We will discuss how we leverage the data in the next section.

Additionally, we use the *Chinese Multi-Regional Input-Output Table* (MRIO) for 2002 and 2007, along with the *World Input-Output Database* (WIOD), to construct bilateral trade flows across regions and calibrate production function parameters. These bilateral trade flows allow us to back out the bilateral iceberg trade costs, as described below.

One limitation of the MRIO is that they do not provide sector-level import and export data for each Chinese region. To address this, we supplement the input-output tables with the *China Customs Data* from 2002 and 2007, which records the universe of Chinese export and imports to construct the regional export and import across sectors.[11]

In addition, we use data from the *2000 Fifth National Population Census* and the *2005 1% National Population Sample Survey* to calculate the share of urban and rural populations in each province. Following the approach of Tombe and Zhu (2019), we assume that the population structure in 2000 is representative of the situation in 2002, while the 2005 data serve as a proxy for the population distribution in 2007.

4.2 Structural Parameters

Sectoral expenditure shares in final consumption, α^j, are directly obtained from the input-output table. We use the 2002 WIOD to compute the shares for China and the RoW. Table 2 summarizes the results.

We analogously calibrate the labor share β^j and intermediate input shares γ^{ji} in the production function using the WIOD for China and the RoW, respectively, which are summarized

[11] The dataset includes HS codes for each transaction, which we match to our sector classification using the concordance table provided on the WTO website.

Table 2: Parameters in Cobb-Douglas Preferences and Technology

		α^j	β^j	γ^{ji}					
	Sector			Food	Chemicals	Metals	Machinery	Electronics	Others
China	Agriculture	0.252							
	Food	0.268	0.279	0.722	0.121	0.029	0.024	0.011	0.093
	Chemicals	0.015	0.225	0.030	0.722	0.063	0.046	0.033	0.107
	Metals	0.031	0.262	0.011	0.106	0.700	0.066	0.023	0.094
	Machinery	0.238	0.274	0.013	0.042	0.322	0.440	0.090	0.094
	Electronics	0.137	0.225	0.005	0.056	0.217	0.048	0.554	0.120
	Others	0.059	0.329	0.053	0.287	0.066	0.027	0.021	0.545
RoW	Agriculture	0.083							
	Food	0.298	0.310	0.658	0.093	0.062	0.022	0.013	0.152
	Chemicals	0.073	0.284	0.035	0.730	0.062	0.019	0.016	0.138
	Metals	0.035	0.348	0.009	0.076	0.764	0.047	0.033	0.072
	Machinery	0.256	0.315	0.015	0.026	0.246	0.521	0.091	0.102
	Electronics	0.130	0.345	0.008	0.049	0.182	0.048	0.607	0.105
	Others	0.126	0.388	0.042	0.220	0.099	0.041	0.041	0.558

in Table 2. For the agricultural sector, we set the labor share as $\beta^A = 0.509$, sourced from Tombe and Zhu (2019).[12]

For the elasticity of substitution across varieties σ^j, we use the model-implied relationship between firm-level revenue and total variable cost, following Aw et al. (2008). Specifically, as implied by (6), the revenue is proportional to the total variable cost with a factor of markup. The regression equation is given by:

$$r_l^j = \mu^j \times tvc_l^j + \varepsilon_l^j,$$

where r_l^j is the revenue of firm l in sector, and tvc_n^j is the total variable costs, and ε_l^j is the measurement error. We measure the total variable cost as the sum of total wage payments and intermediate input purchases. Having the estimates of μ^j in hand, the elasticities σ^j are obtained by $\sigma^j = \mu^j/(\mu^j - 1)$. See Table 3 for the results.

To calibrate the Pareto shape parameter θ^j, we follow Chaney (2008) and Eaton et al. (2011) and regress the ranking of a firm size on the firm size itself. Specifically, we run the following regression:

$$\log(Rank_l^j) - 0.5 = \Gamma_0^j - \Gamma_\ell^j \log(\ell_l^j) + \varepsilon_l^j,$$

where ℓ_l^j is firm l's size measured in sales and $Rank_l^j$ is its ranking. If the firm's TFP is distributed Pareto with shape θ^j, then the firm's sale is distributed Pareto with shape $\Gamma_\ell^j = \frac{\theta^j}{\sigma^j - 1}$. To mitigate the small-sample bias often inherent in conventional OLS rank-size

[12] Since Tombe and Zhu (2019) specify the agricultural production function with intermediate, we scale up the labor and land shares so that they sum up to one.

Table 3: Pareto Shape Parameter (θ^j) and Elasticities of Substitution (σ^j, ϵ^j, ρ^j)

	σ^j	θ^j	ξ^j	ϵ^j	ρ^j
Food	5.608	5.320	0.615	3.988	1.994
Chemicals	5.420	4.817	0.615	3.807	1.904
Metals	5.648	5.257	0.590	3.879	1.940
Machinery	6.031	5.376	0.607	4.131	2.066
Electronics	6.132	5.152	0.690	4.545	2.273
Others	5.690	5.485	0.578	3.885	1.942

regressions, we implement the correction proposed by Gabaix and Ibragimov (2011) and Di Giovanni et al. (2011). We estimated the equation using the 2002 CIED data. Following Shapiro and Walker (2018), we focus on the upper tail of the sales distribution for each sector.[13] The calibrated values for θ^j are summarized in Table 3.

We calibrate the two elasticities of substitutions, ϵ^j for across provinces and ρ^j for across countries, in the nested CES aggregator for the final good producer as follows. First, by combining (13), (14), (15), and (16), we can express the inter-privincial trade share λ^j_{nm} as:

$$\lambda^j_{nm} = \frac{\left(\left(\tilde{\mu}^j_n\right)(\tilde{b}^j_m)^{\theta^j} T^j_m \left(\frac{w^M_m f^j_{nm}}{X^j_{nC}}\right)^{\frac{\sigma^j-\theta^j-1}{\sigma^j-1}}\right)^{\xi^j} \left(c^j_{nm}\right)^{-\theta^j \xi^j}}{\left(\tilde{P}^j_{nC}\right)^{(1-\epsilon^j)-\frac{1-\sigma^j}{(\sigma^j-\theta^j-1)(1-\epsilon^j)}\xi^j}},$$

where $\tilde{\mu}^j_n$ is a constant and $\xi^j = \left(1 + \theta^j \left(\frac{1}{\epsilon^j-1} - \frac{1}{\sigma^j-1}\right)\right)^{-1}$. We then externally calibrated the trade elasticities for each industry from the literature (Bartelme et al. 2025, Sogalla 2023) and back out ϵ^j.[14] Finally, following Hillberry and Hummels (2013) and Feenstra et al. (2018), we apply the "Rule of Two" to back out the elasticity of substitution across China-sourced and the RoW-sourced varieties, such that $\rho^j = \epsilon^j/2$.

We set the location choice elasticity, the inverse of η, to 0.5 following Caliendo et al. (2021). The location choice elasticities, often referred to as the migration elasticity in the spatial literature, vary substantially across studies, even for the same country.[15] Our preliminary

[13]CIED covers the universe of the state-owned establishments and the private firms above the cutoff sales. The number of firms in the 2002 CIED accounts for approximately 20% of the population. Following the literature that conventionally focuses on the top 10 percent of firms, we limit the CIED sample to the top 50 percent in estimating the Pareto shape parameters.

[14]Bartelme et al. (2025) estimated the trade elasticities for each manufacturing sector in the WIOD, which has more disaggregated sectoral classifications than ours. We compute the trade elasticities of six sectors by computing the simple average according to the concordance table in Table A2

[15]Some studies found a more inelastic response: 0.15 for developing countries (Cruz 2024; Cai et al. 2025), 0.2 for the U.S. (Caliendo et al. 2019), 0.5 for Europe (Caliendo et al. 2021), and 0.64 for Japan (Doi and Suzuki 2025). Other studies report higher elasticities: 1.5 for China (Tombe and Zhu 2019), 1.8 for the U.S. (Fajgelbaum et al. 2019), 2 for Japan (Suzuki 2023) and 3 for Vietnam (Balboni 2025).

estimates exploiting the variation in real wages and location choice probabilities within a country over time suggest the elasticity lies in the range of 0.3–0.6, which is lower than the estimates of 1.5 by Tombe and Zhu (2019) using the bilateral inter-provincial migration data. The lower elasticity captures migration costs not modeled in our framework.

4.3 Base Year Equilibrium Outcomes

The exact hat algebra solves the general equilibrium of the model in relative changes, conditioning on the base-year equilibrium outcomes (which we observe in the data). We set 2002 as the base year. We need to construct all the endogenous variables *without* hat notation that appear in the equilibrium conditions listed in Appendix G, such as trade shares and distribution of workers across regions and sectors. We constructed those base-year equilibrium outcomes using the MRIO, WIOD, Customs Data, CIED, and *National Population Census*.[16]

5 Counterfactuals

We conduct counterfactual analyses to determine the underlying determinants of sectoral and regional growth of China in the early 2000s. Specifically, we discuss the impacts of reductions in domestic and international trade costs and sunk entry costs. To this end, we will solve the equilibrium in relative changes to the base year (2002) by giving a specific set of shocks to the model (e.g., a reduction in domestic trade costs). By comparing results, we can assess how Chinese regional economies would have evolved under different combinations of shocks, and can determine which factor contributes most significantly to the variables of interest, such as output, productivity, and real wages.

5.1 Measuring the Shocks to Fundamentals

In our counterfactuals, instead of giving the model arbitrary shocks to the fundamentals, such as a 10% uniform reduction in trade costs, we calibrate the changes in fundamentals over the period 2002-2007 to capture the heterogeneity in economic reforms across regions and sectors.

Trade costs, both domestic and international, are calibrated as Head-Ries index (Head and Ries 2001), assuming symmetric trade costs ($\tau^j_{nm} = \tau^j_{mn}$ for all n, m) and zero trade costs for the own trade ($\tau_{nn} = 1$). Figure A5 presents the relative changes in trade costs over the period from 2002 to 2007. Values below 1 (blue) indicate declining trade costs over the period, reflecting reforms such as infrastructure improvements and trade liberalization. The numbers

[16] We use the 2000 census data to construct the population shares across regions and sectors. Calculate regional population levels. Assuming the population structure in 2000 is representative of the year 2002, we compute the region-area share as $\psi^k_{n,2002} = \psi^k_{n,2000}$.

on the axes correspond to the 29 Chinese provinces and the RoW. Except for the electronics sector, trade costs fall almost every pair of regions.[17]

We measure the change in sunk entry costs using the free entry condition (22). Change in sunk entry cost can be expressed as:

$$\hat{f}_m^{jE} = \frac{\hat{Y}_m^j}{\hat{T}_m^j \hat{w}_m^M}.$$

The equation above implies that having changes in sectoral total sales Y_m^j, manufacturing wages, $\hat{w}_m^M$, and mass of entrants $\hat{T}_m^M$ over time allows us to compute the change in sunk entry costs. The mass of entrants who draw productivity to obtain a blueprint but are not necessarily active in any market is a theoretical concept, and there is no direct empirical counterpart in the data. Widely used firm-level data, CIED, records firms with positive production and, more importantly, rules out private firms with sales below the threshold. Therefore, we leverage registration data from CERD to capture the number of entrepreneurs, regardless of their sales. Indeed, over the sampled period from 2002 to 2007, 22% of the registered firms that report the number of insured employees (13% of the total sample) report zero employees, implying no actual production. As the data set only records the entry and exit of establishments, we cumulatively sum up the number of entries (register) and subtract the number of exits (de-register) to get the mass of entrants in 2002 and 2007. Changes in total sales are constructed from the CIED, and the manufacturing wage is recovered by dividing the total value added from the IO table by the total employment. Table A7 in Appendix I summarizes the relative changes in sunk entry costs over the period 2002-2007. For most regions and sectors, entry costs have fallen substantially. However, in some regions (e.g., Heilongjiang and Guangxi), entry costs for chemicals and metals have notably increased. Also, the entry costs for the electronics sector have risen in many regions, potentially reflecting stricter regulations.[18]

While trade and entry costs are our primary interests, we also feed the model the change in total labor supply, L_C, and amenity, B_n^k, as they affect the overall production capacity of the country. We use the *2000 China National Population Census* and the *2005 China 1% National Population Sample Survey* to calculate the growth in the total labor force from 2000 to 2005, which we feed into the model as a shock. The data suggests that the total labor supply in China grew by 34.8% over the time period. We calibrate the change in amenity using model inversion implied by (23). We use the 2000 and 2005 *National Population Census* following

[17] As a robustness check, we also calibrate trade costs using a structural gravity as in Eaton and Kortum (2002). The two approaches yield very close results with a correlation of 0.96.

