Domestic Market Segmentation and Spatial Income Inequality

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Abstract

In this paper, we study spatial income inequality within China. Using unique inter-regional trade data, we document a significant negative provincial border effect: in the industrial sector, trade between two cities in different provinces is about 92% lower than trade between cities within the same province, suggesting the presence of strong domestic market segmentation. To quantify these effects, we develop and calibrate a multi-region, multi-sector quantitative general equilibrium model that features provincial trade frictions. Counterfactuals show that removing provincial trade frictions reduces variance of log real wages by about 8% and lowers the 90/10 income ratio by about 17%.

JEL Classification: F14, R12, O53.

Keywords: Domestic borders and trade; spatial income inequality.

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1 Introduction

Efficiency versus equality is one of the most important topics in economics. As one of the fastest-growing economies in the world, China has experienced a dramatic increase in GDP per capita over the past four decades. However, this rapid growth has been accompanied by a pronounced rise in income inequality, particularly across regions. For instance, Beijing, one of the wealthiest cities in China, has a GDP per capita more than ten times that of Yushu, a city in Qinghai Province. Figure 1 plots nominal GDP per capita in 2017 for cities in mainland China and shows a clear spatial gradient. High-income cities are concentrated along the eastern coast, while low-income cities are predominantly located in central and western China. In many of these poorer cities, GDP per capita is only about 10% of Beijing's level.

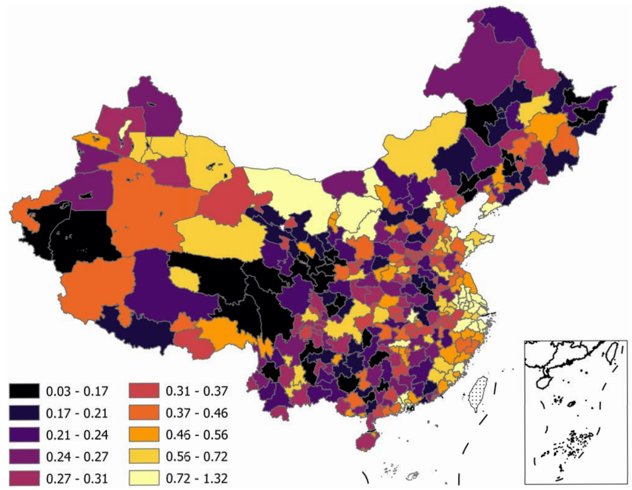
These disparities are also evident at broader regional levels and in international comparisons. Zhang (2021) documents that the income gap between China's eastern and western regions is roughly a factor of two and has widened over time. Tombe and Zhu (2015) report that the ratio of per capita income at the 90th percentile to that at the 10th percentile was about 3.5 in China in the early 2000s, compared with about 1.5 in the United States. Accordingly, for both economic development and policy implementation, it is crucial to identify the forces behind these spatial income gaps and to quantify their implications.

In this paper, we study China's spatial income inequality through the lens of internal trade. Using unique inter-regional trade-flow data, we document pronounced provincial border frictions: cities in different provinces trade substantially less, even when they share a city border. These barriers can limit specialization based on comparative advantage and thereby widen regional income gaps. To quantify their effects, we develop and calibrate a multi-region, multi-sector quantitative general equilibrium model with provincial trade frictions, allowing regions to differ in productivity, factor endowments, and input–output structure. Counterfactual analysis shows that removing provincial trade frictions reduces cross-city variance of log real wages by about 8% and lowers the 90th to 10th income ratio by roughly 17%.[1]

Our inter-regional trade flow data are derived from China's 2017 city-level multi-regional input–output (MRIO) table (Wang et al., 2025), which covers 341 regions consisting of 340 Chinese cities and an aggregated rest-of-world region.[2] The MRIO table provides detailed

[1]Spatial income inequality is measured as the cross-region variance of log real wages.
[2]The MRIO table excludes Hong Kong and Macao.

Figure 1: GDP per capita across Chinese cities



Notes: The figure plots nominal GDP per capita in 2017 for 340 cities in mainland China (337 prefecture-level cities plus Beijing, Tianjin, and Shanghai). GDP per capita is normalized to Beijing.

cross-regional and cross-sectoral input–output linkages, which we use to construct sectoral bilateral trade flows between distinct origin and destination regions.

In our empirical analysis, we aim to quantify the impact of domestic borders on inter-regional trade. Specifically, we distinguish between two types of borders: city borders and provincial borders. For provincial borders, we consider three cases: (i) two cities located within the same province; (ii) two cities located in different but contiguous provinces; and (iii) two cities located in different and non-contiguous provinces.

Given our data and definitions of domestic borders, we estimate an empirical model based on the gravity equation. The results indicate that city borders promote trade, while provincial borders dampen it. In the industrial sector, if two cities share a common city border, bilateral trade is about 17% higher relative to non-contiguous cities. In contrast, provincial borders have a significant and negative effect, reducing trade in industrial goods by about 92%. The empirical results suggest that domestic market segmentation in China arises primarily from provincial administrative divisions rather than the municipal level. Moreover, trade frictions are even larger in agriculture and services and exhibit substantial heterogeneity across provinces, underscoring both the strength and unevenness of local trade barriers within China.

To assess how this demostic market segmentation contributes to income differences across regions, we build on Caliendo and Parro (2015) and develop a multi-region, multi-sector quantitative general equilibrium model with provincial frictions. In the model, labor is immobile across regions but freely mobile across sectors. Goods produced in each sector are tradable and can be used either as intermediate inputs in production or as final consumption by households. Trade is subject to standard iceberg trade costs plus provincial border frictions. We calibrate the model to match the data on inter-regional trade flows.

In our model, removing provincial trade frictions strengthens specialization through comparative advantage and thus increases regional and sectoral effective productivity. Importantly, the presence of regional heterogeneity, such as value-added ratios, can amplify the effects of domestic trade liberalization.[3] Moreover, lower trade costs also reduce home expenditure shares and lower sectoral price indices, so real wage gains operate through both a productivity channel and a price channel. Because these channels are weighted by local value-added ratios and input shares, identical policy changes can generate uneven real wage gains across cities and can reshape the spatial income distribution.

We conduct three counterfactual exercises. First, we remove sector-specific provincial border frictions in all sectors. This lowers the cross-city variance of log real wages by 0.037 variance units, about 8% relative to the baseline, and reduces the 90/10 income ratio by about 17%. To clarify why inequality falls, we further decompose each city's log real wage as the sum of an effective labor productivity term, an input-output linkage term that captures how intermediate input prices affect production costs, and a term reflecting sectoral expenditure shares, and then decompose the cross-city variance into the variances and covariances of these components. This accounting shows that the reduction in inequality is driven mainly by a compression in the dispersion of effective labor productivity across cities. Second, we impose a uniform reduction in provincial border frictions across sectors. In this case, the cross-city variance of log real wages increases slightly, even though the 90/10 and 80/20 income gaps still narrow. Third, we remove regional heterogeneity in selected elements of the production and expenditure structure. These exercises show that value added ratios are pivotal: when all cities share a common value added ratio, liberalization increases the variance of log real wages, whereas homogenizing input-output coefficients or expenditure shares does not overturn the baseline reduction in inequality.

The paper is related to the literature that empirically investigates intra-national and inter-regional trade flows and market segmentation. This literature includes studies such as (Santamaria, Ventura, and Yeşilbayraktar, 2023; García-Santana and Santamaría, 2023; Coughlin and Novy, 2013; Xing and Li, 2011; Zheng, Lu, and Li, 2022; Hillberry and Hum-

[3]For example, a region-sector with a high value-added ratio may benefit less since it relies less on intermediate inputs from other regions.

mels, 2008; Poncet, 2003, 2005). In particular, Xing and Li (2011) and Zheng, Lu, and Li (2022) use inter-provincial value-added tax and truck flows as proxies to estimate inter-provincial trade, and find the presence of home trade bias at the provincial level. In our paper, we extend administrative districts to regions within provinces, and show that border frictions for trade concentrate at provincial administrative districts instead of regional administrative districts. More broadly, Santamaria, Ventura, and Yeşilbayraktar (2023) analyze home trade bias by studying intra-national and international trade across 24 countries and 269 regions in Europe, finding that European regions exhibit a strong home trade bias and that national borders are an important determinant of regional trade. García-Santana and Santamaría (2023) then extend this line of research by examining how home trade bias influences government procurement in Europe.[4]

The paper is also related to the literature on intra-national trade flows and income distribution in China (Tombe and Zhu, 2019, 2015; Jiang and Mei, 2020). Specifically, Tombe and Zhu (2019, 2015) employ a quantitative spatial model to assess how reductions in internal and external trade frictions, as well as migration frictions, affect regional and aggregate productivity and income distribution. They find that internal trade and migration frictions are more important than external trade frictions. While internal trade frictions declined substantially between 2000 and 2005, they remained at relatively high levels. In addition, Jiang and Mei (2020) show that leadership rotations significantly contribute to the expansion of inter-provincial trade, especially from new to old provinces. Our paper contributes to this literature by looking at inter-city trade, and we find that the provincial border effect plays a significant role in explaining internal trade frictions and regional income inequality in China.

