

# Gains from trade boom, regional redistribution and inequality \*

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## Abstract

Are geographically asymmetric gains from trade liberalization reflected in localized public goods provision or are they redistributed across regions to mitigate spatial inequality? Leveraging spatial variation in exposure to China's expanded access to U.S. market, we find that Chinese prefectures with greater exposure to the policy experienced significantly faster growth in their tax bases and revenues. Importantly, these same high-exposure prefectures also exhibited accelerated expansion in public goods provision relative to less-exposed counterparts. We find statistically significant redistribution from winning to losing regions in terms of transfer but the magnitudes are too small to mitigate trade-induced inequality. Consequently, inter-prefecture disparities in government revenues, expenditures, and public goods widened markedly between 2000 and 2013. These results highlight how spatially uneven trade gains can amplify fiscal and developmental divides, underscoring the need for targeted regional redistribution mechanisms to counteract trade-induced inequality and promote balanced regional development.

Keywords: Intergovernmental transfers, Regional inequality, Public goods provision, Trade liberalization

JEL Codes: F14, F16, H41, H51, H52, R12

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# 1 Introduction

Empirical evidence robustly demonstrates that the gains from trade liberalization are usually asymmetrically distributed across regions, generating stark winners and losers within the same country.<sup>1</sup> This has important implications for the fiscal capacities of regions, especially in fiscally decentralized countries. As booming regions experience expansion in their tax bases and revenues, lagging ones struggle to generate sufficient revenues for essential public goods and services, thereby exacerbating regional inequality. Recent evidence links such trade-induced regional inequality to heightened political polarization and the rise of right-wing populism in the U.S. and Europe (Autor et al., 2020; Che et al., 2022; Backes and Mueller, 2024). Yet, despite these profound implications, the nexus between trade exposure, local public finance, and public goods provision has received scant attention in the literature.<sup>2</sup>

In an economy with effective regional distribution, asymmetric gains from trade liberalization across regions are not reflected in localized public goods provisions, as the gains are redistributed to lagging regions and equalize outcomes nationwide. In the absence sufficient regional redistribution, uneven gains from trade boom cause uneven regional distribution of public goods. In this paper we test this hypothesis by examining the effects of trade liberalization on local revenues and public goods provision in China. From 2000 to 2020, China’s global export share skyrocketed from 4% to 15%.<sup>3</sup> However, these gains have been profoundly uneven, with coastal provinces specializing in tradable sectors reaping substantial economic windfalls, while interior regions reliant on non-tradable industries have been left behind. Consequently, local governments (LGs) in export-oriented hubs have experienced dramatic expansions in their tax bases and revenues. How has this spatially uneven trade boom reshaped the regional allocation of public goods and inequality? Do the existing intergovernmental transfers meaningfully mitigate the trade-induced inequality?

The answers to these questions are theoretical ambiguous. Regional gains from trade shocks not only increase the region’s revenue bases directly through economic expansion but also attracts workers from losing regions. While this migration fuels further tax-base expansion in the winning region, it may as well induce dilution in the per capita consumption of rival local public goods and services. In such environment, transfers play key role in determining how the gains from trade boom are distributed

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<sup>1</sup>See, for instance, Autor et al. (2013, 2019); Coşar and Fajgelbaum (2016); Dix-Carneiro and Kovak (2017); Pavcnik (2017).

<sup>2</sup>A notable exception is Feler and Senses (2017), which reveals that U.S. regions more exposed to Chinese import competition suffered declines in public goods quality due to eroding local government revenues, driven by economic downturns including reduced employment, sluggish wage growth, and population outflows (Che et al., 2018; Autor et al., 2019; Adda and Fawaz, 2020; Greenland et al., 2019).

<sup>3</sup>See <https://unctad.org/news/china-rise-trade-titan>.

across regions.

China presents a compelling case for this inquiry, as it embodies a paradoxical fiscal structure: while politically one of the most centralized nations globally, it is among the most fiscally decentralized in terms of expenditure, with subnational governments responsible for approximately 85% of total public spending (Wingender, 2018; Shen et al., 2012). LGs also collect roughly 60% of government revenues. Nonetheless, as in many unitary states, the central government retains exclusive authority over tax rates and bases, leaving LGs unable to adjust these parameters independently. As elaborated below, LG revenue growth primarily stems from tax base expansions fueled by trade-induced local economic growth.

We leverage China’s fiscal decentralization and the substantial spatial heterogeneity in gains from trade liberalization to examine the effects on local public finance and public goods provision. We combine prefecture-level panel data on local government (LG) revenues, inter-governmental transfers, and expenditures across various public goods categories with detailed information on the industrial composition of Chinese prefectures. Our identification strategy exploits the U.S. granting of Permanent Normal Trade Relations (PNTR) status to China in 2001, following China’s WTO accession, as an exogenous shock to trade opportunities and LG tax bases. Prior to 2001, the U.S. Congress annually renewed Normal Trade Relations (NTR) status for China, ensuring Chinese exporters faced most-favored-nation (MFN) tariff rates applicable to WTO members. Failure to renew would have subjected Chinese goods to substantially higher Smoot-Hawley tariff rates (Pierce and Schott, 2016). The conferral of PNTR eliminated this recurrent tariff uncertainty, significantly boosting Chinese exports to the U.S. market after 2001. Because Smoot-Hawley tariff rates varied markedly across industries, pre-2001 tariff uncertainty differed substantially by sector—and thus across prefectures, given their differing industrial concentrations. We exploit this plausibly exogenous variation to identify the causal impact of expanded LG tax bases on public goods provision.

Our identification approach closely resembles the shift-share research design (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020) and has been used in recent studies (Erten and Leight, 2021; Facchini et al., 2019). Here, the “shifts” consist of industry-level reductions in tariff uncertainty, while the “shares” are prefecture-level employment shares in those industries. As demonstrated by Borusyak et al. (2021), identification in shift-share frameworks holds when the shifts are as-good-as-random and numerous (and small) independent shifts exist, irrespective of share exogeneity. These conditions are plausibly met in our context: (i) the magnitude of shifts (tariff uncertainty reductions) stems from the Smoot-Hawley Tariff Act of 1930, which is exogenous to contemporary U.S. and Chinese economic conditions; and (ii) we draw on variation across 487 industries, each comprising only a small

fraction of manufacturing employment in any given prefecture. We subject our strategy and inferences to a comprehensive set of robustness checks and diagnostic tests recommended in the shift-share literature. We also present robustness exercises using Chinese export boom to all destinations following its WTO accession.

Our empirical analysis reveals that trade liberalization generated substantial increases in LG revenues in prefectures more exposed to the shock relative to less exposed ones. However, LG expenditures<sup>4</sup> did not rise proportionately to the revenue gains due to redistributive intergovernmental transfers. We find that regions that benefited relatively less from the trade boom received significantly more transfers from upper level governments. Nevertheless, the magnitude of these transfers is too small relative to the disparities in the revenue gains from trade boom and hence fail to mitigate regional inequality in the provision of public goods and services.

These uneven gains from trade, coupled with lack of sufficient interregional transfers designed to mitigate the inequality, translated into differential improvements in key public goods and services across winning and losing regions. Winning prefectures experienced significantly larger increases in educational infrastructure (schools and teachers), healthcare infrastructure (doctors and hospital beds), paved roads and per capita government spending on education and science.