[18] In 2003, China first established a formal e-waste management system. Subsequently, during 2006–2007, the implementation of China RoHS introduced restrictions on hazardous substances in electronic information products. This may represent one of the institutional mechanisms contributing to rising costs within the electronics industry.

Tombe and Zhu (2019) to construct the population shares of each region, ψ_n^k. Wages are computed using the MRIO data in 2002 and 2007. Consumer price index P_n is constructed by using the agriculture and manufacturing price indices sourced from *Wind Financial Terminal*.

5.2 Regional and Sectoral Outcomes

In what follows, we introduce distinct shocks to the model sequentially. Specifically, we begin by increasing the total labor supply and amenity levels, as is indicated by "L" in the figures and tables below and referred to as "labor shock" henceforth. The counterfactual results with the labor shock will serve as the benchmark. Then, we will give the model the change in domestic ($L+\tau^{Dom}$ in the table, domestic trade cost shock), international ($L+\tau^{Int}$ in the table, international trade cost shock), and both domestic and international trade costs ($L+\tau^{Both}$, trade cost shock). Finally, we change the sunk entry costs ($L + f^E$, sunk entry cost shock). For instance, the international trade cost shock exercise shows what the Chinese economy would look like if total labor supply and international trade costs changed as suggested by the data over 2002–2007, while keeping all other fundamentals fixed as in 2002.

We present results for two representative provinces: Guangdong (southern coastal) in Table 4 and Sichuan (southwestern inland) in Table 5. The table summarizes the change in manufacturing employment L_n^M, mass of firms T_{nn}^j, GDP $\beta^j Y_n^j$, and average productivity $\overline{\phi}_{nn}^j$. For the mass of firms and average productivity, we compute them based on firms serving their own local markets.

Mass of Firms Starting from the benchmark labor shock, the mass of firms increases by approximately 90% in Guangdong and 30% in Sichuan. These magnitudes are close to the proportional changes in total labor supply. By comparing the domestic and international trade cost shock scenarios in Guangdong, we see that, while the mass of firms with an international trade cost shock (101.7%) is greater than that in the benchmark labor shock scenario (92.74%), adding the domestic trade cost shock reduces the firm growth to 72.06%.

To explain the results, it is worth noting that reductions in trade costs will have two implications for the local economy: increased import competition and greater export opportunities. Import competition allows only productive firms to survive, raising the cutoff productivity and lowering the mass of firms (reallocation within an industry towards more productive firms). Export opportunities, in contrast, allow firms to sell more in the external markets, lowering the productivity cutoffs and increasing the number of firms. In Guangdong, the results suggest that the import competition effect dominates for internal trade, while the export opportunity effect dominates for external trade. This is consistent with the widely known export-led growth of Guangdong in the early 2000s.

In Sichuan, reductions in trade costs lower the mass of firms in both scenarios, implying that the import-competition effect dominates in both internal and international trade. Yet, compared to the benchmark labor shock scenarios, the fall in mass of entry is small in the

Table 4: Guangdong (Southern Coastal)

	All	L	$L+\tau^{Dom}$	$L+\tau^{Int}$	$L+\tau^{Both}$	$L+f^E$
			Manufacturing Employment $\hat{L}_n^M$			
Total	**64.37%**	**78.17%**	**74.19%**	**83.12%**	**78.64%**	**64.05%**
			Mass of Firms $\hat{T}_{nn}^j$			
Food	-69.09%	94.51%	144.84%	113.63%	182.92%	-44.99%
Chemicals	80.62%	105.99%	127.80%	117.13%	156.00%	68.87%
Metals	-39.39%	91.13%	-13.17%	117.72%	-5.29%	-15.43%
Machinery	6.20%	96.05%	35.49%	101.59%	43.28%	51.06%
Electronics	213.99%	94.26%	40.32%	71.24%	1.18%	230.93%
Others	27.84%	80.12%	72.52%	87.40%	77.59%	37.83%
Total	**31.75%**	**92.74%**	**72.06%**	**101.79%**	**81.23%**	**47.47%**
			Sectoral GDP $\hat{Y}_n^j$			
Food	-68.24%	91.81%	193.36%	117.64%	246.01%	-60.28%
Chemicals	107.02%	112.98%	183.82%	140.02%	246.47%	52.24%
Metals	-40.70%	92.20%	0.94%	125.30%	12.67%	-28.53%
Machinery	14.89%	93.92%	52.79%	129.52%	84.14%	24.23%
Electronics	164.77%	79.63%	41.92%	59.91%	3.38%	158.26%
Others	23.83%	81.11%	92.02%	90.29%	98.96%	20.45%
Total	**45.08%**	**90.10%**	**96.21%**	**102.79%**	**110.58%**	**39.45%**
			Average Productivity $\hat{\tilde{\phi}}_{nn}^j$			
Food	9.81%	-1.37%	1.61%	-1.03%	1.71%	3.65%
Chemicals	15.91%	-0.54%	2.61%	0.55%	4.05%	11.31%
Metals	4.26%	-1.02%	1.05%	-0.75%	1.20%	2.27%
Machinery	8.34%	-1.30%	0.46%	1.04%	2.63%	3.83%
Electronics	18.63%	-2.64%	-1.62%	-2.72%	-1.73%	17.89%
Others	16.40%	-0.98%	0.21%	-1.06%	0.05%	15.18%
Mean	**12.23%**	**-1.31%**	**0.72%**	**-0.66%**	**1.32%**	**9.02%**

Note: The table shows relative changes in outcomes from the base year. Mass of active firms (measured as the mass of firms serving in its own local market), GDP, productivity cutoff (measured as the average productivity of firms serving in its own local market), and manufacturing employment are reported.

Table 5: Sichuan (Southwestern Inland)

	All	L	$L+\tau^{Dom}$	$L+\tau^{Int}$	$L+\tau^{Both}$	$L+f^E$
			Manufacturing Employment $\hat{L}_n^M$			
Total	**36.21%**	**31.64%**	**26.64%**	**29.05%**	**23.95%**	**45.90%**
			Mass of Firms $\hat{T}_{nn}^j$			
Food	8.29%	31.57%	1.19%	30.20%	-0.14%	41.92%
Chemicals	45.39%	34.21%	25.35%	31.96%	22.34%	49.25%
Metals	39.66%	30.52%	22.14%	27.14%	20.22%	51.51%
Machinery	14.95%	34.05%	15.52%	31.69%	13.05%	44.18%
Electronics	29.78%	36.32%	39.89%	29.00%	29.87%	52.31%
Others	34.46%	27.51%	7.81%	25.97%	5.66%	54.86%
Total	**29.40%**	**32.13%**	**17.28%**	**29.43%**	**14.52%**	**48.39%**
			Sectoral GDP $\hat{Y}_n^j$			
Food	42.78%	44.18%	16.98%	38.63%	12.31%	82.85%
Chemicals	101.04%	44.42%	42.40%	35.42%	32.42%	99.64%
Metals	90.94%	39.82%	34.58%	30.46%	28.16%	105.87%
Machinery	46.39%	43.54%	36.03%	32.56%	25.19%	83.97%
Electronics	46.27%	42.89%	67.26%	23.03%	37.54%	75.27%
Others	67.17%	38.96%	12.66%	32.10%	6.08%	106.62%
Total	**67.94%**	**42.31%**	**32.83%**	**32.95%**	**23.48%**	**93.22%**
			Average Productivity $\hat{\tilde{\phi}}_{nn}^j$			
Food	19.33%	0.27%	1.70%	0.67%	2.21%	17.39%
Chemicals	22.92%	-0.08%	1.51%	-0.03%	1.63%	20.47%
Metals	28.03%	-0.16%	0.80%	-0.03%	1.20%	26.33%
Machinery	8.62%	-0.17%	2.03%	-0.39%	1.89%	7.37%
Electronics	11.25%	-0.58%	2.43%	-1.44%	1.10%	10.32%
Others	31.03%	0.16%	-0.21%	0.37%	0.05%	31.19%
Mean	**20.20%**	**-0.09%**	**1.38%**	**-0.14%**	**1.35%**	**18.84%**

Note: See the footnote of Table 4.

case of international trade cost, consistent with the finding for Guangdong.

Next, we examine the impact of reducing entry barriers. Lower entry cost increases the mass of firms in both Guangdong and Sichuan. According to Equation (15), the mass of firms depends on the mass of entrants and the productivity cutoff. Reduced sunk entry costs stimulate entry, intensifying competition and raising the productivity cutoff through the selection effect.

When comparing this against the benchmark labor shock scenario, firm growth exhibits different regional patterns. In Sichuan, the reduction of sunk entry costs triggers intense competition and a strong selection effect. The resulting rise in both the mass of entrants and cutoff productivity leads to higher firm growth by 48.39% compared to 32.13% in the benchmark scenario. In Guangdong, however, the selection is not as tight as in Sichuan. While the mass of entrants increases, the rise in cutoff productivity is lower than in Sichuan (a point we will discuss later), resulting in less firm growth by 47.47% compared to 92.74% in the benchmark scenario. Compared with the reduction of trade costs, a fall in sunk entry leads to tighter competition in Sichuan, the inland province, and looser competition in Guangdong, the coastal province.

Finally, we observe substantial heterogeneity across sectors. When all shocks are applied, the electronics sectors in Guangdong experience the largest increases in the mass of firms, rising by 312.99%. This is because, as a coastal region, Guangdong provides electronics firms with easier access to international markets. In Sichuan, its core industries, the metals and chemicals sectors, are growing the most. This is due to Sichuan's advantage of an early industrial foundation and rich resource reserves.

Average Productivity and Sectoral GDP We now analyze the impact on average productivity ($\hat{\tilde{\phi}}^j_{nn}$) and sectoral GDP ($\hat{Y}^j_n$). In the benchmark labor shock scenario, both provinces see total GDP rise significantly. Guangdong's total GDP increases by 90.10% and Sichuan's by 42.31%, values that largely track the change in labor supply. At the same time, mean average productivity decreases slightly, by -1.31% in Guangdong and -0.09% in Sichuan. This indicates that the labor shock expands market size, allowing less productive firms to survive and thereby lowering average productivity, as the scale effect outweighs the selection effect.

In contrast to the scale-driven effects of the labor shock, trade cost reductions introduce sharper selection mechanisms. In Sichuan, all trade shock scenarios result in a positive mean productivity increase, ranging from 1.35% to 1.70%. This increase is consistent with the dominance of the import competition effect in Sichuan, which forces selection and raises the productivity cutoff. This selection helps drive significant GDP growth, with total GDP rising between 23.48% and 32.95% across these scenarios. By comparison, the results in Guangdong are mixed. Adding domestic trade cost reduction increases mean productivity by 0.72%, supporting the view that its inherent import competition raises the cutoff. However, the international shock still results in a mean decline of -0.66%, suggesting that the export opportunity effect allows less productive entrants to survive. Total GDP growth in Guangdong is highest under both trade shocks, reaching 110.58%.

Beyond trade barriers, we further investigate the impact of reducing sunk entry costs, which yields the most pronounced efficiency gains. The reduction in sunk entry costs leads to the largest productivity gains, which confirms the tight selection effect seen earlier. Mean average productivity rises significantly in both provinces, by 9.02% in Guangdong and 18.84% in Sichuan. This selection effect translates directly into GDP outcomes. Especially in Sichuan, where fall in sunk entry costs causes the largest overall GDP increase of 93.22%.