The rest of the paper is organized as follows. Section 2 describes our data and empirical analysis. Section 3 describes the model. Section 4 presents the quantitative analysis, including calibration and counterfactual exercises. Finally, Section 5 concludes.

[4]Other studies, such as Coughlin and Novy (2013) and Hillberry and Hummels (2008), investigate intra-national trade by focusing on regions within the United States. We contribute to this literature by examining domestic border effects on inter-regional trade in China. Our sample covers 34 provinces and 340 cities in China, plus an aggregated rest-of-world region. We provide a comprehensive analysis of intra-national trade within a single country, and find a pronounced negative provincial border effect that impeded inter-regional trade.

2 Data and Empirics

In this section, we briefly discuss the main data that we use in this paper, and then present the empirical strategy and key empirical findings.

2.1 Data

Inter-city trade. We construct inter-regional sectoral trade flows by using the 2017 China city-level inter-city input-output (ICIO) table developed by Wang et al. (2025). The 2017 ICIO dataset covers 341 regions, including 337 prefecture-level cities, three provincial-level municipalities (Beijing, Tianjin, and Shanghai), and an aggregate rest-of-world region (ROW).

Geographies. To construct the distance between cities, we collect the geographic coordinates of 340 Chinese cities and 221 foreign capitals from Google Maps and compute pairwise great-circle distances between these locations. To aggregate ROW, we use population data from the 5th National Census of China (2000) and Penn World Table version 10 (Feenstra, Inklaar, and Timmer, 2015) in 2000, and then we calculate population-weighted distances between each Chinese city and foreign capitals. For tractability, each Chinese city is approximated by the geographic coordinates of its corresponding provincial capital. Therefore, distance measures the straight-line geographic distance between region n and i.

Table 1: Summary Statistics

VarName	Mean	SD	Min	P5	Median	P95	Max	N
$\log(X_{ni}^{agr.})$	-2.20	3.32	-18.33	-7.99	-1.92	2.89	7.92	94379
$\log(X_{ni}^{ind.})$	1.46	2.44	-21.60	-2.57	1.59	5.12	9.59	113966
$\log(X_{ni}^{ser.})$	0.20	2.89	-17.36	-4.83	0.41	4.50	10.55	115167
$\log(Distance_{ni})$	7.06	0.69	2.88	5.76	7.15	8.03	8.42	115260

Notes: This table reports summary statistics for the variables used in the empirical analysis. *Mean*, *SD*, *Min*, *P5*, *Median*, *P95*, and *Max* denote the sample mean, standard deviation, minimum, 5th percentile, median, 95th percentile, and maximum respectively. N is the number of non-missing observations. For variables defined in logs, observations with (a) zero values or (b) values that are missing by construction (e.g., the distance from a city to itself) are treated as missing because $\log(\cdot)$ is undefined for such values.

Summary Statistics and Others. Table 1 reports summary statistics for the key bilateral variables used in the gravity regressions. Inter-city trade flows vary substantially across city pairs and sectors. On average, agricultural trade flows are the smallest and exhibit greater dispersion relative to the other sectors. Inter-regional trade is primarily concentrated in the industrial sector, while the services sector lies between agriculture and industry in terms of trade volume. Dispersion of trade flows is large across all three sectors, indicating pronounced heterogeneity in trade intensity across city pairs.

2.2 Empirical Strategy

Given data on inter-city trade and geographies, we estimate the following reduced-form gravity model from Anderson and Van Wincoop (2003),

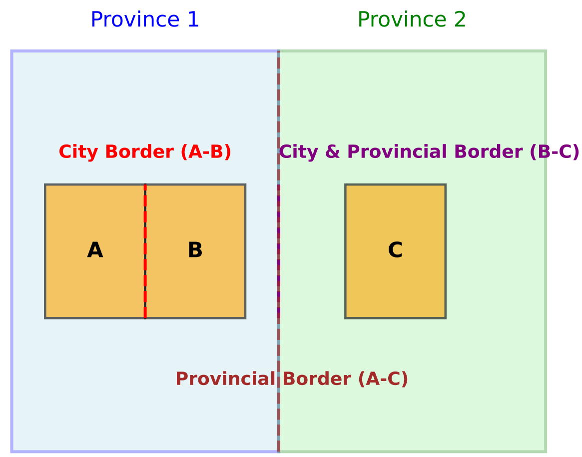
$$\begin{aligned}\log(X_{ni}) = \beta_0 + \beta_1 CtyBorder_{ni} + \beta_2 ProBorder_{ni} + \beta_3 CtyBorder_{ni} \times ProBorder_{ni} \\ + \beta_4 log(Dist_{ni}) + \beta_5 Non-contiguousPro_{ni} + f_n + f_i + \varepsilon_{ni}\end{aligned} \tag{1}$$

In equation (1), X_{ni} is city n's imports from city i. $CtyBorder_{ni}$ is a dummy variable that equals 1 if city n and city i share a common city border, and 0 otherwise. $ProBorder_{ni}$ is a dummy variable that equals 1 if city n and city i are in different provinces, but their provinces share a common border, and 0 otherwise. $Dist_{ni}$ is the straight-line geographic distance between city n and city i. f_n and f_i are importer and exporter fixed effects. ε_{ni} is the error term. Finally, we include $Non\text{-}contiguousPro_{ni}$, a dummy variable that equals 1 if city n and city i are located in non-contiguous provinces, and 0 otherwise.

Figure 2 illustrates the domestic city and provincial borders captured in equation (1). For simplicity, we consider an economy with three cities and two provinces. Specifically, cities A and B are located in Province 1, while City C is located in Province 2. Cities A and B share a common city border; cities B and C share both a common city and a provincial border; and cities A and C share only a provincial border.

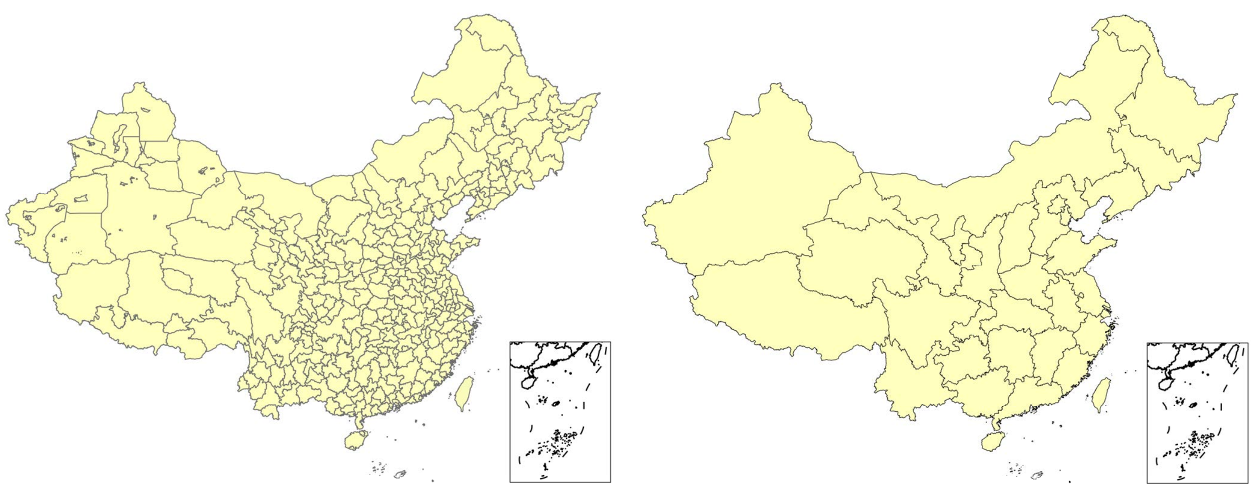
Figure 3 presents city and provincial borders in China. Panel (a) shows the administrative boundaries of the 340 mainland Chinese cities in our sample and highlights city pairs that share a common city border, corresponding to $CtyBorder_{ni} = 1$. Panel (b) shows provincial boundaries and highlights province pairs that share a common provincial border. This information determines the cross-province indicators: $ProBorder_{ni} = 1$ for city pairs located in different but contiguous provinces, and $Non\text{-}contiguousPro_{ni} = 1$ for city pairs located in non-contiguous provinces.

Figure 2: Domestic Borders: City and Provincial Boundaries



Notes: The figure illustrates domestic borders relevant for inter-city trade. Cities A and B are located in the same province (Province 1), while City C is located in a different province (Province 2).

Figure 3: City and Provincial Borders in Mainland China



(a) City borders

(b) Provincial borders

Notes: Panel (a) shows city administrative boundaries; Panel (b) shows provincial boundaries.

In our empirical specification, the coefficients β_1 to β_3 are of primary interest. β_1 captures the average effect of a city border between A and B, β_2 captures the average effect between A and C, and β_3 captures the average effect between B and C where two cities share a common city and provincial border.

2.3 Empirical Results

Table 2 reports the estimation results for equation (1). The dependent variable is the logarithm of city n's imports from city i in the industrial sector.