LG revenue growth primarily stems from tax base expansions fueled by trade-induced local economic growth. The bases for the major tax categories such as VAT, corporate income tax, personal income tax and social security contribution significantly expanded in prefectures more exposed to trade liberalization compared to less exposed prefectures. Moreover, investment in fixed assets such as residential real estate soared in prefectures more exposed to trade liberalization, thus expanding the tax bases for property related taxes which are entirely received by LGs.

Taken together, these findings demonstrate that trade liberalization, by producing spatially asymmetric economic booms, markedly exacerbates fiscal and developmental disparities across China's prefectures. Existing intergovernmental transfers mechanisms are significant but they are not designed to counteract the trade induced inequality. As a result, between-prefecture inequality in government revenues, expenditures, and public goods provision rose sharply since 2000. This divergence is evident in both tail-end measures (e.g., the 90th-to-10th percentile ratio) and central dispersion (e.g., the interquartile range), both increasing significantly relative to the baseline. Such patterns highlight the lack of sufficient inter-regional redistribution from winning to losing regions. In the presence of effective redistribution, the localized benefits of trade exposure on public goods provision would have been attenuated, as gains in more exposed areas would have been shared more equitably nationwide

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<sup>4</sup>LG expenditures are financed from all sources including LG revenues transfers from higher governments and debts.

rather than reinforcing spatially concentrated fiscal advantages.

These results carry important policy implications. While governments in advanced economies often deploy targeted programs—such as the U.S. Trade Adjustment Assistance (TAA) or the EU’s European Globalization Adjustment Fund—to support individuals displaced by trade,<sup>5</sup> analogous mechanisms for redistributing trade gains across regions remain largely absent. A recent body of empirical research links trade-induced regional inequality to heightened political polarization and the rise of right-wing populism in the U.S. and Europe (Autor et al., 2020; Che et al., 2022; Backes and Mueller, 2024). Policies that channel gains from trade toward lagging regions are therefore well justified. The same logic applies to China: regions benefiting more directly from trade (via profits, wages, and employment) also enjoy amplified gains through enhanced public goods, further disadvantaging other areas. Designing regional redistribution to counteract trade-driven inequality is thus essential.

This paper contributes to an emerging literature on trade liberalization’s effects on LG fiscal capacity and public goods provision. For instance, Feler and Senses (2017) document that U.S. locales more exposed to Chinese import competition experienced declines in local public goods quality and amenities, driven by eroded revenue bases from falling housing prices and business activity. Similarly, Dix-Carneiro et al. (2018) find that Brazilian regions facing greater import competition saw rising crime, mediated by adverse labor market outcomes, reduced public goods, and increased inequality—particularly lower per capita revenues and expenditures, including on public safety. In contrast, we show that Chinese prefectures benefiting from reduced U.S. tariff uncertainty experienced tax base and revenue growth, leading to expanded public goods. Collectively, evidence from the U.S., Brazil, and China suggests that trade policies often lack accompanying effective regional redistribution, thereby amplifying inter-regional inequality.

Trade liberalization is also associated with broader socio-economic challenges tied to inequality and constrained LG fiscal responses. Studies show, for example, that U.S. counties more exposed to Chinese imports experienced elevated crime rates (especially property crimes), though mitigated somewhat by higher government transfers (Che et al., 2018). Other work links import competition to declining male earnings, reduced marriage and fertility, higher child poverty (Autor et al., 2019), slower population growth (especially among younger and less-educated groups) (Greenland et al., 2019), and worse mental/physical health and mortality outcomes (Pierce and Schott, 2020; Adda and Fawaz, 2020).

The remainder of the paper is organized as follows. Section 2 provides background on fiscal decentralization in China. Section 3 outlines a theoretical model and testable

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<sup>5</sup>TAA offers temporary income support, unemployment benefits, retraining subsidies, or relocation aid to trade-affected workers.

implications. Section 4 describes the datasets and outlines the empirical methodology. Section 5 presents the main results, followed by mechanism analysis in Section 6. Section 7 explores implications for regional inequality in public goods, and Section 8 concludes.

## 2 Fiscal decentralization in China

Though China is formally constituted as a unitary state, its fiscal system exhibits a high degree of de facto decentralization, with the central government delegating substantial responsibilities for both revenue collection and public expenditures to sub-national (local) governments (LGs). Local governments collect approximately 50% of total government revenues while accounting for over 85% of total government expenditures (Wingender, 2018). This pronounced expenditure decentralization—among the highest worldwide—underscores the critical role of LGs in fiscal policy implementation and public service delivery.

### 2.1 Roles of LGs in revenue collection

In China’s multi-tiered fiscal structure, different levels of government are assigned responsibility for collecting specific tax categories, with revenues allocated to the central government, LGs, or shared between them according to formally established rules. The central government primarily collects consumption taxes, international trade-related taxes (such as tariffs), vehicle purchase taxes, and similar levies, which together comprise roughly 10% of total tax revenues and accrue exclusively to the center. During much of the sample period under study, revenues from major taxes were shared: domestic value-added tax (VAT) at a 75-25 ratio (central-LG), corporate income tax at 60-40, personal income tax at 60-40, and stamp taxes on securities at 97-3. These shared taxes collectively account for more than 55% of total tax revenue. The remaining taxes—most notably social security contributions and property- and land-related taxes—are largely collected and retained by LGs, representing over one-third of total tax revenue (see detailed discussions in Wingender (2018), Shen et al. (2012), and Qiao et al. (2022)).

Consistent with the unitary nature of the Chinese state, LGs receive nearly half of total tax revenues but lack autonomous taxing authority: the central government exclusively determines tax rates and bases (Qiao et al., 2022). This institutional feature strengthens the exogeneity of revenue fluctuations at the local level, as changes in LG revenues and expenditures predominantly stem from exogenous expansions in the tax base driven by economic activity rather than discretionary policy choices by LGs. The present analysis exploits precisely such an exogenous shock to the tax

base—an export-oriented trade boom triggered by the U.S. granting of Permanent Normal Trade Relations (PNTR) to China. This policy shift was plausibly exogenous to the pre-existing economic, institutional, or geographic characteristics of Chinese prefectures, thereby providing a robust source of identification for causal effects of interest.

## 2.2 Roles of LGs in public goods provision

China’s expenditure assignment is among the most decentralized globally, with LGs responsible for approximately 85% of total government spending as of 2019 (Qiao et al., 2022). LGs bear the overwhelming share—over 90%—of expenditures in key social sectors, including health, education, environmental protection, general public services, and social security and employment. The Chinese fiscal system operates under a hierarchical budget management framework, in which each tier’s budget encompasses its own outlays as well as those of subordinate tiers. While the central government exerts influence through intergovernmental transfers and overarching policies, provincial governments directly oversee fiscal management at lower levels. Counties shoulder the largest fiscal burden, accounting for roughly 12% of GDP in expenditures and revenues, followed by prefectures (approximately 7% of GDP) and provinces (around 4% of GDP). On the revenue side, prefectural governments collect about 5% of GDP, counties 4%, and provinces 2% (Lam et al., 2016).