Underlying these aggregate regional figures is significant sectoral heterogeneity. The metals and chemicals sectors are core growth drivers in Sichuan, showing GDP gains of over 100% when entry costs are reduced, which aligns with their high firm growth rates. In Guangdong, the chemicals sector shows the largest percentage GDP increase under trade shock scenarios, rising up to 246.47% under both trade shocks. Meanwhile, the electronics sector maintains high growth, particularly under all shocks, reinforcing its prominence in the coastal region's economy.

Overall, the coastal and inland provinces show distinct responses to shocks. While trade cost reductions yield mixed productivity results in Guangdong, reflecting competing import and export effects, Sichuan consistently sees positive productivity gains from trade due to import competition. Notably, the largest efficiency gains in both regions result from reducing sunk entry costs, confirming this as a primary mechanism for boosting productivity and economic growth, especially in the inland province.

5.3 Sectoral Specialization

The changes in economic activities are closely linked to regional specialization, as industries tend to concentrate in regions where they have a comparative advantage and increasing returns to scale, driven by factors such as labor costs, trade accessibility, and local market conditions. Figure 2 shows the changes in the Ellison-Glaeser concentration index after applying different shocks.

Overall, we find that while expanding labor supply and reducing trade and entry costs generally increase sector-level concentration, substantial heterogeneity exists across sectors. For example, sectors such as metals and machinery show relatively modest growth in concentration.

We also observe that different shocks have varying impacts across sectors. For instance, the electronics sector's concentration intensified significantly in response to reduced entry costs, an effect that far outweighs that of trade cost reductions. In contrast, for the chemicals sector, the increase in concentration was driven primarily by the reduction in trade costs. This reflects two complementary processes of regional specialization. First, there is market-driven specialization: lower trade costs facilitate a more efficient allocation of resources by

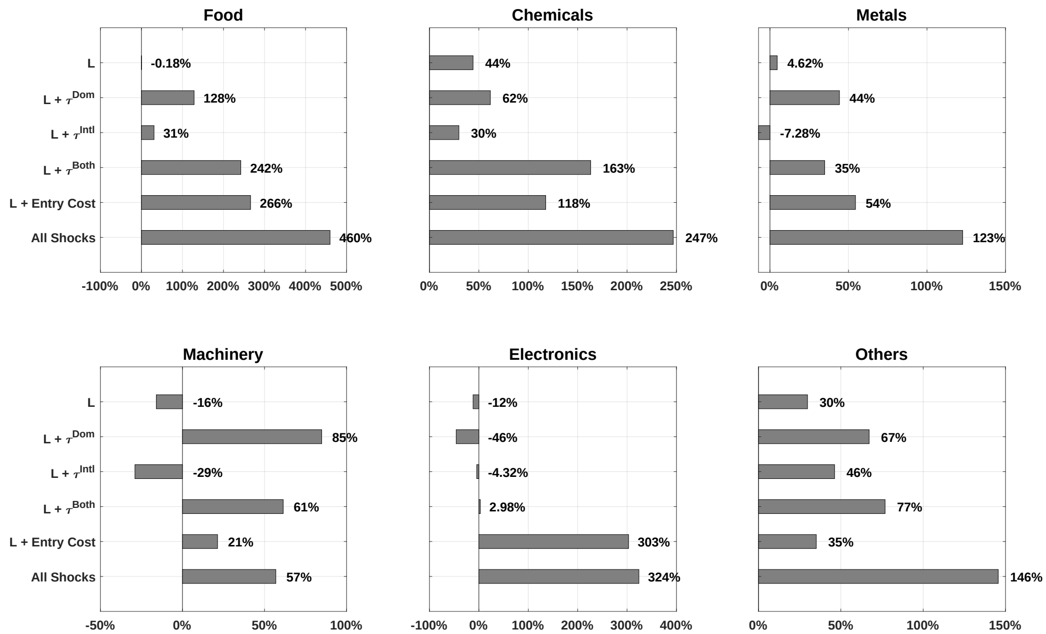


Figure 2: Change of Sectoral Concentration Index

allowing regions or industries to fully realize their Ricardian comparative advantages and by enabling firms to exploit increasing returns to scale. The latter often leads to spatial clustering and agglomeration of firms within the same sector, consistent with Krugman-style economic geography. Second, policy-driven regional specialization occurs when local industrial policies, such as the reduction of firm entry barriers, directly promote sectoral development and shape the unique specialization patterns of different regions (Aghion et al. 2015). Thus, the observed changes result from both endogenous market forces and exogenous policy interventions.

5.4 Drivers of Welfare Change

In this section, we investigate the drivers of the observed changes in expected utility. Figure 3 shows how each shock contributes to the overall welfare change. In the scenario with all shocks, the total welfare increases 164%.

Removing the domestic trade cost shock reduces the welfare gain to 140%. This suggests that reduced domestic trade costs enhance welfare by increasing competition, forcing less productive firms out of the market while enabling more productive firms to expand. In contrast, eliminating the international trade cost shock has a tiny effect, implying that while greater international competition and export opportunities bring small benefits, domestic trade liberalization plays a far larger role in boosting welfare. Excluding the labor supply and

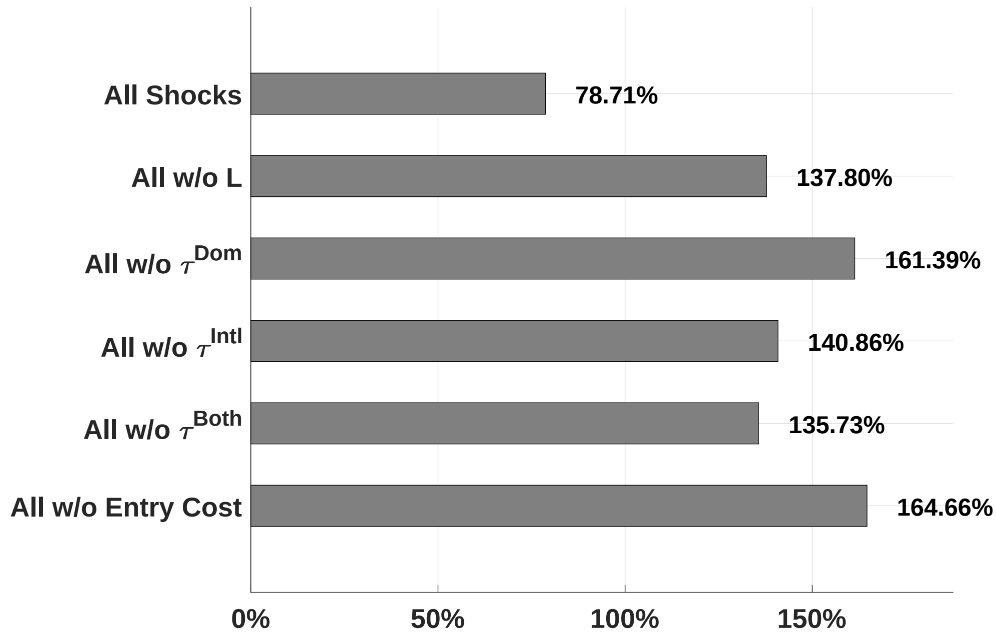


Figure 3: Drivers of the Change in Expected Utility

amenity improvement reduces welfare to 135%.[19] However, the most substantial effect arises from the reduction in sunk entry costs: when it is excluded, the welfare gain declines to only 78%. This highlights that lower entry barriers are the primary engine of welfare improvement, operating by facilitating firm entry, intensifying competition, and effectively lowering the price index for consumers.

5.5 Variety and Selection

Finally, given the significance of variety and selection effects and the substantial welfare gains observed relative to prior literature, it is essential to identify the sources of these gains. To this end, we decompose the real wage improvements according to the four principal components as in (26). The results are in Table 6.

[19]This is not surprising given the key migration policy changes over those years. In 2003, Zhigang Sun, a university graduate from Hubei Province, died after being beaten while in police custody in Guangzhou, after being detained for failing to present a temporary residence permit under China's custody and repatriation system. The incident attracted extensive media coverage and public criticism. In response to the widespread outcry, the State Council abolished the system later that year, replacing it with a new mechanism intended to provide assistance to migrants. This landmark abolition not only significantly reduced constraints on labor mobility but, crucially, also removed a major source of personal insecurity, directly increasing amenity for migrant populations.

Table 6: Decomposition of Changes in Real Wage

Shock	Term 1: Wage	Term 2: Variety	Term 3: Armington	Term 4: Costs
All	21.31%	57.93%	2.15%	18.61%
L	48.18%	38.79%	-6.35%	19.38%
$L + \tau^{Dom}$	50.31%	19.03%	8.72%	21.93%
$L + \tau^{Int}$	39.47%	40.34%	-3.94%	24.13%
$L + \tau^{Both}$	42.06%	22.54%	8.83%	26.58%
$L + f^E$	18.78%	62.39%	-0.59%	19.43%

Note: Following Fields (2003) and Caliendo et al. (2023), the 4 coefficients are from a regression of each term on real wage. By construction, the coefficients add up to 100% of the change in real wage.

A key finding is the significant role of variety effects (Term 2) in driving improvements in real wages. Under the combined all shocks scenario, this effect accounts for 57% of the total gain by providing more variety. Notably, the largest variety effect occurs in scenarios with reduced sunk entry costs that effectively lowers the price index. In contrast, the combined contribution of Terms 1, 3, and 4 is smaller.

Complementing these findings on real wages, we now turn to the sources of aggregate productivity growth. Based on the decomposition in equation (27), Figure 4 provides insights into the differential impacts of various shocks on regional productivity, shown separately for coastal and inland regions. In both groups, reductions in entry costs and the resulting selection effects play a dominant role in driving average productivity growth. This dominance is even stronger in inland regions than in coastal regions, which helps explain the earlier observation that inland regions experienced faster manufacturing productivity growth between 2002 and 2007. Such cost reductions facilitate a more efficient sorting process, allowing a greater share of highly productive firms to emerge and thrive while forcing the least efficient firms to exit. It is worth noting that the larger effects of reduced entry costs in inland regions do not necessarily imply that selection mechanisms operate differently there; rather, they may reflect that entry costs were initially higher and declined more sharply in those regions during the period.

Having explored the mechanisms through which shocks influence average productivity, we now turn our attention to the disparity in labor productivity (value-added per worker) as shown in the decomposition in equation (28). Figure 5 presents a result: reduced sunk entry costs explain the differential change in labor productivity across regions. When we apply all shocks simultaneously in the model (Panel A), the inland regions experience a greater increase in labor productivity, which is consistent with the evidence we presented earlier. When we isolate the effects of improving amenities and expanding employment (Panel B) or lowering international trade costs (Panel D), the resulting maps consistently show that coastal regions experience a larger productivity gain due to intensified competition. Introducing a reduction in domestic trade costs (Panel C) begins to affect some inland regions, leading to a slight

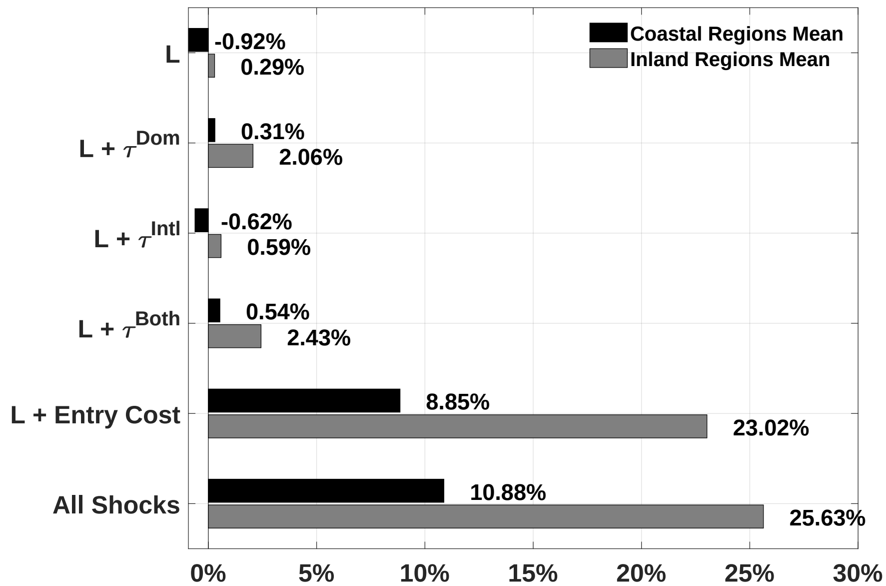


Figure 4: Increasing in Average Productivity through Selection Effect across Regions
Note: Coastal regions include Tianjin, Hebei, Liaoning, Guangdong, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Guangxi.