Table 2: City and provincial border effects on inter-city trade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CtyBorder	2.848***	2.685***	0.078	-0.0261	-0.900***	-0.305***	0.193***
	(0.058)	(0.057)	(0.060)	(0.077)	(0.076)	(0.033)	(0.033)
ProBorder		1.012***	-2.766***	-2.798***	-1.632***	-2.088***	-2.515***
		(0.019)	(0.040)	(0.043)	(0.044)	(0.020)	(0.019)
Non-contiguous provinces			-4.019***	-4.047***	-1.554***	-2.828***	-3.765***
			(0.038)	(0.041)	(0.046)	(0.022)	(0.018)
CtyBorder * ProBorder				0.264**	-0.525***	-0.227***	-0.0304
				(0.123)	(0.118)	(0.051)	(0.052)
Log distance					-1.399***	-0.608***	
					(0.013)	(0.009)	
N	114979	114979	114979	114979	114979	114979	114979
Origin FE	N	N	N	N	N	Y	Y
Destination FE	N	N	N	N	N	Y	Y

Notes: The table reports the estimation results of equation (1) using OLS. The dependent variable is city n's imports from city i in the industrial sector. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In column (1), *CtyBorder* is a dummy variable that equals 1 if two cities share a common city border and 0 otherwise. The estimated coefficient is positive and statistically significant. If two cities share a common city border, the trade flows of industrial goods is, on average, 1600% ($(e^{2.848} - 1) \times 100\%$) higher than the trade flow between two cities that do not share a city border.

In columns (2) and (3), we include additional border dummy variables, *ProBorder* and *Non-contiguous provinces*. *ProBorder* is 1 if two cities are located in different but contiguous provinces, and 0 otherwise. *Non-contiguous provinces* is 1 if two cities are located in different and non-contiguous provinces, and 0 otherwise. In column (2), the coefficient on *ProBorder* is positive and statistically significant, suggesting that trade between two cities located in different but contiguous provinces is, on average, 175% $(e^{1.012} - 1) \times 100\%$ higher than trade between two cities located in the same province. However, the specification in column (2) also compares trade between two cities located in different contiguous provinces to those located in non-contiguous provinces. Therefore, once *Non-contiguous provinces* is incorporated in column (3), the coefficient on *ProBorder* becomes negative and statistically significant.

The negative coefficients on *ProBorder* and *Non-contiguous provinces* in column (3) suggest a pronounced provincial border effect, or intra-provincial market segmentation. Moreover, the specification in column (3) captures all possible geographical relationships between two cities. As mentioned earlier, there are three possible cases: (i) two cities located within the same province; (ii) two cities located in different but contiguous provinces; and (iii) two cities located in different and non-contiguous provinces. If two cities are located within the same province, both *ProBorder* and *Non-contiguous provinces* equal 0, and the coefficient on *CtyBorder* is positive but statistically insignificant. Therefore, domestic market segmentation appears to be more concentrated at the provincial level rather than at the city level.

What are the effects of provincial borders on inter-regional trade when two cities are contiguous? In column (4), we include the interaction term *CtyBorder * ProBorder*. The estimated coefficient on this interaction is positive and statistically significant, suggesting that when two cities are located in different but contiguous provinces and share a common city border, the provincial border effect is mitigated. Specifically, relative to two cities located in the same province, trade between two cities located in different but contiguous provinces is, on average, 94% $(e^{-2.798} - 1) \times 100\%$ lower, but 92% $(e^{-2.798+0.264} - 1) \times 100\%$ lower when the two cities share both a city border and a provincial border.

In columns (5) and (6), we further control for the logarithm of distance between two cities, as well as origin and destination fixed effects. The estimated coefficient on distance is negative and statistically significant, consistent with gravity models of trade. One important point to note is that the estimated coefficient on the city border dummy becomes negative and statistically significant. However, this does not imply that cities trade less with their neighbors. For example, in our data, the average logarithm of distance for two contiguous and non-contiguous cities within the same province is 4.9 and 5.7, respectively. Therefore, the predicted log trade between two contiguous cities is $-0.305 - 0.6 \times 4.9 = -3.25$, while it is $-0.6 \times 5.7 = -3.42$ for two non-contiguous cities. In other words, on average, contiguous cities trade approximately $17\% = (-3.25 + 3.42) \times 100\%$ more than non-contiguous cities within the same province. For example, column (7) in Table 2 excludes distance control. City border is positive and significant, while provincial border has estimates consistent with previous model specifications.[5]

In the industrial sector, we document that domestic market segmentation primarily originates from provincial administrative barriers. How does market segmentation differ across sectors? In Table A.2, we compare the gravity estimates across the agriculture, industry, and services. In fact, city and provincial borders have distinct impacts on inter-city trade. In the agriculture and services sectors, sharing a common city border does not increase trade, whereas sharing a provincial border significantly reduces inter-city trade. Moreover, provincial border frictions are much larger in the agriculture and services sectors compared to the industrial sector.

2.4 Heterogeneous provincial border frictions

In the previous section, we explored the average impact of border frictions on inter-city trade and found that provincial borders significantly reduce bilateral trade flows among cities. However, provinces exhibit substantial heterogeneity in terms of the ratio of trade to GDP, implying that border frictions may differ across provinces. Therefore, in this section, we further explore the heterogeneous provincial border frictions by estimating the following equation,

$$\begin{aligned} log(X_{ni}) = \beta_0 &+ \sum_{P=1}^{31} \beta_P * ProBorder_{ni} \times Province_{n\in P} \\ &+ \sum_{P=1}^{31} \gamma_P * Non-contiguousPro_{ni} \times Province_{n\in P} + f_n + f_i + \varepsilon_{ni} \end{aligned} \quad (2)$$

In equation (2), $Province_{n\in P}$ is a dummy variable that indicates whether the destination region n belongs to province P. In our main sample, there are 31 provinces. Therefore, β_P captures the heterogeneous border effects across provinces, or equivalently, provincial-level market segmentation. As in the previous empirical specification, we control for the non-contiguous provinces border, so the point estimates are interpreted as inter-provincial trade

[5] Our estimated negative effect of provincial border is consistent with other literature that studies inter- and intra-provincial trade in China. For example, Xing and Li (2011) find that intra-provincial trade is about 54 times larger relative to inter-provincial trade. Using truck traffic flow data, Zheng, Lu, and Li (2022) report that intra-provincial truck traffic flows are about 3.5 times larger than inter-provincial truck traffic flows.

relative to intra-provincial trade.

Table 3: Heterogeneous cross-provincial border effects β_P

Province	β_P	**S.E.**	**Province**	β_P	**S.E.**
Anhui	-2.877	0.065	Jiangxi	-2.606	0.092
Beijing	1.027	0.265	Jilin	1.513	0.118
Chongqing	-0.186	0.643	Liaoning	-2.627	0.081
Fujian	-4.543	0.117	Ningxia	-1.556	0.214
Gansu	-2.540	0.074	Qinghai	-4.952	0.156
Guangdong	0.306	0.054	Shaanxi	-0.864	0.101
Guangxi	-2.245	0.075	Shandong	-2.148	0.063
Guizhou	-0.976	0.114	Shanghai	1.361	0.191
Hainan	-3.502	0.386	Shanxi	-4.082	0.095
Hebei	-2.713	0.093	Sichuan	-4.086	0.052
Heilongjiang	-1.319	0.092	Tianjin	1.858	0.265
Henan	-2.320	0.058	Tibet	-7.154	0.157
Hubei	-6.038	0.080	Xinjiang	-1.529	0.079
Hunan	-3.708	0.074	Yunnan	-3.615	0.068
Inner Mongolia	-2.347	0.085	Zhejiang	-1.004	0.096
Jiangsu	-2.353	0.083			

Notes: The table reports the estimation results for β_P from equation (2). The estimator is OLS. The dependent variable is city n's imports from city i for the industrial sector. Standard errors are reported in parentheses.

Table 3 reports the heterogeneous provincial border frictions, β_P, for the industrial sector.[6] The estimates reveal substantial heterogeneity in provincial border effects, or domestic market segmentation, across provinces. For example, Tibet exhibits the strongest market segmentation, with inter-provincial trade approximately 99.92% $(e^{-7.154} - 1) \times 100\%$ lower than intra-provincial trade. In contrast, Beijing, Shanghai, and Tianjin display positive provincial border effects. These three cities are all provincial-level municipalities located on China's east coast and are among the country's most important port regions. Therefore, it is unsurprising that neighboring cities tend to trade more if they are contiguous with these three regions.

To sum up, the gravity estimates reveal a pronounced provincial border effect in China's internal trade. Once we control for distance and origin–destination fixed effects, city contiguity plays at most a limited role, whereas crossing a provincial boundary substantially

[6] Appendix A.3 presents the corresponding estimates for the agriculture and services sectors.

depresses inter-city trade flows, even for contiguous city pairs. These border effects are strongly sector-specific, with much larger trade impediments in agriculture and services than in industry. Moreover, provincial border frictions vary widely across provinces, reflecting substantial heterogeneity in domestic market segmentation. These findings motivate the following sections, where we quantify their implications in a multi-region, multi-sector trade model with provincial border frictions.

3 Model

In this section, we develop a quantitative trade model based on Eaton and Kortum (2002). We index regions (or cities) in China as $n = 1, 2, ..., N$, and aggregate all foreign countries as the rest-of-world region (ROW). There are three sectors: agriculture, industry, and services, which are indexed by j. All markets are competitive. Firms in each region and sector produce output by hiring labor and using intermediate inputs from other sectors (Caliendo and Parro, 2015). Output can be traded across regions and ROW, and is subject to iceberg trade costs plus provincial trade frictions. Labor is immobile across regions but can move freely across sectors. Through this model, we quantify provincial market segementation and evaluate its implications for spatial income inequality operating through inter-regional trade.