County and prefectural governments are primarily responsible for delivering core public goods and services, such as education, health care, sanitation, and local infrastructure. In education, counties finance compulsory education (primary and junior secondary), while prefectures oversee senior secondary (high school) education; tertiary education remains under central government purview through the Ministry of Education (Yuan and Zhang, 2015). The 1995 Education Law further mandates LG commitment to education funding via the so-called “two-growth” rule: (i) LG education spending must grow faster than LG revenues overall, and (ii) per-student education expenditures must increase annually. Given that most LG education outlays are financed from own-source revenues, jurisdictions with larger tax bases enjoy greater fiscal capacity for education investment (Yuan and Zhang, 2015). Nonetheless, lower-tier governments receive substantial supplementary funding from central and provincial sources for teacher salaries, school infrastructure, and related purposes (Hu, 2022).

In the health sector, county and prefectural governments assume primary responsibility for public healthcare delivery (Tan and Wong, 2022). County-level hospitals anchor a three-tier primary healthcare system, with township hospitals serving as intermediaries and village clinics as the foundational layer (Zhu et al.,

2021). County hospitals occupy the middle tier in the broader hospital hierarchy, bridging primary care facilities with higher-level (tier-three) institutions offering specialized services (Shi et al., 2021). Prefectural and county governments finance investments in personnel, equipment, and facilities, while central and provincial authorities provide policy guidance and fiscal transfers.

Finally, road infrastructure follows a similar pattern: the Highway Law assigns construction and maintenance responsibilities to LGs at the appropriate jurisdictional level. Central, provincial, and prefectural governments handle financing and oversight, while county governments execute implementation (Wood and Maurice, 2007; Fan, 2011). This assignment reinforces the pivotal role of subnational governments in translating fiscal resources into tangible public goods provision.

## 2.3 Intergovernmental transfers in China

Following the 1994 tax reform which increased the central government’s revenue share, fiscal transfer increased steadily to bridge the spending gap created by the reform (Fan and Wan, 2017; Wingender, 2018). The fiscal transfer from central to local governments increased from approximately 182 billion Yuan in 1994 to 4.8 trillion Yuan in 2013, representing an average annual growth rate of about 20% (Fan and Wan, 2017). These transfers finance nearly two-thirds of LG spending and follow hierarchical/tiered system where the central government only transfers funds to provincial governments and provincial governments transfer to prefectures (and counties) under their jurisdiction (Shah and Shen, 2006).

Intergovernmental transfers are divided into two major categories: general and specific transfers. General transfer includes revenue sharing transfers, tax rebates and *equalization* transfers motivated to mitigate widening inequality. Specific transfer includes grants for increasing wages, minorities and rural tax reform as well as earmarked transfers for specific infrastructure projects (see Shah and Shen (2006)). Revenue sharing and tax rebates represent the largest categories of overall transfers followed by earmarked transfers, which account for the lions share of specific transfers. Earmarked transfers require local matching funds.

# 3 Trade shock and local public finance

## 3.1 Model environment

Consider an economy consisting of  $i = 1, \dots, N$  geographic prefectures and two periods. Prefectures differ in their industrial composition, giving them differential exposure to tariff uncertainty reduction (trade shock  $\Delta T_i$ ).

## Households and spatial equilibrium

Prefecture  $i$  is populated by a measure  $L_i$  of households. A household residing in prefecture  $i$  receives wage  $w_i$ , consumes private goods  $c_i$ , and derives utility from local public goods  $G_i$  (e.g., education, health, infrastructure) subject to congestion.

Preferences are given by:

$$U_i = \ln c_i + \gamma \ln \left( \frac{G_i}{L_i^\phi} \right) + \epsilon_i$$

where  $\gamma > 0$  parameterizes preference for public goods,  $\phi \in [0, 1]$  captures the degree of public good congestion ( $\phi = 0$  corresponds to pure public goods;  $\phi = 1$  to per-capita public goods), and  $\epsilon_i$  represents idiosyncratic location preference.

**Migration:** Moving across prefectures involves a lump sum friction cost of  $\kappa$ . Indirect utility in region  $i$  is:

$$V_i = \ln((1 - \tau_w)w_i) + \gamma \ln G_i - \gamma\phi \ln L_i$$

where  $\tau_w$  wage income tax rate.

Under spatial mobility, local population  $L_i$  responds endogenously to relative real income and public goods availability with migration elasticity  $\eta$ :

$$L_i = \bar{L} \left( \frac{V_i}{\bar{V}} \right)^\eta \implies \frac{d \ln L_i}{d \ln G_i} = \eta_G > 0, \quad \frac{d \ln L_i}{d \ln w_i} = \eta_w > 0$$

where  $\bar{V}$  and  $\bar{L}$  denote average values of indirect utility and population across locations

## Local production and trade shocks

Firm production in prefecture  $i$  uses local labor  $L_i$  and capital  $K_i$  (which we assume is immobile across prefectures):

$$Y_i = A_i(\Delta T_i) L_i^\alpha K_i^{1-\alpha}$$

where local productivity  $A_i(\Delta T_i)$  is an increasing function of trade expansion  $\Delta T_i$ . An equivalent way is to assume that export trade exposure increases prices of baskets of local goods.

Total local nominal output (and local tax base  $B_i$ ) expands with trade exposure:

$$B_i = P_i Y_i = P_i \cdot A_i(\Delta T_i) L_i^\alpha K_i^{1-\alpha}$$

where  $P_i$  is exogenous prices of baskets of goods produced in region  $i$ . We assume

that  $P_i$  are internationally determined so that regions are price takers.

### 3.2 Public finance and central transfers

#### Fiscal revenue and shared taxes

Subnational governments collect revenue from local tax bases at statutory rate  $\tau$ . Under China's fiscal sharing rules, a fraction  $\alpha_{LG} \in (0, 1)$  is retained locally:

$$R_i^{local} = \alpha_{LG} \cdot \tau \cdot B_i(A_i(\Delta T_i), L_i)$$

In addition, trade-induced activity stimulates off-budget/land-finance revenues  $D_i$ , proportional to local output:  $D_i = \delta B_i$ . Total local fiscal capacity before transfers is:

$$F_i = (\alpha_{LG} \cdot \tau + \delta) B_i(A_i(\Delta T_i), L_i)$$

#### Intergovernmental transfer rule

The central government collects the remaining shared taxes  $(1 - \alpha_{LG}) \cdot \tau \cdot \sum_{i=1}^N B_i$  and redistributes transfers  $TR_i$  to prefectures. The central allocation rule balances fiscal capacity equalization against administrative/policy priority costs:

$$TR_i = \bar{T}R - \lambda (F_i - \bar{F})$$

where  $\bar{T}R$  is the baseline transfer and  $\lambda \in [0, 1]$  measures the rate of fiscal equalization. The case of  $\lambda = 1$  represents full equalization (i.e., transfers fully neutralize local tax revenue booms) whereas  $\lambda = 0$  corresponds to the case of no equalization (transfers are completely unresponsive to local fiscal expansion).

### 3.3 LG optimization

Prefectural leadership optimizes total expenditure  $E_i = F_i + TR_i$  between direct public goods provision  $G_i$  (education, health, roads) and local administrative/non-public-good spending  $N_i$ , facing unit costs  $p_g$  and  $p_a$ :

$$\max_{G_i, N_i} W_i = U(G_i, L_i) + \omega v(N_i)$$

$$\text{s.t. } p_g G_i + p_a N_i \leq E_i = (1 - \lambda) F_i(A_i(\Delta T_i), L_i) + \bar{T}R + \lambda \bar{F}$$

Solving the optimization yields optimal public goods investment:

$$G_i^* = \frac{\theta}{p_g} \left[ (1 - \lambda)(\alpha_{LG}\tau + \delta) B_i(A_i(\Delta T_i), L_i) + \bar{T}R + \lambda \bar{F} \right]$$

where  $\theta \in (0, 1)$  is the budget share allocated to public goods and services.