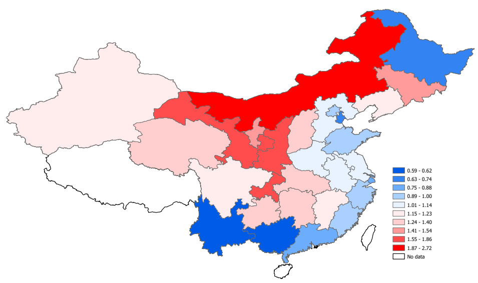
increase in their labor productivity relative to the coast.

However, when we reduce the sunk entry costs (Panel F), the inland regions benefit from a stronger selection effect, resulting in a greater enhancement of their labor productivity. Therefore, we propose that the decline in sunk entry costs can help replicate the pattern of higher productivity growth in inland provinces than in coastal provinces and account for the observed heterogeneity in regional economic growth presented in Figure 1.

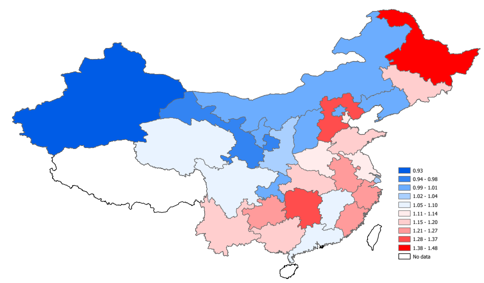
6 Conclusion

This study examines the drivers of China's provincial economic growth during the early 2000s. We develop a multi-sector, multi-region spatial general equilibrium model based on the Melitz–Chaney framework to analyze how policy reforms, specifically reductions in trade costs and firm entry costs, shaped regional productivity and economic growth. The model is calibrated to Chinese data from 2002 to 2007.

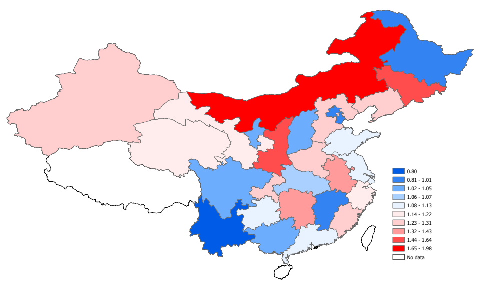
We show that lower trade and entry costs intensify competition, driving economic growth through the selection effect: resources are reallocated toward more productive firms while less



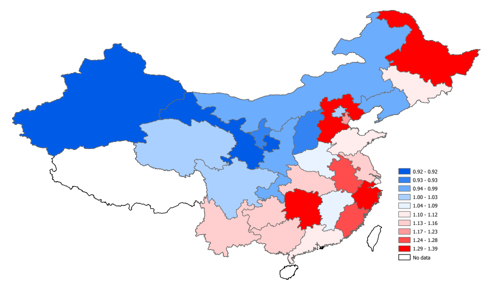
A: All Shocks



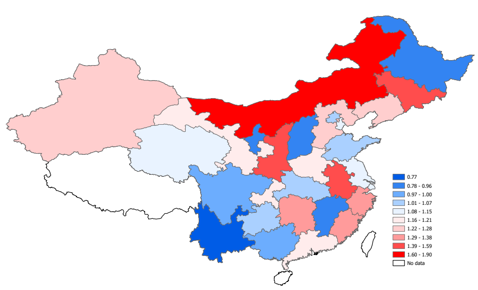
B: L



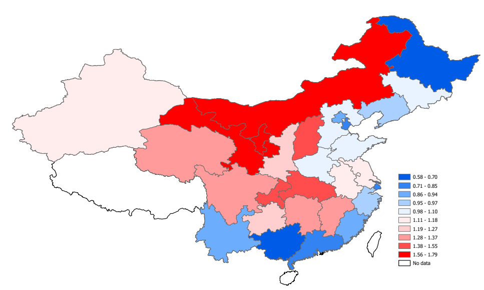
C: $L + \tau^{Dom}$



D: $L + \tau^{Intl}$



E: $L + \tau^{Both}$



F: $L + f^{E}$

Figure 5: Increasing in Value-Added per Worker through Selection Effect across Regions
Note: Each map illustrates the relative change in value-added per worker ($\frac{\hat{Y}_n}{\hat{L}_n^M}$) across each region of China following the corresponding shock. All shocks used are identical to those employed previously.

productive ones exit. This process raises average productivity, increases welfare, and fosters regional specialization.

Our key findings underscore the dominant role of entry costs. Reductions in business entry costs generated larger welfare and productivity gains than lower trade costs. Productivity was primarily driven by the selection effect, which was especially pronounced in inland provinces, though both coastal and inland regions benefited. Regional real wage growth, driven by firm entry, results primarily from the expansion of product varieties, which effectively lowers the price index.

Our paper contributes to the literature by embedding a system of regional economies within a standard Melitz–Chaney framework and bridging studies on China's trade and migration costs with research on the local business climate. By quantifying the relative importance of these factors within a unified framework, we show that improvements in the local business climate were a more powerful driver of China's "economic miracle" than reduced trade costs.

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Appendix

A Table of Chinese Provinces and Sectors

Table A1: List of Chinese Provinces

1	Beijing	11	Zhejiang	21	Chongqing
2	Tianjin	12	Anhui	22	Sichuan
3	Hebei	13	Fujian	23	Guizhou
4	Shanxi	14	Jiangxi	24	Yunnan
5	Inner Mongolia	15	Shandong	25	Shaanxi
6	Guangdong	16	Henan	26	Gansu
7	Jilin	17	Hubei	27	Qinghai
8	Heilongjiang	18	Hunan	28	Ningxia
9	Shanghai	19	Guangdong	29	Xinjiang
10	Jiangsu	20	Guangxi		

Table A2: List of Sectors

Abbreviation	Sector	MRIO 2002	MRIO 2007	WIOD
Agriculture	Agriculture, Forestry, and Fisheries	1	1	A
Food	Food and Textile	3, 4	6, 7, 8	C10-C15
Chemicals	Chemical and Petroleum	7, 8	11, 12	C19-C20
Metals	Metals and Mineral Processing	9, 10, 11	13, 14, 15	C23-C25
Machinery	Machinery and Equipment	12, 13	16, 17	C28-C30
Electronics	Electrical and Electronic	14, 15, 16	18, 19, 20	C26-C27
Others	Paper, Wood, and Other	5, 6, 17	9, 10, 21	C16-C18, C21-C22, C31-C33

B Regional Productivity Growth

To document the differences in regional productivity, we calculate value-added per worker from the *CIED* data. Table A3 presents the disparities in regional productivity between inland and coastal regions. In 2002, productivity was higher in coastal regions for half of the sectors. However, by 2007, inland regions showed a higher productivity in almost all sectors.

Table A3: Productivity in Inland vs. Coastal Regions

Year	Sector	Mean Inland	Mean Coastal	Median Inland	Median Coastal	Q1 Inland	Q1 Coastal	Q3 Inland	Q3 Coastal
2002	Food	71.58	64.77	41.68	36.71	20.75	20.51	86.24	70.78
	Chemicals	79.93	94.10	46.93	54.74	25.30	29.94	89.56	103.13
	Metals	56.31	75.66	33.77	44.14	18.51	24.74	65.74	83.67
	Machinery	62.26	70.84	35.75	42.22	19.98	25.94	67.57	74.22
	Electronics	109.07	79.03	53.97	46.60	26.31	26.08	104.97	87.55
	Others	56.14	53.40	34.25	33.18	18.49	19.83	67.79	61.28
2007	Food	188.45	125.39	105.61	65.86	49.54	36.13	222.03	132.04
	Chemicals	195.22	196.00	110.16	100.63	55.72	52.04	221.47	206.92
	Metals	203.51	169.73	102.72	86.55	49.61	46.29	215.45	178.92
	Machinery	153.60	136.01	85.25	76.07	46.46	44.86	167.79	145.01
	Electronics	212.13	139.20	106.56	67.96	52.66	38.76	216.62	138.30
	Others	149.84	101.47	82.42	56.18	42.64	33.36	160.48	107.09

We then use firm-level data to examine changes in the distribution of firm productivity. Figure A1 presents a density plot, which reveals that the productivity distribution for firms in inland regions exhibits a more pronounced rightward shift compared to those in coastal regions. To further explore this difference, we also estimate a quantile regression specified as follows:

$$Q_q(\text{Productivity}_{it}|t) = \beta_{2002,q} + \sum_t \beta_{qt}\text{Dummy}_t + \epsilon_{qit},$$

where $Q_q(\text{Productivity}_{it}|t)$ represents the q_{th}-quantile firm i's productivity, given its year of observation. The intercept ($\beta_{q,2002}$) captures the baseline productivity level in the reference year of 2002. The independent variables are a series of dummy variables for each year from 2003 to 2007. The coefficients for these dummy variables (β_{qt}) represent the change in productivity at the q^{th} quantile relative to the 2002 baseline. ϵ_{qit} is the error term. Table A4 shows the results. From 2002 to 2007, firm productivity in inland regions had clearly increased more than that in coastal regions.

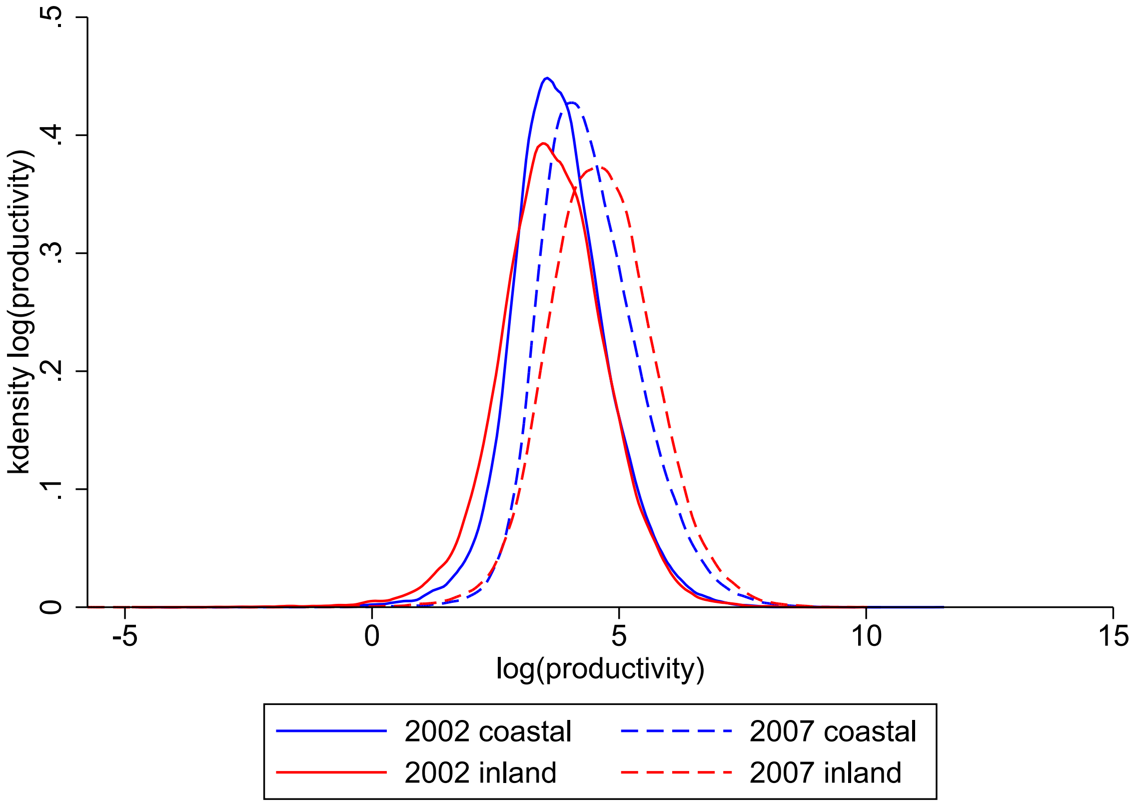


Figure A1: Density Distribution of Firm Productivity in 2002 and 2007

Table A4: Quantile Regression of Firm Productivity Distribution

	10%	50%	90%
		All Regions	
Dummy_2007	51.866	56.747	63.099
Std. Err.	14.89	8.149	13.679
Observations	895,325	895,325	895,325
		Inland	
Dummy_2007	68.661	77.156	87.86
Std. Err.	8.151	5.556	11.209
Observations	220,578	220,578	220,578
		Coastal	
Dummy_2007	46.918	50.595	55.4
Std. Err.	8.469	4.793	8.457
Observations	674,747	674,747	674,747

Note: The regression includes dummy variables for 2003, 2005, 2006, and 2007. The table above shows only the results for 2007. Due to missing data, year 2004 is not included.