3.1 Household

In each region n, a representative household chooses sectoral consumption to maximize a Cobb–Douglas utility function. The utility function is $U(C_n) = \prod_{j=1}^{J} (C_n^j)^{\omega_n^j}$, where C_n^j is consumption in sector j in region n, and ω_n^j is the expenditure share on sector j in region n, which satisfies $\sum_{j=1}^{J} \omega_n^j = 1$. The budget constraint is $\sum_{j=1}^{J} P_n^j C_n^j = W_n L_n + D_n$, where P_n^j is the price of the sector-j composite good in region n, D_n is the exogenous trade deficit, and $W_n L_n$ is labor income in region n. Given the utility function and the budget constraint, the aggregate price index is $P_n = \prod_{j=1}^{J} (P_n^j/\omega_n^j)^{\omega_n^j}$.

3.2 Production

Composite goods. Each sector j consists of a unit interval of tradable varieties indexed by $v \in [0, 1]$. In each region n, a competitive aggregator combines these varieties into a non-tradable sectoral composite good with constant elasticity of substitution:

$$Q_n^j \;=\; \left(\int_0^1 q_n^j(v)^{\frac{\sigma^j-1}{\sigma^j}}\, dv\right)^{\frac{\sigma^j}{\sigma^j-1}},$$

where $q_n^j(v)$ is the quantity of variety v used in sector j and region n, and σ^j is the elasticity of substitution across varieties. The composite good Q_n^j can be consumed by households or used as an intermediate input.

Production. In each region n and sector j, competitive firms produce variety v using labor and intermediate inputs according to a Cobb–Douglas production function,

$$q_n^j(v) \;=\; z_n^j(v)\; \left(L_n^j(v)\right)^{\alpha_n^j} \left[\prod_{k=1}^{J} M_n^{jk}(v)^{\gamma_n^{jk}}\right]^{1-\alpha_n^j}, \tag{3}$$

where $L_n^j(v)$ is labor used to produce variety v in sector j, α_n^j is the labor cost share, and $M_n^{jk}(v)$ is the quantity of the sector-k composite input used in producing sector-j output. Input-output linkages are captured by γ_n^{jk}, with $\sum_{k=1}^{J}\gamma_n^{jk} = 1$. Productivity $z_n^j(v)$ is independently drawn from a Fréchet distribution with $F_n^j(z) = \exp\Big(-T_n^j z^{-\theta^j}\Big)$, where T_n^j is the sectoral technology parameter and θ^j governs productivity dispersion.

Given the production function, the unit cost of an input bundle in region n and sector j:

$$c_n^j \;=\; B_n^j\,(W_n)^{\alpha_n^j} \left[\prod_{k=1}^{J} \left(P_n^k\right)^{\gamma_n^{jk}}\right]^{1-\alpha_n^j}, \tag{4}$$

where $B_n^j \equiv \prod_{k=1}^{J}(\alpha_n^j)^{-\alpha_n^j}((1-\alpha_n^j)\gamma_n^{jk})^{-(1-\alpha_n^j)\gamma_n^{jk}}$ is a constant. Under perfect competition, the price of variety v in sector j and region n equals marginal cost,

$$p_n^j(v) \;=\; \frac{c_n^j}{z_n^j(v)}.$$

Inter-regional trade. Trade between two regions is subject to trade barriers. Motivated by our empirical findings, we assume two components of bilateral trade costs. First, iceberg trade costs satisfy $\tau_{ni}^j > 1$ for $n \neq i$ and $\tau_{nn}^j = 1$. Second, provincial market segmentation applies when the destination region n and the origin region i belong to different provinces. Let P_d and P_o denote the destination and origin provinces, respectively. We model this market segmentation by an ad valorem provincial border wedge $PB^j_{ni,\,n\in P_d,\,i\in P_o} \geq 0$, with $PB^j_{ni,\,n\in P_d,\,i\in P_o} = 0$ when $P_d = P_o$.

Therefore, the delivered price of variety v produced in region i and sold to region n is

$$p^j_{ni}(v)_{\,n\in P_d,\,i\in P_o} \;=\; p^j_i(v)\,\tau^j_{ni}\left(1 + PB^j_{ni,\,n\in P_d,\,i\in P_o}\right). \tag{5}$$

In each region n, buyers source each variety from the lowest-cost supplier. Following Eaton and Kortum (2002), the share of sector-j expenditure in region n on goods from region i is

$$\pi^j_{ni} = \frac{T^j_i\left(c^j_i\tau^j_{ni}\left(1 + PB^j_{ni,\,n\in P_d,\,i\in P_o}\right)\right)^{-\theta^j}}{\sum_{l=1}^{N} T^j_l\left(c^j_l\tau^j_{nl}\left(1 + PB^j_{nl,\,n\in P_d,\,l\in P_o}\right)\right)^{-\theta^j}}, \tag{6}$$

and the price index for composite goods in sector j in region n is,

$$P^j_n = \Gamma^j\left(\sum_{l=1}^{N} T^j_l\left(c^j_l\tau^j_{nl}\left(1 + PB^j_{nl,\,n\in P_d,\,l\in P_o}\right)\right)^{-\theta^j}\right)^{-\frac{1}{\theta^j}}, \tag{7}$$

where $\Gamma^j \equiv \Gamma\left(\frac{1+\theta^j-\sigma}{\theta^j}\right)^{\frac{1}{(1-\sigma)}}$ is a constant.

Trade imbalance and market clearing conditions. We allow each region n to run an exogenous trade imbalance D_n, which is financed by a lump-sum transfer (or tax) that the provincial government rebates evenly to households within the province. We define D_n as the difference between total absorption and total sales:

$$D_n \;=\; \sum_{j=1}^{J}\sum_{i=1}^{N} X^j_n\pi^j_{ni} \;-\; \sum_{j=1}^{J}\sum_{i=1}^{N} X^j_i\pi^j_{in}, \tag{8}$$

where the first term is region n's imports (expenditure by n on goods sourced from i) and the second term is region n's exports (expenditure by i on goods sourced from n). Total expenditure in sector j and region n satisfies

$$X^j_n \;=\; \omega^j_n I_n \;+\; \sum_{k=1}^{J}\gamma^{kj}_n\sum_{i=1}^{N} X^k_i\pi^k_{in}, \tag{9}$$

where $I_n = W_n L_n + D_n$ is regional income and ω_n^j is the household expenditure share on sector j. Market clearing condition for the sector j composite good implies

$$Q_n^j = C_n^j + \sum_{k=1}^{J} M_n^{kj}. \tag{10}$$

Equilibrium. A competitive equilibrium is a set of wages $\{W_n\}$, prices $\{P_n^j\}$, expenditure allocations $\{\pi_{ni}^j\}$, and quantities $\{C_n^j, Q_n^j, M_n^{kj}\}$ such that: (i) given prices, households maximize utility subject to the budget constraint; (ii) given prices, firms minimize costs and varieties are sourced from the lowest-cost supplier; and (iii) goods and labor markets clear in each region and sector. Appendix B.1 summarizes the equilibrium conditions.

4 Quantitative analysis

This section quantifies the model using data for 340 Chinese cities plus an aggregated rest-of-world region in 2017. First, we calibrate key parameters and recover productivity and trade costs with provincial border frictions. Then, we remove provincial border frictions and quantify the implications for spatial income inequality. Finally, we compare sector-specific and uniform liberalization and assess the role of regional heterogeneity.

4.1 Calibration

This section describes the data and calibration procedure used in the quantitative analysis. The calibration disciplines the model's production structure, expenditure shares, and trade linkages in 2017, providing a quantitative foundation for the counterfactual exercises. In addition to the trade and geographic variables described in Section 2, we use two additional data sources: (i) a China city-level inter-city input-output (ICIO) table and (ii) population data. The ICIO table reports inter-city trade flows, as well as production, value added, and input-output linkages, for 340 Chinese cities in 2017, plus an aggregated rest-of-world region.

We proceed in two steps. First, we calibrate a set of basic parameters governing production, preferences, and key elasticities. Second, we discipline a set of exogenous variables such as population, fundamental productivity, and bilateral trade costs. Bilateral trade costs combine standard iceberg costs with provincial border frictions. Our counterfactual analysis primarily quantifies changes in provincial border frictions PB and assesses their implications for spatial income inequality.

4.1.1 Basic parameters

Production, consumption, and input-output linkages We obtain information on production, consumption, and input-output linkages from the China inter-city input-output (ICIO) table. We take regional production directly from the ICIO table. To construct sectoral consumption, we first compute regional absorption as regional production minus regional net exports. We then subtract intermediate input use from absorption, with the residual interpreted as sectoral expenditure on final goods in each region.

Sectoral value-added ratios are computed as

$$\alpha_n^j \;=\; \frac{VA_n^j}{GO_n^j}, \tag{11}$$

where GO_n^j denotes gross output and VA_n^j denotes value added in sector j and city n.