### 3.4 Comparative statics and testable hypotheses

Taking differentiation of optimal per capita public goods  $g_i^*$  with respect to trade exposure  $\Delta T_i$  and accounting for the endogenous response of population migration  $L_i$ :

$$\frac{d \ln g_i^*}{d \Delta T_i} = \underbrace{(1 - \lambda) \Omega_i \frac{\partial \ln A_i}{\partial \Delta T_i}}_{\text{Direct tax base expansion effect}} + \underbrace{[(1 - \lambda) \Omega_i \alpha - \phi] \frac{d \ln L_i}{d \Delta T_i}}_{\text{Migration \& congestion spillover}}$$

where  $\Omega = \frac{F_i}{E_i}$  is the share of self-generated revenue in total budget.<sup>6</sup> The first term captures the direct effect of trade boom via tax base expansion. Since  $\lambda < 1$  (incomplete equalization),  $\Omega_i > 0$  (share of self-generated revenue is positive), and  $\frac{\partial \ln A_i}{\partial \Delta T_i} > 0$  (export boom raises local productivity), trade exposure directly increases local per-capita public goods through expanded local tax revenues. The second term captures net migration and congestion spillover. First, incoming workers grow local tax base at rate  $\alpha$  (labor share of output), boosting revenues by  $(1 - \lambda) \Omega_i \alpha$ . Second, each new resident dilutes the per-capita availability of existing public goods at a rate of  $\phi$ . The net effect of migration on per capita public goods depends on the magnitude of these two opposing effects.

### Testable hypotheses

The theoretical model above provides three testable empirical hypotheses:

**Hypothesis 1 (Tax base expansion):**  $\frac{\partial \ln R_i^{local}}{\partial \Delta T_i} > 0$ . Trade exposure increases local government revenues through tax base growth and land-finance expansion. We test this by directly regressing LG revenues (and several measures of local tax bases) on exogenous measure of local trade exposure.

**Hypothesis 2 (Incomplete transfer offset):** Winning regions are net payers of intergovernmental fiscal transfers ( $\frac{\partial TR_i}{\partial \Delta T_i} = -\lambda \frac{\partial F_i}{\partial \Delta T_i} < 0$ ). However, because the equalization parameter  $\lambda$  is strictly less than 1, they retain some of their revenue gains so that their revenue increases. We test this hypothesis in two ways. First, we regress measures of transfer receipt of LGs on exogenous measure of local trade exposure. Second, we regress LG expenditure on trade exposure. Because LG expenditure includes financing from LG revenue as well as transfers receipts, significant transfers from higher governments implies weak effect of trade shock on LG spending, compared to its effect on LG revenue.

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<sup>6</sup>See Appendix B for the full derivation.

**Hypothesis 3 (Spatial divergence in public goods):** If equalization is weak ( $\lambda \ll 1$ ), trade exposure leads to a net per-capita expansion of public goods ( $G_i/L_i$ ) in high-exposure prefectures, widening inter-regional inequality, if the dilution effect is not too strong:  $\phi \leq (1 - \lambda)\alpha\Omega_i$ . We test this hypothesis by regressing various measures of local public goods (such as education, health and roads) on local trade exposure.

## 4 Data and Methodology

### 4.1 Data

Our main dataset is Prefectural-level annual panel data for the period 1996-2019 on government revenues and expenditures and various measures of public goods provision in health, education, transport, etc. This data originates from the official government statistics annually published on Provincial Yearbook (PYBs). We obtain the digitized version of the data from China Data Center.<sup>7</sup> Our intergovernmental transfer data covers the period 2000-2019 and it originates from China Fiscal Year Book and City and County Fiscal Statistics of various years. Transfers data are disaggregated into general and specific transfers. However our transfer data has some limitations that are worth mentioning. First, the data starts from 2000. Second, for a small fraction of prefectures the transfer receipts are not consistently reported and in some cases lacks disaggregation into general and specific components. In view of these limitations of our transfer data, we use the difference between LG expenditure and LG revenue as a proxy for transfer to complement our analysis on direct transfers. The difference between LG expenditure and LG revenue is LG debt and transfers and funds from higher governments.

We combine these data with a measure of exposure to trade liberalization (China’s WTO accession) at Prefectural city level. Each prefecture’s exposure to trade liberalization is defined by the prefecture’s industrial composition of employment and variation across industries in the extent of reduction in trade policy uncertainty due to China’s accession to WTO. Details of the trade exposure measure is discussed below.

### 4.2 Empirical methodology

We use prefecture cities as our unit of analysis for three reasons. First, manufacturing employment statistics can be constructed at a detailed industrial classification (489) at prefecture level. We use the Chinese industrial survey data which includes information

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<sup>7</sup>It can be accessed here: <https://chinadatacenter.net/>.

about prefecture location of the firms. Such detailed industrial variation is crucial for our analysis because most of the variation in our analysis comes from cross-sectional variation across industries as well as across prefectures. Second, provision of public goods and services such as healthcare, education and roads is delegated to prefecture and county governments. However, consistent panel data on public goods and services provision is better available at prefecture level. Third, the central and provincial governments significantly influence the revenues and expenditures of LGs under their jurisdiction via budget transfers. Prefectures serve as an intermediate level of government between the counties and provinces, which not only allows us to capture the redistributive transfers made at higher level governments to some extent but also give us sufficient variation in the data. Table 1 presents summary statistics of our main outcome measures across prefectures for our sample period.

### 4.3 Measuring local exposure to trade liberalization

Our empirical exercises leverage geographic variation in exposure to trade liberalization, in particular access to U.S market, across Prefectural cities following China’s accession to WTO in 2001. More specifically, prior to 2001, the U.S congress votes annually to renew China’s Normal Trade Relation (NTR) status in the U.S market. If China’s NTR status is approved in congress, Chinese goods will be subject to low NTR tariffs (MFN tariff rates reserved for WTO members). If congress votes against China’s NTR status, however, Chinese exports to the U.S. market would be subjected to very high non-NTR tariff rates (also known as column 2 tariff rates) usually imposed on nonmarket economies. The non-NTR tariff rates were determined under Smoot-Hawley Tariff Act of 1930 (Pierce and Schott, 2016). In October 2000, the U.S. congress voted to grant Permanent Normal Trade Relation (PNTR) status to China which would become effective upon China’s accession to WTO in 2001.

Though the U.S congress’s annual vote on the bill to revoke China’s NTR status were all concluded with failure, prior to 2001 Chinese firms faced significant uncertainty in their access to the U.S market because firms were not certain whether their products would be subjected to the low NTR tariff rate or the very high non-NTR tariff rate. Moreover, because the NTRgap, difference between the non-NTR and NTR tariff rates, varied massively across industries, firms (products) in different industries faced significantly different level of uncertainty in their access to the U.S market. We exploit this significant heterogeneity in the level of tariff uncertainty across industries together with geographic variation in the concentration of industries to construct prefecture level exposure to trade liberalization. Erten and Leight (2021) use similar methodology to study the effect of trade liberalization on structural transformation in China while Facchini et al. (2019) use it to study migration.