C Spatial Redistribution of Establishments

Figure A2 illustrates the spatial distribution of new establishments in two representative sectors: electronics and steel. In 2002, investments in electronics primarily flowed into coastal regions, especially the Yangtze River Delta and the Pearl River Delta. However, by 2013, many electronics firms emerged in inland regions to capitalize on cheaper labor. In contrast, steel companies, which heavily depend on imported raw materials, continued a high concentration in coastal areas.

Figure A3 shows the footprint of two large multi-establishment corporate groups. For the Foxconn Group (one of the largest electronics manufacturers in the world), we observe a shift from coastal dominance to a more balanced distribution between coastal and inland regions. Meanwhile, the distribution of the Angang Group (one of China's largest steel manufacturers) has transformed from a largely inland cluster to a more dispersed pattern, with new production facilities acquired or built in coastal regions. This evidence underscores the regional and sectoral heterogeneity in the spatial distribution of manufacturing activity.

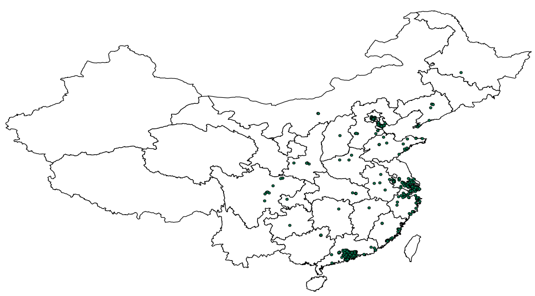
D Changes in Herfindahl-Hirschman Index

We use value added data from the *MRIO* for 2002 and 2007 to compute the Herfindahl–Hirschman Index (HHI) for each region,

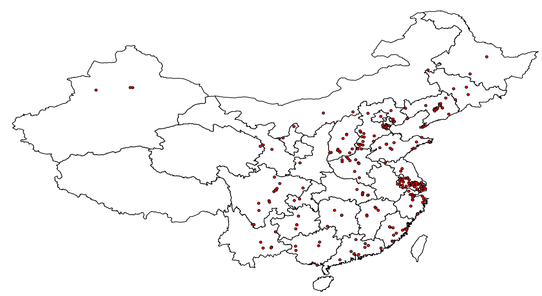
$$HHI_n = \sum_j (\frac{Y_n^j}{Y_n})^2.$$

Defined as the sum of the squared share of each manufacturing sector in the regional economy, the HHI captures the region's degree of specialization across six manufacturing sectors. The maximum possible value of the HHI is 1, which occurs when a single industry accounts for 100% of the regional economy while all other sectors have zero share.

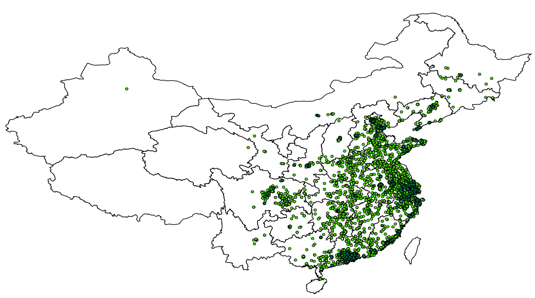
Results in Table A5 suggest that the degree of specialization increased in all regions from 2002 to 2007, with the most pronounced increase in the central region.



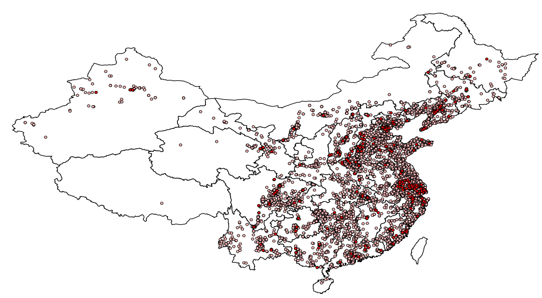
(a) Electronics 1998



(b) Steel 1998



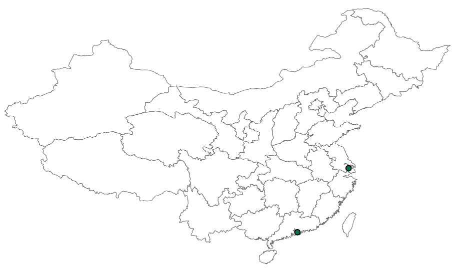
(c) Electronics 2013



(d) Steel 2013

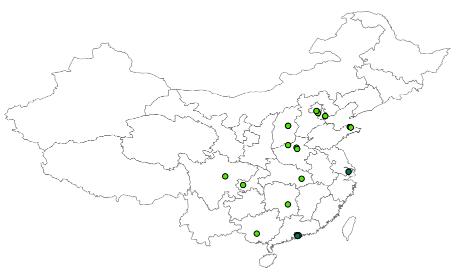
Figure A2: Spatial Distribution of Establishments in Two Industries

Note: These maps display the spatial distribution of existing establishments in 1998 and new entrants in 1999-2013 for both the electronics and steel industries. In (c) and (d), light colors indicate new entrants in 1999-2013, while dark colors represent establishments that existed in 1998.



(a) Foxconn 1998

(b) Angang 1998



(c) Foxconn 2013

(d) Angang 2013

Figure A3: Establishments of Two Corporate Groups

Note: This figure illustrates the spatial distribution of establishments for Foxconn Group (electronics) and Angang Group (steel) in 1998 and 2013.

Table A5: HHI

		2002	2007	Δ	%Δ
Eastern	**Mean**	0.18	0.19	0.00	2.31%
	Beijing	0.18	0.20	0.02	10.60%
	Tianjin	0.18	0.19	0.02	8.71%
	Hebei	0.20	0.20	0.00	-2.18%
	Shanghai	0.17	0.19	0.01	8.13%
	Jiangsu	0.18	0.18	0.00	-0.85%
	Zhejiang	0.18	0.17	-0.01	-3.19%
	Fujian	0.19	0.19	0.01	3.26%
	Shandong	0.20	0.19	-0.01	-4.17%
	Guangdong	0.18	0.18	0.00	0.45%
Central	**Mean**	0.20	0.22	0.02	7.01%
	Shanxi	0.28	0.32	0.05	16.51%
	Anhui	0.18	0.18	-0.01	-3.25%
	Jiangxi	0.18	0.21	0.03	18.93%
	Henan	0.20	0.20	0.01	3.66%
	Hubei	0.20	0.20	0.00	-1.87%
	Hunan	0.18	0.19	0.01	8.10%
Northeastern	**Mean**	0.20	0.21	0.01	4.60%
	Guangdong	0.18	0.19	0.00	1.00%
	Jilin	0.20	0.20	0.00	-0.33%
	Heilongjiang	0.21	0.23	0.03	13.12%
Western	**Mean**	0.23	0.23	0.01	4.21%
	Inner Mongolia	0.27	0.27	0.00	-1.30%
	Guangxi	0.21	0.20	-0.01	-3.82%
	Chongqing	0.22	0.24	0.01	5.70%
	Sichuan	0.19	0.19	0.00	-0.01%
	Guizhou	0.22	0.26	0.04	18.31%
	Yunnan	0.23	0.24	0.01	3.54%
	Shaanxi	0.18	0.19	0.01	4.35%
	Gansu	0.21	0.23	0.02	9.27%
	Qinghai	0.30	0.28	-0.02	-6.33%
	Ningxia	0.19	0.21	0.02	8.64%
	Xinjiang	0.25	0.27	0.02	7.91%

E Decomposition of Real Wage Changes

Using the conditions (9), (10), (13), and (16), we obtain the expression for expenditure share on domestic inputs:

$$\tilde{\lambda}_{nn}^{j} = \lambda_{nn}^{j} g_{nC}^{j} = \frac{\theta^{j}}{\theta^{j}+1-\sigma^{j}} T_{n}^{j} \left(\frac{\tilde{b}_{n}^{j}}{\phi_{nn}^{j}}\right)^{\theta^{j}} \frac{\sigma^{j} w_{n}^{M} f_{nn}^{j}}{X_{nC}^{j}} g_{nC}^{j}. \tag{A.1}$$

Plugging condition (9), (10), and (13) again into (A.1), we solve for the change in price index decomposed into several components:

$$\begin{aligned}
\frac{dP_{n}^{j}}{P_{n}^{j}} = {} & \underbrace{\frac{1}{\theta^{j}}\left(\frac{d\tilde{\lambda}_{nn}^{j}}{\tilde{\lambda}_{nn}^{j}} - \frac{dT_{n}^{j}}{T_{n}^{j}}\right)}_{\text{Entry-adjusted domestic share}} - \frac{1}{\theta^{j}}\underbrace{\left(\frac{\theta^{j}}{\sigma^{j}-1}-1\right)}_{\text{Selection}}\underbrace{\frac{dX_{n}^{j}}{X_{n}^{j}}}_{\text{Scale}} \\
& + \underbrace{\frac{1}{\theta^{j}}\left(\frac{\theta^{j}}{\epsilon^{j}-1} - \frac{\theta^{j}}{\sigma^{j}-1}\right)}_{\text{Armington across regions}} \frac{d\lambda_{nn}^{j}}{\lambda_{nn}^{j}} \\
& + \frac{1}{\theta^{j}}\underbrace{\left(\frac{\theta^{j}}{\rho^{j}-1} - \frac{\theta^{j}}{\sigma^{j}-1}\right)}_{\text{Armington across countries}} \frac{dg_{nC}^{j}}{g_{nC}^{j}} \\
& + \frac{1}{\theta^{j}}\underbrace{\left(\frac{\theta^{j}}{\sigma^{j}-1}-1\right)}_{\text{Selection}}\underbrace{\left(\frac{d\left(w_{n}^{M} f_{nn}^{j}\right)}{w_{n}^{M} f_{nn}^{j}}\right)}_{\text{Fixed costs}} \\
& + \underbrace{\beta^{j}\frac{dw_{n}^{M}}{w_{n}^{M}}}_{\text{Labor costs}} + \underbrace{\left(1-\beta^{j}\right)\sum_{i}\gamma^{ji}\frac{dP_{n}^{i}}{P_{n}^{i}}}_{\text{Intermediate goods costs}}.
\end{aligned} \tag{A.2}$$

Combining (A.2) with equation $\tilde{v}_{n}^{M} = w^{M}/P_{n}^{M}$, we derive (26), which decomposes changes in the real wage.