Intermediate input shares are constructed as

$$\gamma_n^{j,k} \;=\; \frac{M_n^{jk}}{\sum_{k'=1}^{J} M_n^{jk'}}, \tag{12}$$

where M_n^{jk} denotes the value of intermediate inputs from sector k used in sector j production in region n.

Sectoral expenditure shares are given by

$$\omega_n^j \;=\; \frac{GO_n^j + D_n^j - M_n^j}{I_n}, \tag{13}$$

where D_n^j denotes the sector j's trade deficit in region n, and $M_n^j \equiv \sum_{k=1}^{J} M_n^{j,k}$ is total spending on intermediate inputs in sector j and region n. The denominator $I_n = W_nL_n + D_n$ is region n's income, W_nL_n is labor income and $D_n \equiv \sum_{j=1}^{J} D_n^j$ is the aggregate trade deficit of region n across sectors.

Trade and substitution elasticities We take the trade and substitution elasticities from the existing literature. In particular, following Simonovska and Waugh (2014), we set the trade elasticity to $\theta^j = 4$ for all $j \in \{a, i, s\}$. Following Broda and Weinstein (2006), we set the within-sector elasticity of substitution to $\sigma^j = 2$ for all $j \in \{a, i, s\}$.

4.1.2 Exogenous variables

Population We obtain China regional (or city) population data from *China City Statistical Yearbook* (2017). We aggregate all foreign countries as ROW and population data are from Penn World Table (PWT) version 10.0 (Feenstra, Inklaar, and Timmer, 2015).

Trade costs Next, we recover inter-regional trade costs which include iceberg trade costs plus provincial border frictions. We rewrite equation (6) as follows,

$$\log\left(\frac{X_{ni}^j}{X_{nn}^j}\right) = F_i^j - F_n^j - \theta^j \log\left(\tau_{ni}^j \left(1 + PB_{ni}^j\right)\right), \tag{14}$$

Data on region n's total sectoral expenditure X_{ni}^j come from ICIO table, and $F_n^j \equiv \log\left(T_n^j (c_n^j)^{-\theta^j}\right)$. We parameterize the bilateral trade costs as,

$$\kappa_{ni}^j \equiv \tau_{ni}^j \left(1 + PB_{ni}^j\right),$$

and assume trade costs have the following functional form,

$$\log \kappa_{ni}^j = \gamma_1 \log(\text{dist}_{ni}) + \gamma_2 \,\text{CrossPB}_{ni} + \text{ex}_i + \varepsilon_{ni}, \tag{15}$$

where CrossPB_{ni} is an indicator equal to one if region n and i are located in different provinces, and zero otherwise. The term ex_i captures origin-specific effects.

Combining equations (14) and (15), the structural gravity equation becomes

$$\log\left(\frac{X_{ni}^j}{X_{nn}^j}\right) = F_i^j - \theta^j \text{ex}_i - F_n^j - \theta^j \left(\gamma_1 \log(\text{dist}_{ni}) + \gamma_2 \text{CrossPB}_{ni} + \varepsilon_{ni}\right), \tag{16}$$

We estimate equation (16) by OLS. The terms $F_i^j - \theta^j \text{ex}_i$ and $-F_n^j$ correspond to exporter and importer fixed effects, respectively.

Fundamental productivity To calibrate fundamental productivity terms, we first back out the sectoral price index P_n^j based on the structural gravity equation (6). The price index can be rewritten as follows,

$$P_n^j = \left(\frac{T_n^j (c_n^j)^{-\theta^j}}{\pi_{nn}^j}\right)^{-1/\theta^j} = \left(\frac{\exp(F_n^j)}{\pi_{nn}^j}\right)^{-1/\theta^j}. \tag{17}$$

Next, we plug the price index into unit price c_n^j, and together with fixed effects F_n^j to recover fundamental productivity T_n^j,

$$T_n^j = \frac{\exp(F_n^j)}{(c_n^j)^{-\theta^j}}. \tag{18}$$

Table 4: Parameters and Exogenous Variables

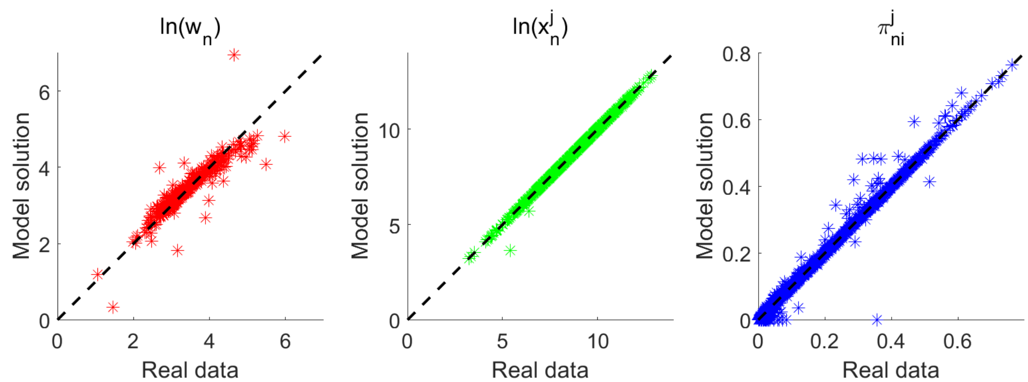
Parameters			
Final expenditure share	ω^a	$0.06\ (0.02, 0.05, 0.12)$	Calibrated
	ω^i	$0.23\ (0.13, 0.23, 0.33)$	Calibrated
	ω^s	$0.71\ (0.60, 0.70, 0.83)$	Calibrated
Value added ratio	α_n^a	$0.60\ (0.55, 0.60, 0.67)$	Calibrated
	α_n^i	$0.28\ (0.18, 0.25, 0.40)$	Calibrated
	α_n^s	$0.46\ (0.38, 0.46, 0.55)$	Calibrated
Fundamental productivity (relative)	$(T_n^a)^{1/\theta}$	$3.45\ (1.67, 2.91, 4.81)$	Calibrated
	$(T_n^i)^{1/\theta}$	$1.53\ (0.90, 1.47, 2.17)$	Calibrated
	$(T_n^s)^{1/\theta}$	$1.06\ (0.55, 0.91, 1.71)$	Calibrated
Trade costs	κ_{ni}^a	$2.78\ (1.35, 1.89, 4.25)$	Calibrated
	κ_{ni}^i	$2.54\ (1.35, 2.10, 4.26)$	Calibrated
	κ_{ni}^s	$2.48\ (1.26, 1.93, 4.35)$	Calibrated
Population (relative)	L_n	$1.06\ (0.55, 0.91, 1.71)$	Calibrated
Trade elasticity	$\theta^j,\ \forall j$	4	Simonovska and Waugh (2014)
Elasticity of substitution	$\sigma^j,\ \forall j$	2	Broda and Weinstein (2006)

Notes: This table reports key calibrated parameters and exogenous variables used in the quantitative analysis. Throughout, sectors are indexed by $j \in \{a, i, s\}$, corresponding to agriculture, industry, and services. For each row, we report the mean, with the 10th, 50th (median), and 90th percentiles in parentheses. Unless otherwise noted, moments are computed as unweighted cross-city statistics. For fundamental productivity, we instead use city labor force as weights. For trade costs, we use bilateral trade flows as weights and exclude diagonal observations ($n = i$). Fundamental productivity and population are reported relative to the first region (Beijing), which is normalized to one.

Table 4 summarizes the calibration results. We report the mean and the 10th and 90th percentiles. On average, the services sector accounts for approximately 71% of total final expenditure. In terms of the value-added ratio, the agricultural sector has the highest value-added ratio of 60%, followed by the services sector at 46%, and the industrial sector at 28%.

Model fit The calibrated productivity terms and trade-cost wedges, together with the time-invariant parameters, are then fed back into the model. Figure 4 shows that the model-generated outcomes closely match the observed wages (in logs), sectoral expenditures (in logs), and expenditure shares, providing a reliable quantitative foundation for the counterfactual analyses in Section 4.

Figure 4: Model Fit



Notes: The figure compares model-implied outcomes with the data, including log wages, log sectoral expenditures, and expenditure shares. The dashed line denotes the 45-degree line.

4.2 Counterfactual analysis

In this section, we use a calibrated model to quantify the impact of provincial market segmentation on spatial income inequality. We first decompose the real wage in each region into contributions from input-output linkages, effective labor productivity, and consumption structure. Second, we remove provincial border frictions, solve for the counterfactual equilibrium, and compare the dispersion of real wages to the baseline using both the variance and inter-percentile income ratios. Finally, we examine how these inequality effects depend on regional and sectoral heterogeneity by repeating the comparison exercise under alternative assumptions on production and expenditure structures and by contrasting sector-specific with uniform reductions in provincial trade barriers.