Our prefecture-level exposure to China’s accession to WTO (granting of PNTR) is given as:

$$\text{NTRgap}_c = \sum_j \alpha_{jc} \text{NTRgap}_j \quad (1)$$

where  $\text{NTRgap}_j$  the difference between the non-NTR and NTR tariff rates for industry  $j$ ;  $\alpha_{jc}$  is industry  $j$ ’s employment share in prefecture  $c$  in 1998.<sup>8</sup> Our industry classification includes 489 four-digit industries in Chinese Industrial Classification for 2002 (CIC 2002).

Figure 1 presents the distribution of NTRgap across prefectures. In an average prefecture, tariff uncertainty on Chinese exports to the U.S decreased by 25 percentage points. However, notice that there is significant heterogeneity across prefectures ranging from 10 percentage points in the 1st percentile prefecture to 40 percentage points in the 99th percentile prefecture.

The above identification strategy has been used in influential previous papers such as [Erten and Leight \(2021\)](#) and [Facchini et al. \(2019\)](#), who provide detailed arguments for its exogeneity. We provide further diagnosis of the identification strategy through the lens of recent developments in the literature of shift-share instruments.

#### 4.4 Baseline regression and hypothesis

To estimate the causal effect of trade liberalization on local public finances, we exploit prefecture-level variation in exposure to China’s Permanent Normal Trade Relations (PNTR) status with the United States, which was granted in 2000 and implemented in 2001. Our baseline econometric specification is:

$$Y_{ct} = \beta_0 + \beta_1(\text{PostPNTR}_t \times \text{NTRgap}_c) + \text{PostPNTR}_t \times \mathbf{X}_c' \delta + \gamma_c + \gamma_t + \varepsilon_{ct} \quad (2)$$

where  $Y_{ct}$  denotes the outcome variables in prefecture  $c$  and year  $t$ . The variable  $\text{PostPNTR}_t$  is an indicator equal to one from 2001 onward and zero otherwise. The vector  $\mathbf{X}_c$  contains time-invariant prefecture characteristics measured prior to trade liberalization—most notably the share of manufacturing employment, share of employment in state-owned enterprises (SOEs) and share of employment in foreign-affiliated firms (including wholly foreign-owned enterprises and joint ventures). These pre-reform characteristics are interacted with  $\text{PostPNTR}_t$  to absorb any differential trends that may arise from time-varying effects of initial industrial structure.<sup>9</sup>

<sup>8</sup>Alternatively, we use each industry’s 1998 export shares in a prefecture as weights to construct our exposure measure. Our results remain robust.

<sup>9</sup>We also include a host of other control variables used in previous studies such as [Facchini et al. \(2019\)](#).

Prefecture fixed effects  $\gamma_c$  and year fixed effects  $\gamma_t$  control for time-invariant prefecture heterogeneity and common national shocks, respectively. Standard errors are clustered at the prefecture level.<sup>10</sup>

**Accounting for migration:** Our theoretical model suggests migration plays key role in the effect of trade liberalization on local public finance and public goods. Migrants bring taxable income, thus expanding the local tax base and tax revenue. This is automatically captured in the local revenue measures. Moreover, migrants also congest local public goods. To account for this dilution, we normalize local measures using time-varying population counts. Accordingly, we use end-of-year population sizes to construct per-capita measures of our outcomes variables such as LG revenue, expenditure, transfer receipts and public goods/services.

## 4.5 Identification assumption

Identification and causal interpretation of  $\beta_1$  relies on assumptions about exogeneity of regressor  $\text{PostPNTR}_t \times \text{NTRgap}_c$ . This measure of local exposure to trade liberalization has been widely used in a number of recent studies (including [Facchini et al. \(2019\)](#), [Erten and Leight \(2021\)](#)) and we refer interested readers to these papers. The exogeneity assumption can be viewed in light of recent literature in shift-share research designs. Notice that trade exposure measure can be alternatively written as  $\sum_j \alpha_{jc} \text{NTRgap}_{jt}$  using equation 1, where  $\text{NTRgap}_{jt}$  becomes zero for all industries for the post PNTR period. This alternative writing of the regressor shows that our identification strategy is similar to the shift-share research design, where the *shift* is change in tariff uncertainty across industries  $\text{NTRgap}_{jt}$  and the *share* is the employment share of these industries in the economy of prefectures,  $\alpha_{jc}$ .

The literature suggests conditions under which  $\sum_j \alpha_{jc} \text{NTRgap}_{jt}$  can be considered as an exogenous shock to prefecture level outcomes  $Y_{ct}$ . [Borusyak et al. \(2021\)](#) suggest that exogeneity is achieved as long as the “shifts” are exogenous, regardless of whether or not the “shares” are exogenous. This condition is plausibly satisfied in our setting because across industry variation in the  $\text{NTRgap}_{jt}$  is driven by Smoot-Hawley Tariff Act of 1930. The other requirement for identification is that shifts-level law of large numbers should hold, i.e., there should be *many* independent shift-level shocks where each shock contributes small to the average exposure, which is likely guaranteed in our setup given that the shift term captures variation across 489 industries and such high industry disaggregation means that each industry’s contribution to the prefecture’s economy is relatively modest. We provide further evidence on diagnosis of these assumptions in the appendix.<sup>11</sup>

<sup>10</sup>The precision of our estimates is robust to clustering at province levels.

<sup>11</sup>[Goldsmith-Pinkham et al. \(2020\)](#) suggest an alternative condition under which the exogeneity

## 5 Results

In this section we present our main estimation results. To facilitate comparison of the estimates across different outcomes, we standardize NTRgap measure, so that coefficients are interpreted as the effect of one standard deviation higher decrease in tariff uncertainty relative to the average prefecture. Because the distribution of the NTRgap measure can be approximated as normal, we often compare a prefecture at the 25th percentile against a prefecture at 75th percentile (i.e., two standard deviation difference in measured decrease in tariff uncertainty) to benchmark the magnitude of our estimates.

### 5.1 The effect on LG revenues, expenditures and transfers

Before we delve into discussion of the results, it is important to note that our LG revenue measure includes only locally-raised revenues. This includes locally retained portion of shared tax revenues (such as VAT) and non-tax revenues (such as revenue from land sales). Later, we will delve into specific revenue categories such as VAT and corporate profit taxes and document similar patterns and magnitudes of effects. However, the LG expenditure measure includes total expenditure which includes financing from local revenue, transfer and fund income from upper level governments and LG borrowing. This is reflected in Table 1, where LG per capital expenditure is larger than per capita revenues, on average. The implication is that, in the presence of sufficient interregional redistribution of unequal gains from trade, our LG expenditure measure should not be correlated to exposure to trade shock.

Table 2 presents the effect of decrease in tariff uncertainty on prefecture-level government revenues, expenditures and transfers. In Panel A, we use log values for the revenue and expenditure measures, and transfers are measured as shares of LG expenditure. In Panel B, we use per capita *levels* as outcome variables.