Although not discussed in the main text, it is worth noting here that reducing sunk entry costs directly affects the scale term in (A.2), $\frac{dX_{n}^{j}}{X_{n}^{j}}$. Plugging conditions (20) and (22) into the total expenditure equation (17), we derive its change as:

$$dX_{n}^{j} = \alpha^{j} d(E_{n}) + \sum_{i=1}^{J} \frac{\frac{\sigma^{i}\theta^{i}}{\sigma^{i}-1}(1-\beta^{i})\gamma^{ij}}{\mu^{i}} \left(w_{n}^{M} f_{n}^{iE} dT_{n}^{i} + T_{n}^{j} f_{n}^{iE} dw_{n}^{M} + T_{n}^{i} w_{n}^{M} df_{n}^{iE}\right).$$

Dividing both sides by X_n^j, we obtain

$$\frac{dX_n^j}{X_n^j} = \left(1 - \tilde{S}_n^j\right)\frac{dE_n}{E_n} + \sum_{i=1}^{J}\tilde{S}_n^j\left(\frac{dT_n^i}{T_n^i} + \frac{d\left(w_n^M f_n^{iE}\right)}{w_n^M f_n^{iE}}\right), \tag{A.3}$$

where

$$\tilde{S}_n^j = \frac{\frac{\sigma^i\theta^i}{\sigma^i-1}(1-\beta^i)\gamma^{ij}T_n^i w_n^M f_n^{iE}}{\mu^i X_n^j},$$

and

$$\left(1 - \tilde{S}_n^j\right) = \frac{\alpha^j E_n}{X_n^j}.$$

It is clear from (A.3) that the change in sunk entry cost $\frac{d\left(w_n^M f_n^{iE}\right)}{w_n^M f_n^{iE}}$ affects the change in total expenditure.

F Model Fit

Here we compare the simulation results of our model with actual data. We first solve the model in levels, assuming Pareto location parameter $\tilde{b}_n^j = 1$, agricultural technology $\mathcal{A}_n^A = 1$, agricultural land $D_{n\neq 0} = \frac{1}{N-1}, D_0 = 1$, and fixed costs $f_{nm}^j = 1$. These assumptions are necessary because we do not have credible methods to calibrate these values. We then compare model outcomes with the actual economic data in China in 2002, which is shown in Figure A4. The x-axis represents the observed data, while the y-axis shows the simulated results. Along many dimensions, our model captures the variation in real data reasonably well.

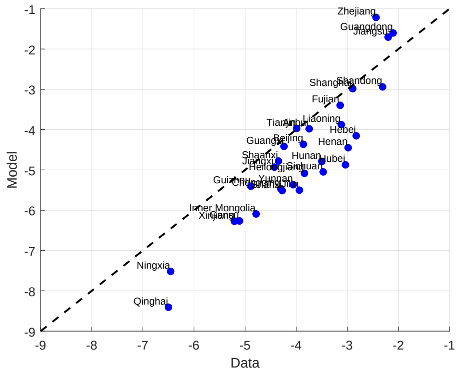
G Solution Algorithm

We solve the model in the following way.

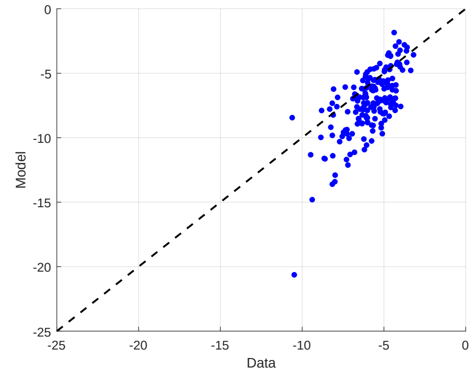
1. Guess $\{T_m^j\}_{n,j}$, $\{\phi_{nm}^j\}_{n,m,j}$, $\{\hat{Y}_n^j\}_{n,j}$, $\{\hat{L}_n^k\}_{n,k}$, $\{w_n^k\}_{n,k}$, normalized such that $w_{Beijing}^M = 1$.

    A. Compute $\hat{P}_n$ as follows.

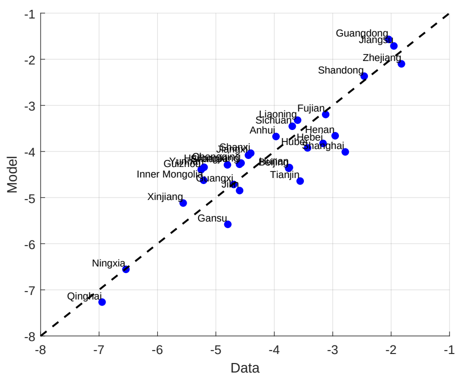
    - Guess $\hat{\hat{P}}_{nC}^j$ and $\hat{\hat{P}}_{n0}^j$.
    - Compute $\hat{T}_{nm}^j$ using (F1).
    - Compute $\hat{P}_n^j$ using (F2).
    - Compute $\hat{c}_{mn}^j$ using (F3).
    - Compute $\hat{\bar{\phi}}_{mn}^j$ using (F4).



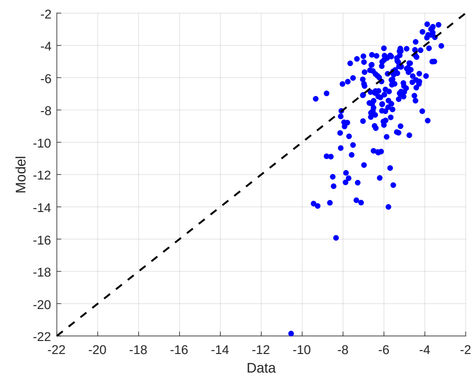
$$\ln\left(\frac{Y_n}{Y_C}\right)$$



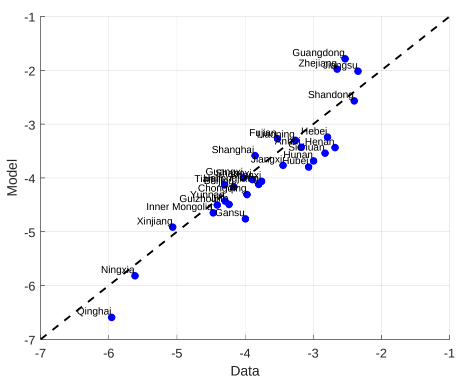
$$\ln\left(\frac{Y_n^j}{Y_C}\right)$$



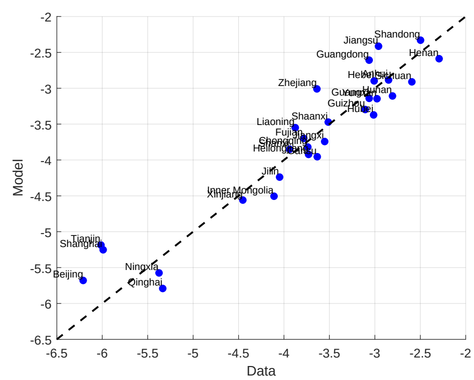
$$\ln\left(\frac{T_{nn}}{T_C}\right)$$



$$\ln\left(\frac{T_{nn}^j}{T_C}\right)$$



$$\ln\left(\frac{L_n^M}{L_C^M}\right)$$



$$\ln\left(\frac{L_n^A}{L_C^A}\right)$$

Figure A4: "Fit" of the Model in Level

- Compute $\hat{\zeta}^j_{nm}$ using (F5).
- Update $\hat{\hat{P}}^j_{nC}$ using (F6).
- Update $\hat{\hat{P}}^j_{n0}$ using (F7).
- Check if $\hat{\hat{P}}^j_{nC}$ and $\hat{\hat{P}}^j_{n0}$ obtained in the last step is close to $\hat{\hat{P}}^j_{nC}$ and $\hat{\hat{P}}^j_{n0}$ initially guessed. If it does, stop. Otherwise, update $\hat{\hat{P}}^j_{nC}$ and $\hat{\hat{P}}^j_{n0}$, and return to the first step.
- Compute $\hat{E}^A_n$ using (H4)
- Compute $\hat{\hat{r}}_n$ using (A1).
- Compute $\hat{P}^A_n$ using (A2)
- Compute $\hat{P}_n$ using (H1)

B. Compute $\hat{Y}^j_n$ as follows.

- Compute $\hat{\psi}^k_n$ using (H2).
- Update $\hat{L}^k_n$ using (H3).
- Compute $\hat{E}^j_n$ using (H4).
- Compute $\hat{M}^j_n$ using (F8).
- Compute $\hat{X}^j_n$ using (F9).
- Compute $\hat{g}^j_{nC}$ using (F10).
- Compute $\hat{g}^j_{n0}$ using (F11).
- Compute $\hat{\lambda}^j_{nm}$ using (F12).
- Compute $\hat{X}^j_{nm}$ using (F13) and (F14).
- Update $\hat{Y}^j_n$ using (F15).

C. Update w^M_n using (H5).

D. Update $\hat{\phi}^j_{nm}$ using (F16) and (F17).

E. Update $\hat{T}^j_m$ using (F18).

F. Compute w^A_n as follows.

- Update $\hat{\hat{r}}_n$ using (A1).
- Update $\hat{P}^A_n$ using (A2).
- Update $\hat{w}^A_n$ using (H6).

2. Check if $\{T^j_m\}_{n,j}$, $\{\phi^j_{nm}\}_{n,m,j}$, $\{\hat{Y}^j_n\}_{n,j}$, $\{\hat{L^k_n}\}_{n,k}$, $\{w^k_n\}_{n,k}$ obtained in the last step is close to $\{T^j_m\}_{n,j}$, $\{\phi^j_{nm}\}_{n,m,j}$, $\{\hat{Y}^j_n\}_{n,j}$, $\{\hat{L^k_n}\}_{n,k}$, $\{w^k_n\}_{n,k}$ initially guessed. If it does, stop and normalize $w^M_{Beijing} = 1$ to one. Otherwise, update all and return to step 1.