4.2.1 Real wage decomposition

Given the price of sectoral composite goods $\{P_n^j\}_{j=1}^J$, the real wage in region n is

$$\frac{w_n}{P_n} = \prod_{j=1}^{J} \left(\frac{1}{B_n^j \Gamma^j}\right)^{\frac{\omega_n^j}{\alpha_n^j}} \left(\omega_n^j\right)^{\omega_n^j} \left(\frac{T_n^j}{\pi_{nn}^j}\right)^{\frac{\omega_n^j}{\theta^j \alpha_n^j}} \left(\frac{P_n^j}{\prod_{k=1}^J (P_n^k)^{\gamma_n^{jk}}}\right)^{\frac{\omega_n^j(1-\alpha_n^j)}{\alpha_n^j}}. \tag{19}$$

Taking logs yields

$$\begin{aligned}\ln\left(\frac{w_n}{P_n}\right) = &\underbrace{\sum_{j=1}^{J} \omega_n^j \left(\frac{1-\alpha_n^j}{\alpha_n^j}\right) \left(\ln P_n^j - \sum_{k=1}^{J} \gamma_n^{jk} \ln P_n^k\right)}_{\text{Input-output linkage (IO)}} \\ &+ \underbrace{\sum_{j=1}^{J} \omega_n^j \left(\frac{1}{\alpha_n^j}\right) \ln\left(\frac{(T_n^j/\pi_{nn}^j)^{1/\theta^j}}{\Gamma^j B_n^j}\right)}_{\text{Agg. labor productivity (LP)}} + \underbrace{\sum_{j=1}^{J} \omega_n^j \ln \omega_n^j}_{\text{Consumption structure (CS)}}\end{aligned} \tag{20}$$

Equation (20) expresses a region's real wage as a function of *input-output linkages*, IO_n; the *effective labor productivity* term, LP_n; and the *consumption structure* term, CS_n, which captures a region's consumption structure. In our counterfactual exercises, we remove provincial border frictions, which is equivalent to a domestic trade liberalization. Lower trade costs reduce the share of total expenditure on home-produced goods π_{nn}^j, strengthen specialization, and thereby increase sectoral effective productivity $(T_n^j/\pi_{nn}^j)^{1/\theta^j}$. Moreover, lower trade costs transmit their effects through input-output linkages by reducing sectoral prices P_n^j.

Regional heterogeneity is important too. For example, regional input-output linkages and labor productivity are scaled by sectoral value-added ratio α_n^j and sectoral expenditure share on final goods ω_n^j.

Let $y_n \equiv \ln(w_n/P_n)$. Taking the variance of both sides of equation (20), we have

$$\begin{aligned}\mathrm{Var}(y) &= \mathrm{Var}(IO) + \mathrm{Var}(LP) + \mathrm{Var}(CS) \\ &\quad + 2\,\mathrm{Cov}(IO, LP) + 2\,\mathrm{Cov}(IO, CS) + 2\,\mathrm{Cov}(LP, CS).\end{aligned} \tag{21}$$

From equation (21), the variance of regional real wages is our primary measure of spatial income inequality. Spatial income inequality is determined by the dispersion of each of the three components, as well as by the co-movement among them. Trade liberalization may reduce the dispersion of regional productivity, $\mathrm{Var}(LP)$. However, the overall impact of labor productivity also depends on its interaction with input-output linkages and consumption structure, as well as on the dispersion of these two components.

4.2.2 Removing provincial border frictions

Table 5 reports the results of the variance decomposition. We evaluate the decomposition in the baseline equilibrium and counterfactual equilibrium with provincial border frictions removed.

Table 5: Variance-covariance decomposition

	Baseline	Counterfactual	Difference
VAR(log real wage)	0.477	0.440	-0.037
VAR(IO)	0.011	0.005	-0.006
VAR(LP)	0.524	0.445	-0.079
VAR(CS)	0.017	0.017	0.000
COV(IO, LP)	-0.029	-0.008	0.021
COV(IO, CS)	0.000	-0.001	-0.001
COV(LP, CS)	-0.008	-0.004	0.004
90 / 10 ratio	1.706	1.412	-0.294
80 / 20 ratio	1.400	1.261	-0.139

Notes: Table above reports the variance-covariance decomposition in baseline and counterfactual. Counterfactual here is removing the provincial border.

In the baseline model, the variance of real wages is 0.477. The variances of input-output linkages, regional labor productivity, and consumption structure are 0.011, 0.524, and 0.017, respectively. As expected, regional productivity accounts for the largest share of the variation in the spatial income distribution. Input-output linkages and consumption structure make only minor direct contributions; however, their interactions with other variables play a more important role. The covariance between regional productivity and input-output linkages is -0.029, and that between regional productivity and consumption structure is -0.008. In other words, regions with higher productivity tend to have lower input-output linkages and lower average expenditure shares.

In the counterfactual, provincial border frictions are removed. Income inequality, or income dispersion, measured by the cross-city variance of log real wages, decreases by 0.037 variance units. This corresponds to an $8\% \approx (0.037/0.477) \times 100\%$ reduction in dispersion relative to the baseline variance. Among the components, the variance of input-output linkages declines by 0.006 units, and the variance of regional labor productivity declines by 0.079 units. By construction, consumption structure depends only on exogenous sectoral expenditure shares, so the variance of consumption structure is identical in the baseline and counterfactual scenarios. Overall, consumption structure plays a negligible role in explaining changes in the spatial income distribution.

Input-output linkages alone have a negligible negative effect on income inequality. However, their co-movement with regional labor productivity tends to increase income inequality. In the counterfactual, the covariance between input-output linkages and regional labor productivity rises by 0.021 units. This increase reflects the fact that the distributions of both regional productivity and input-output linkages become more compressed, with a larger reduction in dispersion for regional productivity than for input-output linkages, combined with their negative correlation. Consequently, the covariance between regional productivity and input-output linkages becomes less important in accounting for changes in income inequality.

In addition to the variance of log income, we also report the 90th to 10th and 80th to 20th income ratios. The income gap between cities at the 90th and 10th percentiles declines by 0.294, from 1.706 in the baseline to 1.412 in the counterfactual, or approximately 17%. Similarly, the gap between cities at the 80th and 20th percentiles declines by about 0.139, or 10%. These results suggest that trade liberalization reduces overall regional income dispersion and narrows the gap between top and bottom regions.

In sum, removing provincial border frictions reduces spatial income inequality. In the counterfactual equilibrium, the variance of log real wages falls by 0.037 variance units, and the 90–10 and 80–20 gaps shrink by about 17% and 10%, respectively. The variance-covariance decomposition shows that this decline is driven primarily by a compression in regional labor productivity dispersion, while input-output linkages contribute little directly and consumption structure is unchanged by construction. Overall, trade liberalization mainly narrows the gap between high- and low-income cities by reducing cross-city productivity differences.

4.2.3 Regional heterogeneity

Given that the model and data incorporate a rich set of regional heterogeneity, we conduct a series of counterfactual exercises in which regional heterogeneity in production and expenditure structures is removed. Specifically, we impose that all regions share the same production and expenditure structures as aggregate China.[7] We then assess the quantitative impact of removing provincial border frictions.

Table 6: Variance-covariance decomposition: regional heterogeneity

	Panel A: Homo. VA Ratio			**Panel B: Homo. IO**		
	Baseline	Counterfactual	Diff.	Baseline	Counterfactual	Diff.
VAR(log real wage)	0.567	0.604	0.036	0.408	0.380	-0.029
VAR(IO)	0.015	0.008	-0.007	0.011	0.011	0.000
VAR(LP)	0.589	0.640	0.051	0.458	0.374	-0.084
VAR(CS)	0.017	0.017	0.000	0.017	0.017	0.000
COV(IO, LP)	-0.020	-0.023	-0.003	-0.032	-0.009	0.024
COV(IO, CS)	0.009	0.007	-0.002	-0.001	-0.004	-0.003
COV(LP, CS)	-0.015	-0.015	0.000	-0.006	0.001	0.008
90 / 10 ratio	1.741	1.458	-0.283	1.666	1.364	-0.302
80 / 20 ratio	1.427	1.294	-0.133	1.362	1.253	-0.108

	Panel C: Homo. Expend. Share		
	Baseline	Counterfactual	Diff.
VAR(log real wage)	0.482	0.444	-0.038
VAR(IO)	0.010	0.021	0.011
VAR(LP)	0.529	0.494	-0.035
VAR(CS)	0.000	0.000	0.000
COV(IO, LP)	-0.029	-0.036	-0.007
COV(IO, CS)	0.000	0.000	0.000
COV(LP, CS)	0.000	0.000	0.000
90 / 10 ratio	1.681	1.405	-0.276
80 / 20 ratio	1.396	1.253	-0.144

Notes: Table above reports variance - covariance decomposition by removing regional heterogeneity in production and expenditure. In panel A, we remove the heterogeneous value-added ratio across cities. Panel B removes heterogeneous IO linkage across cities. Panel C removes heterogeneous expenditure share across cities.

Table 6 reports the results. In Panel A, we remove regional heterogeneity in value-added ratios and sector-specific provincial border effects. When regions are identical in their value-added ratios, eliminating provincial border frictions increases spatial income dispersion.

[7]Data on China value-added ratios, input-output linkages, and sectoral expenditure shares are obtained from the OECD input-output table.

However, the inter-percentile income gaps, as captured by the 90th to 10th and 80th to 20th income ratios, decline. This pattern suggests that the increase in income inequality is not driven by widening gaps between high income and low income cities. Instead, overall regional incomes become more dispersed around the average. Furthermore, the variance of sectoral specialization is the main driver of the increase in income inequality, rising by 0.051 variance units. In Panel B, we remove regional heterogeneity in input-output coefficients. Eliminating provincial border frictions reduces income inequality by 0.029 units. Based on our definition of input-output linkages in equation (20), input-output coefficients enter only through the input-output linkage term. Nevertheless, forcing all regions to have identical input-output coefficients has a trivial effect on the variance of input-output linkages relative to Table 5. Moreover, after removing provincial border frictions, input-output linkages change very little. In contrast, the dispersion of regional productivity declines by 0.084 units, which is the main driver of the reduction in spatial income inequality.