Focusing on Panel A, the results in Column 1 show that greater reductions in tariff uncertainty lead to substantial increases in LG per capita revenue. Specifically, a one-standard-deviation larger reduction in tariff uncertainty increases LG per capita revenue by 10.4%. Comparing a prefecture at the 75th percentile of exposure with a prefecture at the 25th percentile of exposure (which are two standard deviations apart), the former experiences 20.8 percent higher per capita revenue growth. In contrast to this, Column 2 shows a tiny and statistically insignificant effect on LG expenditure. In conjunction with the result in column 1, this suggests significant

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can be achieved in the shift-share research design. In their approach exogeneity can be achieved as long as the “shares”  $\alpha_{jc}$  are exogenous, regardless of whether or not the “shifts” are exogenous. In our setup, this assumption is strong because industrial composition of local economies could be related to the outcome variables via other channels. Hence, our identification strategy relies on the exogeneity of the “shifts”.

redistribution of revenue gains from trade boom from winning to losing regions. The results in columns 3-7 corroborate this.

In column 3, we regress LG deficit (LG per capita expenditure *minus* LG per capita revenue) as a share of LG per capita expenditure on trade exposure. The difference between LG expenditure and LG per capita revenue is financed by a combination of transfers from higher governments and borrowing. Hence, our deficit measure captures these two sources of finances combined. The result shows that in more trade exposed prefectures, the share of transfers and borrowing in LG expenditure decreased. One s.d higher exposure to reduction in tariff uncertainty is associated with 4.5 percentage point decrease in the share of transfers and borrowing in LG expenditure.

In columns 4-6, we look at the effects on direct transfers from higher governments. We look at the effect on total transfer receipts (column 4) and its components: general transfer (column 5) and specific transfers (column 6). The results across the three columns show that the share of transfers in LG expenditure decreased in regions more exposed to the reduction in tariff uncertainty. In other words, regions that gained least from the trade boom received more transfers from higher governments. These transfers include both general transfers as well as specific transfers tied to specific purposes. The lions share of specific transfers constitutes earmarked transfers for infrastructure development, implying that regions less exposed to trade boom received relatively more support for infrastructure from higher governments.

In Panel B, we replicate similar analysis using *levels* of the per capita measures.<sup>12</sup> Column 1 shows that one s.d higher exposure to reduction in tariff uncertainty is associated with an additional 1,591 Yuan increase in per capita revenue. This implies economically meaningful differences across prefectures: a prefecture at the 75th percentile of exposure (larger reduction in uncertainty) experiences nearly 3,200 Yuan additional (approximately \$380 at the 2002 average exchange rate of roughly 8.28 CNY/USD) in per capita revenue growth compared to a prefecture at the 25th percentile. This relatively large effect is not surprising because the trade boom led to significant expansion in the tax bases of the LGs as we discussed in the previous subsection and below.

Column 2 reveals a significant effect on the levels of LG per capita expenditure. A one-standard-deviation larger reduction in tariff uncertainty corresponds to an additional 1,228 Yuan increase in per capita expenditure relative to the sample mean. Consequently, the 75th-percentile prefecture sees 2,456 Yuan (approximately \$297 in 2002 USD) more per capita expenditure growth than the 25th-percentile prefecture. This is in contrast to the statistically insignificant effect on logs of LG expenditure in

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<sup>12</sup>To minimize the effect of extreme values, all outcome measures are winterized at the 2nd and 98th percentiles.

Panel A. Part of the difference can be attributed to very high per capita expenditure in few affluent prefectures. However, it is important to note that this result does not invalidate our above evidence on interregional redistribution because even though the effect of trade shock on LG per capita expenditure level is positive and significant, it is smaller than the effect on LG per capita revenue. Columns 3-6 corroborate this.

Column 3 shows that per capita LG deficit (which is a proxy for transfers) is negatively correlated with exposure to trade shock where one s.d decrease in tariff uncertainty is associated with lower deficit per capita by 310 Yuan. Note that this point estimate is just the difference between the point estimates corresponding to revenue and expenditure in Table 2. This point estimate suggests that there is some degree of redistribution from gaining to losing regions. Switching to our direct measure of transfers, Column 4 shows that regions that are more exposed to reduced tariff uncertainty receive less total transfers. One s.d. higher exposure to reduced tariff uncertainty is associated with 384 Yuan lower per capita transfer receipt. Crucially, this point estimate is reasonably close to the one in Column 3, implying that deficit per capita is a reasonably good proxy for transfer receipts. Columns 5 and 6 present the estimated results for per capita levels of general and specific transfers separately. Both columns show a significant negative effect of exposure to trade shock on per capita transfer receipts.

Overall, the results in Table 2 clearly show that there is a statistically significant redistribution from winning to losing regions, though the magnitude of this redistribution is small relative to the effect of trade on LG revenues. This seems paradoxical in view of the fact that the level of total fiscal transfer in China is sizable and growing—transfers from central to local governments reached 4.8 trillion Yuan in 2013, after nearly 20 percent annual growth over the preceding decade (Fan and Wan, 2017). However, because these transfers are not specifically designed to redistribute uneven gains from trade across regions, their effect on mitigating the trade induced inequality is modest. As a result, regions that gain more from trade spend proportionately more on public goods. Below we provide evidence that corroborate how the uneven gains from trade liberalization are reflected in specific categories of local public goods such as education, healthcare and roads.

## 5.2 The effects on public goods and services

### 5.2.1 The effect on education

To examine the impact on educational provision, we focus on the number of schools and teachers across primary, secondary, and tertiary levels.<sup>13</sup> Table 3 reports the

<sup>13</sup>An arguably superior measure of school infrastructure quality would be the number of schools (and teachers) per school-age child. Unfortunately, consistent annual data on school-age population

estimated effects of reduced tariff uncertainty on the number of schools and teachers. Panel A reports the effects on number of schools while panel B presents the effects on number of teachers.

Column 1 shows no significant effect on number of primary schools but a positive and significant effect on primary school teachers. Because primary education is compulsory and coverage is nearly universal, it is not surprising that changes in number of primary schools is not systematically related to gains from trade. Moreover, China experienced a widespread trend of school consolidation during the sample period, which led to a net decline in the total number of primary schools in many prefectures particularly in regions experiencing large population outflows due to migration. This is also reflected in Table 12 where inter-prefecture inequality in number of primary schools per 1000 people decreased between 2000 and 2010. However, the significant positive effect on number of primary school teachers shows that regions that gained from trade boom has invested in improving primary school quality by hiring more teachers and reducing student-teacher ration, an important metrics of education quality. A one-standard-deviation larger decrease in tariff uncertainty is associated with a 6.7 percent increase in the number of primary school teachers per 1000 people.

Column 2 presents significant effect on number of secondary schools and secondary school teachers. A one-standard-deviation larger decrease in tariff uncertainty is associated with a 5.7 percent increase in the number of secondary schools and a 4.9 percent increase in the number of secondary school teachers. Unlike primary school, secondary school is not universal and secondary school enrollment in China was among the lowest in the middle income countries around the beginning of our sample period. However, over our study period secondary school enrollment increased dramatically from nearly 40 percent in 2000 to 80 percent in 2015. Our estimation results in column 2 of Table 3 show that this fast increase in secondary school expansion was skewed towards areas that gained from the export boom.

Column 3 shows no significant effect on number of tertiary institutions or their personnel. This result serves as natural placebo test for our analysis because prefecture governments have almost no influence on tertiary education. As discussed in section 2, tertiary education is a mandate of higher-level governments (provincial and central government) and local gains from trade boom should not have any significant direct effect on the number of tertiary education institutions or their human capital in a prefecture.