Table A6: Equilibrium Conditions

(H1)	$\hat{P}_n = \prod_j \left(\hat{P}_n^j\right)^{\alpha^j}$	$\forall(n,j)$
(H2)	$\hat{\psi}_n^k = \frac{\left(\hat{B}_n^M \frac{\hat{w}_n^k}{\hat{P}_n}\right)^{1/\eta}}{\sum_m \psi_m^k \left(\hat{B}_m^k \frac{\hat{w}_m^k}{\hat{P}_m}\right)^{1/\eta}}$	$\forall(n,k)$
(H3)	$\hat{L}_n^k = \hat{\psi}_n^k \hat{L}_C$	$\forall(n,k), n \neq 0$
(H4)	$\hat{E}_n^j = \hat{E}_n = \frac{L_n^M w_n^M}{L_n^M w_n^M + L_n^A w_n^A} \hat{L}_n^M \hat{w}_n^M + \frac{L_n^A w_n^A}{L_n^M w_n^M + L_n^A w_n^A} \hat{L}_n^A \hat{w}_n^A$	$\forall(n)$
(H5)	$\hat{w}_n^M = \frac{\sum_j \frac{\left(\frac{\beta^j(\sigma^j-1)+1}{\sigma^j}\right) Y_n^j}{\sum_j \left(\frac{\beta^j(\sigma^j-1)+1}{\sigma^j}\right) Y_n^j} \hat{Y}_n^j}{\hat{L}_n^M}$	$\forall(n,j), j \neq 0$
(H6)	$\hat{w}_n^A = \frac{\hat{E}_n^A}{\hat{L}_n^A}$	$\forall(n)$
(F1)	$\hat{T}_{nm}^j = \left(\frac{\hat{\tilde{b}}_m^j}{\hat{\tilde{\phi}}_{nm}^j}\right)^{\theta^j} \hat{T}_m^j$	$\forall(m,n,j), j \neq 0$
(F2)	$\hat{P}_n^j = \left(g_{nC}^j \left(\hat{\tilde{P}}_{nC}^j\right)^{1-\rho^j} + (1-g_{nC}^j)\left(\hat{\tilde{P}}_{n0}^j\right)^{1-\rho^j}\right)^{\frac{1}{1-\rho^j}}$	$\forall(n,j), j \neq 0$
(F3)	$\hat{c}_{mn}^j = \hat{\tau}_{mn}^j \left(\hat{w}_n^M\right)^{\beta^j} \left(\prod_i \left(\hat{P}_n^i\right)^{\gamma^{ji}}\right)^{1-\beta^j}$	$\forall(m,n,j), j \neq 0$
(F4)	$\hat{\tilde{\phi}}_{mn}^j = \hat{\phi}_{nm}^j$	$\forall(m,n,j), j \neq 0$
(F5)	$\hat{\zeta}_{nm}^j = \frac{\left(\hat{T}_{nm}^j\right)^{\frac{1}{1-\sigma^j}} \hat{c}_{nm}^j}{\hat{\tilde{\phi}}_{nm}^j}$	$\forall(m,n,j), m \neq 0, j \neq 0$
(F6)	$\hat{\tilde{P}}_{nC}^j = \left(\sum_m \lambda_{nm}^j (\hat{\zeta}_{nm}^j)^{1-\epsilon^j}\right)^{\frac{1}{1-\epsilon^j}}$	$\forall(m,n,j), m \neq 0, j \neq 0$
(F7)	$\hat{\tilde{P}}_{n0}^j = \frac{\left(\hat{T}_{n0}^j\right)^{\frac{1}{1-\sigma^j}} \hat{c}_{n0}^j}{\hat{\tilde{\phi}}_{n0}^j}$	$\forall(n,j), j \neq 0$
(F8)	$\hat{M}_n^j = \sum_{i=1}^J \frac{M_n^{ij}}{M_n^j} \hat{Y}_n^i$	$\forall(m,n,j), j \neq 0$
(F9)	$\hat{X}_n^j = \frac{E_n^j}{X_n^j} \hat{E}_n^j + \frac{M_n^j}{X_n^j} \hat{M}_n^j$	$\forall(n,j), j \neq 0$
(F10)	$\hat{g}_{nC}^j = \frac{\left(\hat{\tilde{P}}_{nC}^j\right)^{1-\rho^j}}{\left(\hat{P}_n^j\right)^{1-\rho^j}}$	$\forall(n,j), j \neq 0$
(F11)	$\hat{g}_{n0}^j = \frac{\left(\hat{\tilde{P}}_{n0}^j\right)^{1-\rho^j}}{\left(\hat{P}_n^j\right)^{1-\rho^j}}$	$\forall(n,j), j \neq 0$
(F12)	$\hat{\lambda}_{nm}^j = \frac{\left(\hat{\zeta}_{nm}^j\right)^{1-\epsilon^j}}{\left(\hat{\tilde{P}}_{nC}^j\right)^{1-\epsilon^j}}$	$\forall(m,n,j), m \neq 0, j \neq 0$
(F13)	$\hat{X}_{n0}^j = \hat{g}_{n0}^j \hat{X}_n^j$	$\forall(n,j), j \neq 0$
(F14)	$\hat{X}_{nm}^j = \hat{\lambda}_{nm}^j \hat{g}_{nC}^j \hat{X}_n^j$	$\forall(m,n,j), m \neq 0, j \neq 0$
(F15)	$\hat{Y}_n^j = \sum_m \frac{X_{mn}^j}{Y_n^j} \hat{X}_{mn}^j$	$\forall(m,n,j), j \neq 0$
(F16)	$\hat{\phi}_{nm}^j = \left(\frac{\hat{w}_m^M \hat{f}_{nm}^j (\hat{c}_{nm}^j)^{\sigma^j-1}}{\hat{X}_{nC}^j \left(\hat{\zeta}_{nm}^j\right)^{\sigma^j-\epsilon^j} \left(\hat{\tilde{P}}_{nC}^j\right)^{\epsilon^j-1}}\right)^{\frac{1}{\sigma^j-1}}$	$\forall(m,n,j), m \neq 0, j \neq 0$
(F17)	$\hat{\phi}_{n0}^j = \left(\frac{\hat{w}_0^M \hat{f}_{n0}^j (\hat{c}_{n0}^j)^{\sigma^j-1}}{\hat{X}_{n0}^j \left(\hat{\tilde{P}}_{n0}^j\right)^{\sigma^j-1}}\right)^{\frac{1}{\sigma^j-1}}$	$\forall(n,j), j \neq 0$
(F18)	$\hat{T}_m^j = \frac{\hat{Y}_m^j}{\hat{w}_m^M \hat{f}_m^{jE}}$	$\forall(m,j), j \neq 0$
(A1)	$\hat{\tilde{r}}_n = \frac{\hat{E}_n^A}{\hat{D}_n}$	$\forall(n)$
(A2)	$\hat{P}_n^A = \frac{\left(\hat{w}_n^A\right)^{\beta^A} \left(\hat{\tilde{r}}_n\right)^{1-\beta^A}}{\hat{\mathcal{A}}_n^A}$	$\forall(n)$

H Trade Elasticity

Following Kucheryavyy et al. (2023), we derive an equation that involves trade elasticity. We first plug (13) into (14) and (15), and then plug both into (16) to get:

$$\left(\zeta_{nm}^{j}\right)^{1-\epsilon^{j}}=\left(\tilde{\mu}_{n}^{j}\right)^{\xi^{j}}\left(\tilde{b}_{m}^{j}\right)^{\theta^{j}\xi^{j}}\left(T_{m}^{j}\right)^{\xi^{j}}\left(c_{nm}^{j}\right)^{-\theta^{j}\xi^{j}}\left(\frac{w_{m}^{M}f_{nm}^{j}}{X_{nC}^{j}}\right)^{\frac{\sigma^{j}-\theta^{j}-1}{\sigma^{j}-1}\xi^{j}}\left(P_{nC}^{j}\right)^{\frac{1-\sigma^{j}}{(\sigma^{j}-\theta^{j}-1)(1-\epsilon^{j})}\xi^{j}},$$

where the constants $\tilde{\mu}_{n}^{j}=\left(\mu^{j}\right)^{-\theta^{j}}\frac{\theta^{j}}{\theta^{j}+1-\sigma^{j}}\left(\sigma^{j}\right)^{\frac{\sigma^{j}-\theta^{j}-1}{\sigma^{j}-1}}$ and $\xi^{j}=\frac{1}{1+\theta^{j}\left(\frac{1}{\epsilon^{j}-1}-\frac{1}{\sigma^{j}-1}\right)}$. Recall from equation (10) $\lambda_{nm}^{j}=\frac{\left(\zeta_{nm}^{j}\right)^{1-\epsilon^{j}}}{\left(\tilde{P}_{nC}^{j}\right)^{1-\epsilon^{j}}}$, so the Chinese regional trade share λ_{nm}^{j} is proportional to $\left(\zeta_{nm}^{j}\right)^{1-\epsilon^{j}}$. From the equation above, we see $\theta^{j}\xi^{j}$ reflects how trade share adjusts to costs c_{nm}^{j}, which is commonly referred to as the trade elasticity. High elasticity indicates that consumers can easily switch products, while low elasticity suggests limited substitutability (Fontagné et al. 2022). In our calibration, we borrow the value of ξ^{j} from existing studies so that we can back out the value of ϵ^{j} based on $\xi^{j}=\frac{1}{1+\theta^{j}\left(\frac{1}{\epsilon^{j}-1}-\frac{1}{\sigma^{j}-1}\right)}$.

I Size of the Shocks

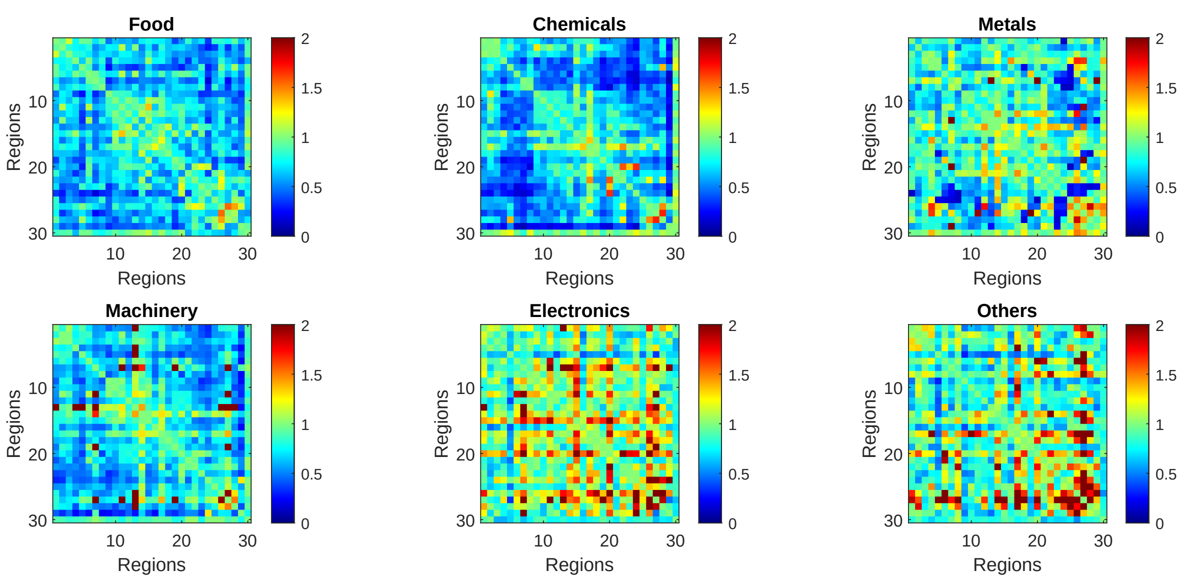


Figure A5: Changes in Trade Costs between 2002 and 2007

Note: The values in the heatmap indicate the relative changes in iceberg trade costs from 2007 to 2002, $\tau_{nm,2007}^{j}/\tau_{nm,2002}^{j}$.

Table A7: Changes in Sunk Entry Costs between 2002 and 2007

	Food	Chemicals	Metals	Machinery	Electronics	Others
Beijing	-59.74%	-50.47%	-50.13%	-31.47%	-57.48%	-72.95%
Tianjin	-40.85%	-33.76%	-52.27%	-44.85%	-52.46%	-38.68%
Hebei	-49.35%	-41.99%	-27.54%	-56.72%	0.31%	-38.20%
Shanxi	-88.15%	-57.80%	-56.12%	-82.93%	-76.51%	-91.85%
Inner Mongolia	-81.28%	-78.28%	-77.78%	-83.77%	-83.00%	-91.45%
Liaoning	-66.34%	-45.89%	-57.57%	-51.11%	-45.54%	-49.59%
Jilin	-74.10%	-61.61%	-74.18%	-28.09%	-78.96%	-73.99%
Heilongjiang	-52.29%	134.71%	287.44%	-12.86%	13.43%	-26.53%
Shanghai	-26.01%	-9.52%	-26.90%	-14.52%	34.56%	-41.68%
Jiangsu	-61.50%	-52.95%	-49.95%	-50.99%	-55.13%	-57.46%
Zhejiang	-51.57%	-29.11%	-45.45%	-13.09%	74.18%	-31.28%
Anhui	-59.67%	-32.93%	-64.00%	-58.32%	48.52%	-69.53%
Fujian	-21.65%	-4.50%	-11.00%	-50.77%	0.40%	-56.78%
Jiangxi	-75.69%	-62.72%	-55.93%	-69.94%	-41.57%	-68.43%
Shandong	-46.20%	-54.13%	-58.12%	-50.65%	-8.52%	-56.21%
Henan	-60.17%	-35.50%	-48.06%	-52.28%	-28.39%	-62.07%
Hubei	-63.90%	-56.61%	-70.44%	-64.57%	-44.74%	-61.62%
Hunan	-67.81%	-47.46%	-60.77%	-58.11%	21.76%	-61.74%
Guangdong	-38.21%	-44.32%	-22.25%	-30.43%	-65.40%	-58.34%
Guangxi	73.49%	-42.96%	-2.22%	-19.34%	115.75%	23.13%
Chongqing	-72.21%	-69.33%	-73.61%	-64.88%	-84.50%	-78.99%
Sichuan	-58.70%	-58.97%	-70.10%	-34.53%	-47.81%	-77.36%
Guizhou	-50.33%	-42.80%	-71.67%	-79.41%	-47.10%	-61.93%
Yunnan	-11.48%	-47.08%	-8.45%	-13.79%	26.55%	-51.78%
Shaanxi	-80.78%	-26.84%	-35.54%	-50.30%	-54.56%	-85.00%
Gansu	-87.31%	-73.15%	-78.94%	-92.12%	-74.97%	-90.75%
Qinghai	-88.36%	-36.98%	-59.60%	-76.49%	-97.24%	-67.51%
Ningxia	-71.22%	-63.46%	-85.33%	-82.27%	-56.66%	-75.96%
Xinjiang	-82.04%	-30.71%	-60.78%	-94.00%	-35.62%	-78.38%
Mean	-55.63%	-39.90%	-40.25%	-52.16%	-27.61%	-60.45%
Mean(Coastal)	-35.26%	-37.24%	-36.67%	-37.63%	-5.39%	-43.46%
Mean(Inland)	-68.08%	-41.53%	-42.44%	-61.04%	-41.19%	-70.83%