In Panel C, we remove regional heterogeneity in expenditure shares while keeping production structures, value-added ratios, and input-output coefficients unchanged. Eliminating provincial border frictions reduces income inequality by 0.038 units and lowers the variance of input-output linkages and regional productivity by 0.494 units and 0.021 units, respectively. Most importantly, compared with the baseline results reported in Table 5, trade liberalization has a very similar impact on income inequality and its components. This finding indicates that regional heterogeneity in expenditure shares plays a limited role in shaping the inequality effects of internal trade liberalization, and suggests that such heterogeneity is less important for policymakers when income inequality is the primary concern. In contrast, the results indicate that heterogeneity in value-added ratios is critically important. As discussed earlier, conditional on homogeneous value-added ratios across regions, trade liberalization increases the dispersion of the overall income distribution, thereby raising spatial income inequality.

In sum, the inequality effects of removing provincial border frictions depend critically on regional heterogeneity in value-added ratios. When value-added ratios are homogenized, liberalization increases the variance of real wages, mainly through greater dispersion in sectoral specialization, even as interpercentile gaps narrow. By contrast, homogenizing input-output coefficients or expenditure shares leaves the main channel intact, so liberalization continues to reduce inequality primarily by compressing the distribution of regional productivity.

4.2.4 Sectoral heterogeneous border frictions

In the previous section, we show that regional heterogeneity plays a key role in shaping the spatial distribution of income under trade liberalization. In particular, spatial income inequality becomes more dispersed when regions are similar in their value-added ratios.

Table 7: Variance-covariance decomposition: uniform trade liberalization across sectors

	Panel A: Hete. CP			**Panel B: Homo. VA Ratio**		
	Baseline	Counterfactual	Diff.	Baseline	Counterfactual	Diff.
VAR(log real wage)	0.477	0.482	0.005	0.567	0.547	-0.021
VAR(IO)	0.011	0.033	0.022	0.015	0.025	0.010
VAR(LP)	0.524	0.583	0.059	0.589	0.605	0.017
VAR(CS)	0.017	0.017	0.000	0.017	0.017	0.000
COV(IO, LP)	-0.029	-0.062	-0.032	-0.020	-0.039	-0.018
COV(IO, CS)	0.000	0.006	0.006	0.009	0.012	0.003
COV(LP, CS)	-0.008	-0.020	-0.012	-0.015	-0.023	-0.008
90 / 10 ratio	1.706	1.451	-0.255	1.741	1.500	-0.240
80 / 20 ratio	1.400	1.282	-0.118	1.427	1.292	-0.135
	Panel C: Homo. IO			**Panel D: Homo. Expend. Share**		
	Baseline	Counterfactual	Diff.	Baseline	Counterfactual	Diff.
VAR(log real wage)	0.408	0.395	-0.014	0.482	0.490	0.008
VAR(IO)	0.011	0.024	0.012	0.010	0.023	0.013
VAR(LP)	0.458	0.505	0.047	0.529	0.546	0.017
VAR(CS)	0.017	0.017	0.000	0.000	0.000	0.000
COV(IO, LP)	-0.032	-0.064	-0.032	-0.029	-0.040	-0.011
COV(IO, CS)	-0.001	0.005	0.006	0.000	0.000	0.000
COV(LP, CS)	-0.006	-0.017	-0.011	0.000	0.000	0.000
90 / 10 ratio	1.666	1.430	-0.236	1.681	1.462	-0.219
80 / 20 ratio	1.362	1.250	-0.112	1.396	1.276	-0.120

Notes: Table above reports variance - covariance decomposition by removing homogeneous sectoral border frictions. In panel A, regional heterogeneity in value-added ratio, input-output linkage, and expenditure shares remain unchanged. In panel B, we remove the heterogeneous value-added ratio across cities. Panel C removes heterogeneous IO linkage across cities. Panel D removes heterogeneous expenditure share across cities.

In this section, we further examine sectoral heterogeneity in provincial market segmentation. Based on our calibration, the agricultural sector faces the strongest local trade barriers, followed by the services sector and the industrial sector. Consequently, removing sector-specific provincial trade frictions may either amplify or dampen the effects of trade liberalization in the presence of regional heterogeneity.

This raises a simple question: instead of eliminating sector-specific provincial trade frictions, what happens if central or local governments reduce provincial market segmentation uniformly across all sectors? Specifically, would uniform reductions in trade barriers reduce spatial income inequality more efficiently?

Table 7 reports the results. In Panel A, we impose uniform trade liberalization across sectors while keeping regional heterogeneity unchanged as in the data. Compared with Table 5, removing uniform border frictions across sectors increases the dispersion of the spatial income distribution rather than reducing it. Moreover, trade liberalization continues to narrow inter-percentile income gaps, although the magnitude of the reduction is smaller compared with Table 5. These results suggest that, if governments aim to foster inter-regional trade, fully removing sector-specific border frictions is more effective than uniform trade liberalization in reducing spatial income inequality.

Panels B through D remove regional heterogeneity in value-added ratios, input-output linkages, and expenditure shares, respectively. The resulting counterfactual outcomes differ substantially from those obtained when removing sector-specific border frictions. For example, when regions are identical in their value-added ratios, uniform sectoral trade liberalization reduces spatial income dispersion, whereas it increases income inequality when regions are homogeneous in expenditure shares.

In sum, uniform reductions in provincial trade barriers are not an effective substitute for removing sector-specific market segmentation. With regional heterogeneity left intact, uniform liberalization raises the variance of real wages even though it still narrows interpercentile gaps, whereas eliminating sector-specific frictions reduces inequality. The sign and magnitude of the uniform liberalization effect also depend on which regional heterogeneity is removed, highlighting that the sectoral pattern of domestic market segmentation interacts with regional production structure in shaping spatial inequality.

5 Conclusion

Spatial income inequality across regions in China remains large. In this paper, we examine spatial income inequality through the lens of inter-regional trade linkages, using inter-regional and sectoral trade flow data. We document the presence of domestic market segmentation at the provincial administrative level, such that two regions (or cities) trade about 92% less when they are located in different provinces.

To quantify the impact of domestic market segmentation on spatial income inequality, we construct a multi-region, multi-sector quantitative trade model with provincial trade frictions. In counterfactual analyses, we find that cross-city variance of log real wages declines by about 8%, and the 90/10 income ratio decreases by about 17%, when sector-specific provincial trade frictions are eliminated. Furthermore, regional heterogeneity plays a crucial role in determining the distributional consequences of trade liberalization. When sectoral value-added ratios are assumed to be homogeneous across regions, domestic trade liberalization would, if anything, increase spatial income inequality. These findings suggest that policymakers should exercise caution when liberalizing domestic trade and explicitly account for both regional and sectoral heterogeneity in policy design.

In our framework, regional production and consumption structures are treated as exogenous, although in practice they may depend on local government policies. A natural question, therefore, is why provincial market segmentation arises. One possible explanation relates to China's political system, in which the central government places substantial weight on local GDP growth and employment outcomes when evaluating and promoting local officials. Such an incentive structure may encourage provincial governments to protect local industries. However, this mechanism alone cannot fully explain the relatively weak effects observed at the city border level. We leave a more detailed investigation of the political economy mechanisms underlying these patterns to future research.

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Appendix

A Tables

A.1 Sector Classification

We aggregate the original China MRIO sector classification into three broad sectors: agriculture, industry, and services. Table A.1 reports the detailed mapping from the MRIO sectors to our three-sector classification.

Agriculture corresponds to sector 01 (Agriculture, Forestry, Animal Husbandry and Fishery). Industry combines all goods-producing activities in sectors 02–27, including mining, manufacturing, and utilities (electric power and heat, gas, and water supply). Services include sector 28 (Construction) and sectors 29–42, covering wholesale and retail trade, transportation and storage, accommodation and catering, information and communication services, finance, real estate, business services, public services, and other service activities.