Taken together, these findings provide robust evidence that the fiscal windfall generated by reduced tariff uncertainty was systematically channeled into educational expansion. Both school and teacher numbers per capita increased for secondary

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at the prefecture level are unavailable.

education. Overall, this increase in education facilities is consistent with the “two-growth” rules mentioned in section 2 where education spending is legally required to grow twice the rate of LG revenue growth. If local revenues grow faster in trade exposed regions, so does spending on education facilities.

We corroborate these infrastructure results with direct evidence on fiscal allocations in Table 4. A one-standard-deviation larger decrease in tariff uncertainty is associated with an increase in per capita expenditure on education of 393 Yuan (column 1) and on science of 176 Yuan (column 2). The 75th–25th percentile comparison implies additional increases of 794 Yuan in education spending and 352 Yuan in science spending per capita—differences that are both statistically significant and substantively large.

### 5.2.2 The effect on healthcare provision

We next investigate the impact on healthcare infrastructure, using the number of doctors, hospital beds, and healthcare facilities (hospitals and centers) as key outcomes. The results, reported in Table 5, are striking. A one-standard-deviation reduction in tariff uncertainty is associated with a 9.4 percent increase in the number of doctors per 1000 people (column 1) and a 6.8 percent increase in hospital beds per 1,000 people (column 3). These effects translate into substantial differences across the treatment distribution: prefectures at the 75th percentile experienced increases of 18.8 percent more doctors and 13.6 percent more beds per 1,000 people relative to those at the 25th percentile. These large percentage gains should be interpreted in the context of low bases; in 2002 the national averages stood at approximately 1.5 doctors and 1.95 beds per 1,000 people. By 2022, the number of doctors per 1000 people more than doubled to reach 3.1.

By contrast, column 2 shows no statistically or economically significant change in the number of hospitals and healthcare centers per 1,000 people. Indeed, this measure remained remarkably stable throughout the sample period. This pattern suggests that local governments responded to increased fiscal resources by intensifying investment within existing facilities, i.e, hiring more physicians and adding beds rather than constructing new hospitals.

### 5.2.3 The effect on road infrastructure expansion

Finally, we assess the impact on transportation infrastructure, focusing on the area of paved roads. These measures are selected due to their consistent availability across most prefectures. Moreover, other transport infrastructure such as railways and highways are mainly planned and financed by higher-level governments. Results are presented in Tables 6.

Table 6 shows clear positive effects on road infrastructure. A one-standard-deviation larger decrease in tariff uncertainty is associated with an increase of over 10,850,000 square meters in total paved road area (column 1) and an increase of 3.33 square meters in paved road area per capita (column 2). The 75th–25th percentile comparison implies differences of approximately 20.17 million square meters in total paved area and 6.66 square meters per capita—substantial expansions in road capacity.

## 6 Mechanisms

### 6.1 The effect on local economic size

We first present evidence demonstrating that China’s granting of Permanent Normal Trade Relations (PNTR) by the United States triggered substantial local economic expansion. While prior studies have documented similar effects, we strengthen and corroborate this evidence by incorporating nighttime luminosity data alongside official statistical measures. The use of satellite-based nighttime lights as a proxy for economic activity is a well-established practice, particularly in contexts where official data may be less reliable (Henderson et al., 2012; Martínez, 2022).

Concerns have long been raised regarding the potential manipulation of national income accounts by authoritarian regimes in general—and by local Chinese governments in particular—to overstate jurisdictional economic performance (Martínez, 2022; Fernald et al., 2021; Chen et al., 2019). Aggregate indicators such as GDP are especially vulnerable to such exaggeration, given their prominence as benchmarks of economic success. To address these concerns, we draw on nighttime luminosity data from the National Oceanic and Atmospheric Administration (NOAA). We construct prefecture-level panel measures of nighttime light intensity by computing the average digital number (DN) across all pixels within each prefecture. The DN values range from 0 to 63, with higher values indicating greater luminosity and, by extension, more intense economic activity.

Table 7 examines the effect of decrease in tariff uncertainty on official GDP per capita growth and average nighttime light intensity growth. Column 1 reveals that a one-standard-deviation larger decrease in tariff uncertainty is associated with approximately 4.9% higher growth in GDP per capita. To illustrate the economic magnitude, comparing prefectures at the 75th percentile of tariff uncertainty reduction to those at the 25th percentile implies that the more exposed prefecture experienced about 10% higher GDP per capita growth.

Column 2 shows that a one-standard-deviation larger decrease in tariff uncertainty corresponds to a 6.5% higher increase in nighttime luminosity. This magnitude is

strikingly similar to the estimated effect on official GDP per capita growth, providing strong reassurance that the documented GDP effects are not merely artifacts of inflated official statistics.

Taken together, the consistent patterns across Table 7 provide robust evidence that the reduction in tariff uncertainty associated with PNTR induced significant real economic expansion in more exposed Chinese prefectures. As demonstrated in subsequent analyses, this expansion meaningfully enlarged the local tax base and boosted prefectural tax revenues.

## 6.2 The effects on specific revenue bases

In Section 5, we establish that prefectures with greater exposure to trade liberalization experienced a substantial expansion in their tax base, as evidenced by accelerated growth in GDP. This section provides a more granular examination of the tax-base expansion by investigating how trade liberalization affected the revenue bases of the major tax categories that dominate local and central government revenues in China.

Value-added tax (VAT), corporate income tax, and personal income tax collectively account for more than half of total government revenue. These taxes are shared between the central government and local governments (LGs) in the following proportions: VAT (75–25), corporate income tax (60–40), and personal income tax (60–40). In addition, LGs derive a non-negligible portion of their revenues from land- and property-related taxes, including real estate taxes.

Table 8 reports the estimated effects of trade liberalization on key indicators of manufacturing activity and the tax bases for the primary tax categories. Column (1) indicates that gross industrial production (across private, state-owned, and foreign-owned firms) rose by 18 percent in prefectures with one standard deviation higher reduction in tariff uncertainty. Column (2) shows a corresponding 11 percent increase in total sales revenue. Column (3) reveals that pre-tax profits—the direct basis for corporate income tax—increased by 13.2 percent. Finally, Column (4) demonstrates that VAT revenue, which constitutes nearly one-third of total government revenue, grew by 6.7 percent in response to a one-s.d. increase in exposure. Taken together, these results indicate a robust expansion in the tax bases for corporate income tax and VAT, which jointly represent nearly half of total revenue accruing to both central and local governments.

Personal income tax contributes over 5 percent of total government revenue. Table 9 examines the implications of trade liberalization for the personal income tax base. Column (1) shows that total employment increased by 15 percent in prefectures with one-s.d. higher exposure. This finding aligns with a growing body of evidence documenting large-scale labor reallocation and worker migration toward regions more

exposed to trade liberalization (Facchini et al., 2019; Imbert et al., 2022). Column (2) further reveals an 8.9 percent increase in total wage payments, which is the tax base for personal income tax, following the same exposure shock.

Several major revenue sources are reserved exclusively for LGs, including social security contributions, deed taxes, urban maintenance and development tax, land appreciation tax, urban land use tax, and house property tax. Social security contributions are closely tied to employment and wage levels, both of which rise significantly in more exposed prefectures (as shown in Table 9).