J Full Counterfactual Results

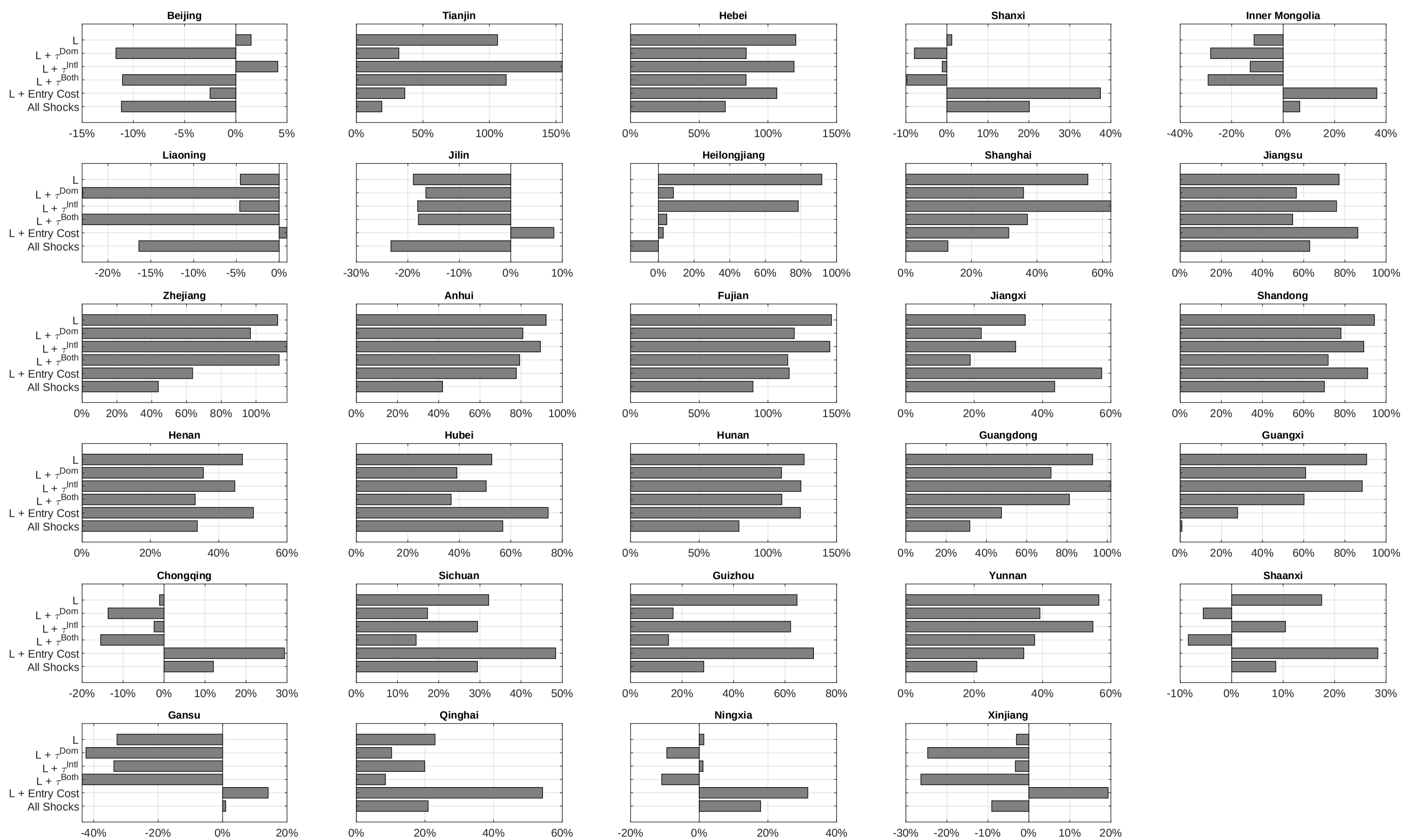


Figure A6: Change in Mass of Firms

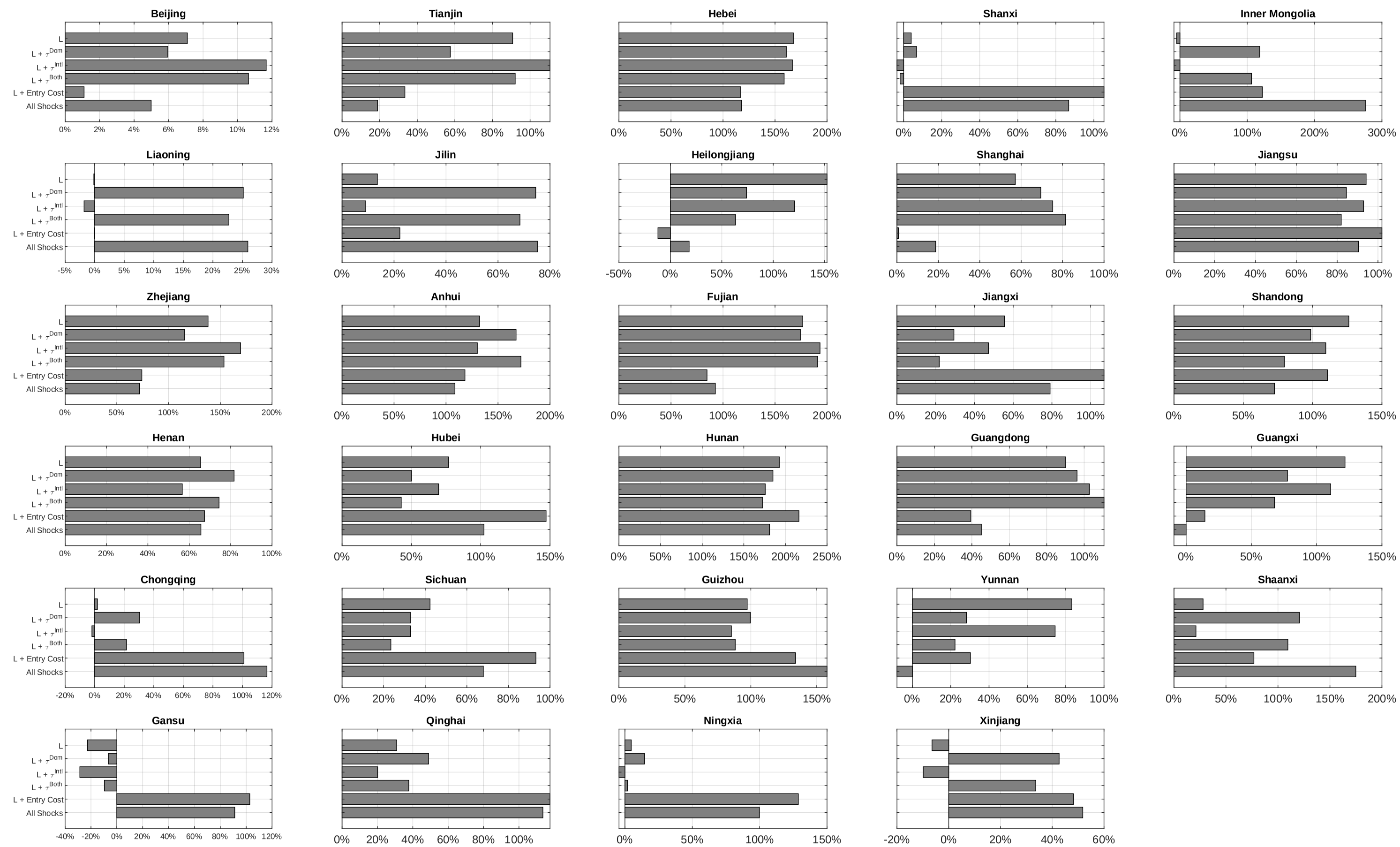


Figure A7: Change in GDP

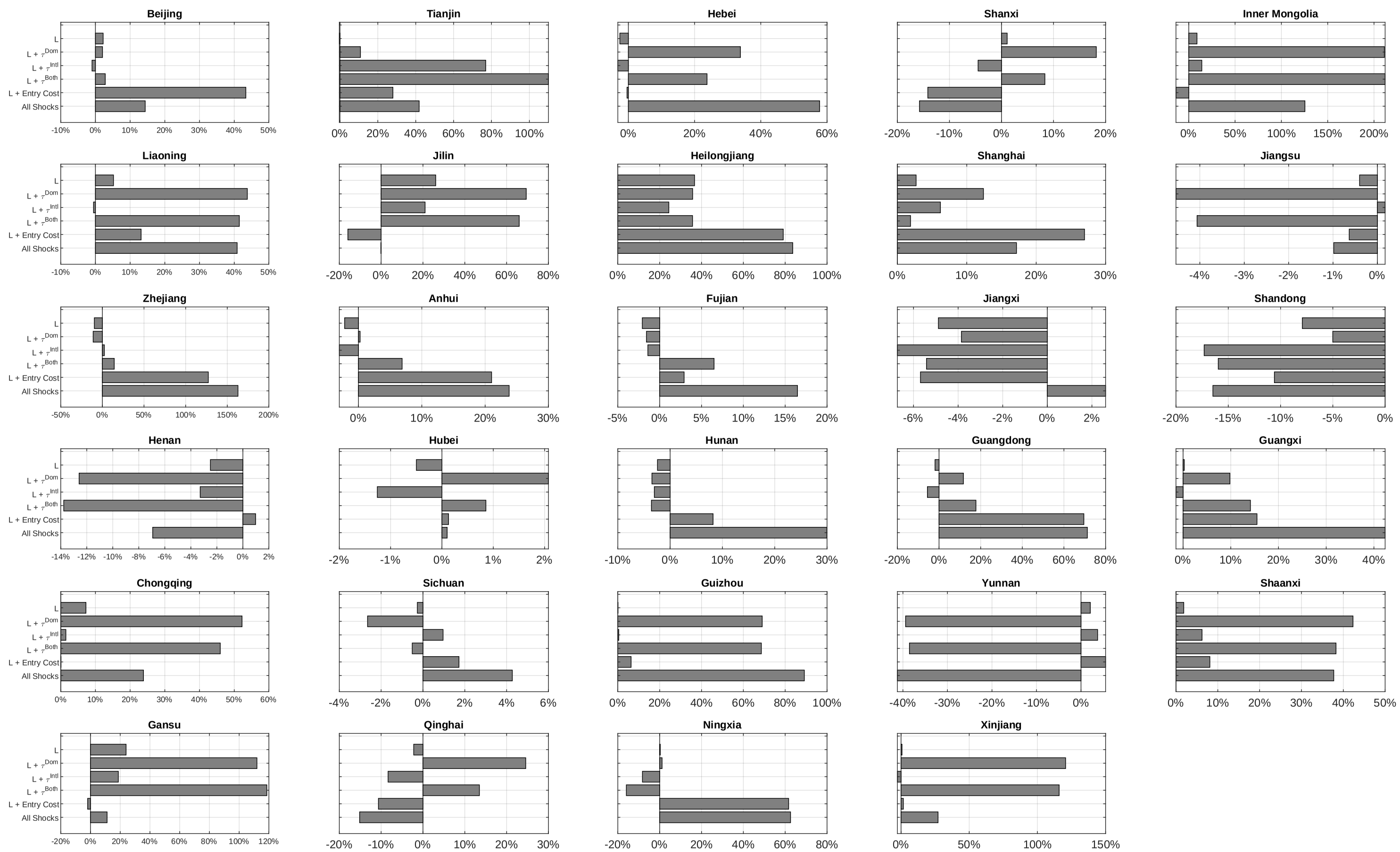


Figure A8: Change in Regional HHI