Table A.1: Sector Classification in China MRIO Table

3 sectors	Num	Sectors (China MRIO Table)
Agriculture	'01'	Agriculture, Forestry, Animal Husbandry and Fishery
Industry	'02'	Mining and washing of coal
Industry	'03'	Extraction of petroleum and natural gas
Industry	'04'	Mining and processing of metal ores
Industry	'05'	Mining and processing of nonmetal and other ores
Industry	'06'	Food and tobacco processing
Industry	'07'	Textile industry
Industry	'08'	Manufacture of leather, fur, feather and related products
Industry	'09'	Processing of timber and furniture
Industry	'10'	Manufacture of paper, printing and articles for culture, education and sport activity
Industry	'11'	Processing of petroleum, coking, processing of nuclear fuel
Industry	'12'	Manufacture of chemical products
Industry	'13'	Manuf. of non -metallic mineral products
Industry	'14'	Smelting and processing of metals
Industry	'15'	Manufacture of metal products
Industry	'16'	Manufacture of general purpose machinery
Industry	'17'	Manufacture of special purpose machinery
Industry	'18'	Manufacture of transport equipment
Industry	'19'	Manufacture of electrical machinery and equipment
Industry	'20'	Manufacture of communication equipment, computers and other electronic equipment
Industry	'21'	Manufacture of measuring instruments
Industry	'22'	Other manufacturing
Industry	'23'	Comprehensive use of waste resources
Industry	'24'	Repair of metal products, machinery and equipment
Industry	'25'	Production and distribution of electric power and heat power
Industry	'26'	Production and distribution of gas
Industry	'27'	Production and distribution of tap water
Services	'28'	Construction
Services	'29'	Wholesale and retail trade
Services	'30'	Transport, storage, and postal services
Services	'31'	Accommodation and catering
Services	'32'	Information transfer, software and information technology services
Services	'33'	Finance
Services	'34'	Real estate
Services	'35'	Leasing and commercial services
Services	'36'	Scientific research and polytechnic services
Services	'37'	Administration of water, environment, and public facilities
Services	'38'	Resident, repair and other services
Services	'39'	Education
Services	'40'	Health care and social work
Services	'41'	Culture, sports, and entertainment
Services	'42'	Public administration, social insurance, and social organizations

A.2 Border frictions across sectors

Table A.2 reports the estimated city and provincial border effects across agriculture, industry, and services.

Table A.2: City and provincial border effects across sectors

	Agriculture	Industry	Services
CtyBorder	-0.0652	0.193***	-0.0184
	(0.073)	(0.033)	(0.032)
ProBorder	-5.277***	-2.515***	-5.405***
	(0.043)	(0.019)	(0.018)
Non-contiguous provinces	-6.344***	-3.765***	-5.494***
	(0.040)	(0.018)	(0.017)
CtyBorder * ProBorder	0.353***	-0.0304	0.0546
	(0.120)	(0.052)	(0.050)
N	94379	113966	115167
Origin FE	Y	Y	Y
Destination FE	Y	Y	Y

Notes: The table reports the estimation results of equation (1) using OLS. The dependent variable is city n's imports from city i for agriculture, industry, and services sectors. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

A.3 Heterogeneous provincial border effects across sectors

Table A.3 reports estimates of heterogeneous provincial border effects in the agricultural sector.

Table A.3: Heterogeneous provincial border effects β_P, Agriculture

Province	β_P	**S.E.**	Province	β_P	**S.E.**
Anhui	-3.376	0.151	Jiangxi	-3.094	0.213
Beijing	0.922	0.607	Jilin	-1.476	0.270
Chongqing	-5.554	1.467	Liaoning	-5.402	0.185
Fujian	-6.646	0.269	Ningxia	-7.276	0.489
Gansu	-5.777	0.171	Qinghai	-1.235	0.326
Guangdong	-3.424	0.127	Shaanxi	-4.755	0.232
Guangxi	-3.635	0.172	Shandong	-10.151	0.192
Guizhou	-2.094	0.260	Shanghai	2.830	0.438
Hainan	1.094	1.064	Shanxi	-7.675	0.225
Hebei	-3.184	0.216	Sichuan	-9.165	0.122
Heilongjiang	-6.617	0.211	Tianjin	2.056	0.607
Henan	-8.260	0.141	Tibet	-2.324	0.394
Hubei	-5.746	0.182	Xinjiang	-3.700	0.205
Hunan	-3.959	0.170	Yunnan	-5.164	0.158
Inner Mongolia	-3.795	0.196	Zhejiang	-4.845	0.218
Jiangsu	-4.918	0.201			

Notes: The table reports the estimation results for β_P from equation (2). The estimator is OLS. The dependent variable is inter-city trade from i to n for the agricultural sector.

Table A.4 reports estimates of heterogeneous provincial border effects in the services sector.

Table A.4: Heterogeneous provincial border effects β_P, Services

Province	β_P	**S.E.**	Province	β_P	**S.E.**
Anhui	-3.925	0.057	Jiangxi	-2.950	0.082
Beijing	-0.036	0.235	Jilin	-3.107	0.105
Chongqing	-2.238	0.570	Liaoning	-3.061	0.072
Fujian	-16.140	0.104	Ningxia	-11.621	0.189
Gansu	-5.799	0.066	Qinghai	-10.816	0.114
Guangdong	-5.559	0.047	Shaanxi	-2.105	0.089
Guangxi	-2.335	0.067	Shandong	-8.883	0.056
Guizhou	-2.461	0.101	Shanghai	-0.073	0.169
Hainan	-2.444	0.342	Shanxi	-8.047	0.085
Hebei	-4.588	0.082	Sichuan	-6.931	0.046
Heilongjiang	-0.880	0.082	Tianjin	0.094	0.235
Henan	-4.025	0.052	Tibet	-7.118	0.130
Hubei	-5.418	0.070	Xinjiang	-5.972	0.069
Hunan	-5.187	0.066	Yunnan	-7.599	0.060
Inner Mongolia	-4.684	0.075	Zhejiang	-3.384	0.085
Jiangsu	-3.254	0.073			

Notes: The table reports the estimation results for β_P from equation (2). The estimator is OLS. The dependent variable is inter-city trade from i to n for the services sector.

B Equilibrium Conditions

Table B.1 summarizes the full set of equilibrium conditions that characterize the competitive equilibrium of the multi-region, multi-sector trade model.

Table B.1: Equilibrium Conditions

ID	**Level equation**	**Scope**
H1	$C_n \equiv \prod_{j=1}^{J} C_n^{j\,\omega_n^j}; P_n = \prod_{j=1}^{J}\left[\frac{P_n^j}{\omega_n^j}\right]^{\omega_n^j}$	$\forall(n)$
F1	$W_n L_n = \sum_{j=1}^{J} \beta_n^j \gamma_n^j \sum_{i=1}^{N} \pi_{in}^j X_i^j$	$\forall(n)$
T1	$c_n^j \ = \ B_n^j \left(W_n\right)^{\alpha_n^j} \left[\prod_{k=1}^{J} \left(P_n^k\right)^{\gamma_n^{jk}}\right]^{1-\alpha_n^j}$ where $B_n^j \equiv \prod_{k=1}^{J} (\alpha_n^j)^{-\alpha_n^j} ((1-\alpha_n^j)\gamma_n^{jk})^{-(1-\alpha_n^j)\gamma_n^{jk}}$	$\forall(n,j)$
T2	$P_n^j = \Gamma^j \left(\sum_{l=1}^{N} T_l^j \left(c_l^j \tau_{nl}^j \left(1 + PB_{nl,n\in P_d,l\in P_o}^j\right)\right)^{-\theta^j}\right)^{-\frac{1}{\theta^j}}$ where $\Gamma^j \equiv \Gamma\left(\frac{1+\theta^j-\sigma}{\theta^j}\right)^{\frac{1}{(1-\sigma)}}$	$\forall(n,j)$
T3	$\pi_{ni}^j \equiv \frac{X_{ni}^j}{\sum_{i=1}^{N} X_{ni}^j} = \frac{T_i^j \left(c_i^j \tau_{ni}^j \left(1+PB_{ni,n\in P_d,i\in P_o}^j\right)\right)^{-\theta^j}}{\sum_{l=1}^{N} T_l^j \left(c_l^j \tau_{nl}^j \left(1+PB_{nl,n\in P_d,l\in P_o}^j\right)\right)^{-\theta^j}} = T_i^j \left(\frac{\Gamma^j c_i^j \tau_{ni}^j \left(1+PB_{ni,n\in P_d,i\in P_o}^j\right)}{P_n^j}\right)^{-\theta^j}$	$\forall(n,i,j)$
T3'	$\pi_{ni}^j \equiv \frac{X_{ni}^j}{\sum_{i=1}^{N} X_{ni}^j} = \frac{T_i^j \left(c_i^j \kappa_{ni}^j\right)^{-\theta^j}}{\sum_{l=1}^{N} T_l^j \left(c_l^j \kappa_{nl}^j\right)^{-\theta^j}} = T_i^j \left(\frac{\Gamma^j c_i^j \kappa_{ni}^j}{P_n^j}\right)^{-\theta^j}$ where $\kappa_{ni}^j \equiv \tau_{ni}^j \left(1 + PB_{ni,n\in P_d,i\in P_o}^j\right)$	$\forall(n,i,j)$
T4	$\sum_{j=1}^{J} P_n^j C_n^j \ = \sum_{j=1}^{J} \omega_n^j P_n C_n = P_n C_n = \ W_n L_n + D_n$	$\forall(n)$
T5	$\sum_{j=1}^{J} \sum_{i=1}^{N} X_{in}^j - \sum_{j=1}^{J} \sum_{i=1}^{N} X_{ni}^j = NX_n = -D_n$	$\forall(n,j)$
T6	$X_n^j = \omega_n^j P_n C_n + \sum_{k=1}^{J} \gamma_n^{jk} \left(\sum_{i=1}^{N} X_{in}^k\right)$	$\forall(n,j)$
T7	$D_n = -\phi_n W_n L_n + \frac{L_n}{\sum_{n=1}^{N} L_n} \sum_{n=1}^{N} \phi_n W_n L_n$	$\forall(n)$