Table 10 evaluates the impact of trade liberalization on fixed-asset investment, which serves as a proxy for the tax base underlying property-related taxes. Column (1) indicates that total fixed assets increased by 14.1 percent in response to a one-s.d. rise in exposure. Column (2) reports an 8.9 percent increase in fixed-asset investment overall, while Column (3) shows that this growth is predominantly driven by a striking 18.9 percent rise in investment in residential real estate. These patterns provide compelling suggestive evidence that the tax bases for property-related levies expanded substantially in prefectures benefiting from trade liberalization.

Finally, land sales represent a critical revenue source for Chinese LGs, with land-sale revenues surging markedly during our sample period. Table 11 investigates whether this boom is systematic related to exposure to trade liberalization. The results indicate no significant association: Column (1) finds no meaningful link between the area of land sold and the trade shock; Columns (2) and (3) similarly show insignificant effects on land-sale revenue and profit.

In summary, the evidence presented in Tables 8–10 demonstrates that trade liberalization induced significant and broad-based expansion in the tax bases of major revenue categories. In particular, heightened industrial production translated into higher profits (and thus greater corporate income tax revenue) and increased value added (and thus higher VAT collections). Concurrently, employment growth drove substantial increases in wage bills, bolstering personal income tax and social security contribution revenues. Collectively, these categories account for more than 80 percent of total tax revenue accruing to LGs. In contrast, revenue from land sales shows no systematic connection to the reduction in trade policy uncertainty.

Feler and Senses (2017) document that, in the United States, exposure to import competition from China eroded LG fiscal capacity by triggering relative declines in housing prices and business activity—the primary bases for local property and sales taxes. Our findings highlight a parallel mechanism operating in the opposite direction: Chinese prefectures more exposed to trade liberalization experienced pronounced growth in industrial production, profits, fixed-asset investment (especially in real estate), employment, and wage incomes. These channels collectively generated a substantial strengthening of LG fiscal capacity, thereby enhancing their ability to

finance and deliver improved public goods and services within their jurisdictions.

## 7 Implications for Regional Inequality

The analysis in the preceding sections demonstrates that trade liberalization contributed to a disproportionate expansion of public spending and public goods provision in prefectures more exposed to trade relative to those less exposed. This section examines the implications of these uneven distributional effects for regional inequality over time. To assess this, we compute two standard measures of between-prefecture inequality in government budgets and public goods provision for each year from 2000 onward.

Table 12 reports these results. Panel A presents the inter-quartile range (IQR) for each measure, normalized relative to the base year 2000 to facilitate interpretation of trends. The findings reveal a marked increase in inequality across most dimensions. The IQR for per capita government expenditure rose by more than sevenfold between 2000 and 2013, while the IQR for per capita government revenue increased fivefold over the same period. Similar upward trends in inequality are observed for key public goods, including the number of doctors, tertiary schools, and teachers in secondary and tertiary education (all expressed per 1,000 people). In contrast, inequality in the number of primary and secondary schools declined over time. This exception is largely attributable to China’s nationwide school consolidation policy, which substantially reduced the total number of such schools. Although the policy was implemented countrywide, its effects were more pronounced in regions experiencing out-migration and population decline, leading to sharper reductions in school numbers in those areas.

Panel B employs an alternative inequality measure—the difference between the 90th and 10th percentiles (90-10 gap)—again normalized to 2000. This metric captures changes in extreme inequality between the top and bottom deciles. The patterns are broadly consistent with those in Panel A, albeit somewhat less pronounced. Overall, these results indicate that both inequality among initially more unequal regions and extreme disparities between the most and least advantaged prefectures widened over the period, with the former showing particularly dramatic growth.

These findings contribute to a broader literature documenting trade-induced inequality. In developed economies, globalization has been linked to rising disparities through mechanisms such as income redistribution from lower- to higher-skilled groups or regions (Autor et al., 2013; Hakobyan and McLaren, 2016; Case and Deaton, 2020; Borusyak and Jaravel, 2024).<sup>14</sup> Parallel evidence exists for developing

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<sup>14</sup>Notably, Case and Deaton (2020) highlight how globalization exacerbates income inequality by shifting resources toward the affluent; see also Rodrik’s overview <https://drodrik.scholar>.

countries (Pavcnik, 2017; Helpman et al., 2016; Dix-Carneiro et al., 2018; Bombardini and Li, 2020; Li and Coxhead, 2011; Zhu et al., 2024). While much of this work focuses on individual- or sector-level income inequality, fewer studies examine inter-regional dimensions. Our results extend this literature by showing that trade liberalization can also widen regional inequality—specifically through divergent trajectories in local government revenues and public goods provision—even in a setting with substantial inter-governmental fiscal transfers such as China. This persistence of disparities despite redistribution suggests that mitigating trade-induced regional inequality may require more targeted policies aimed at supporting adversely affected regions.

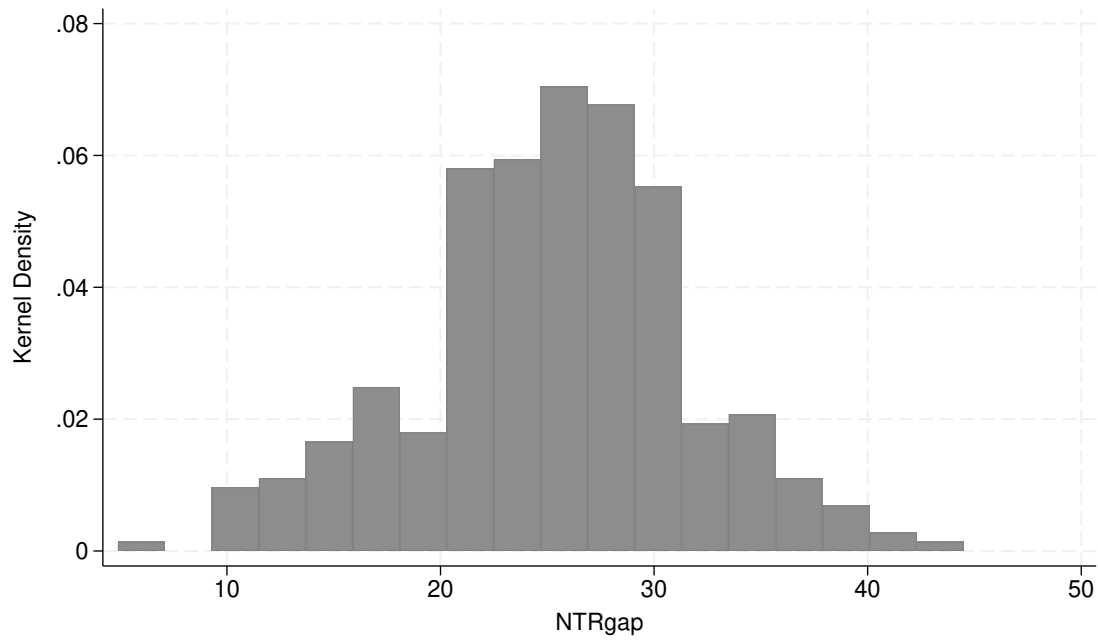
## 8 Conclusions

This study investigates whether the geographically asymmetric gains from trade liberalization are reflected in localized public goods provision leveraging the U.S. granting of Permanent Normal Trade Relations (PNTR) status to China as a quasi-experimental shock. We find that prefectures that were more exposed to reduced tariff uncertainty experienced significant expansion in their tax bases and revenue. While we find that a portion of these revenue gains were redistributed to those regions that did not gain directly from trade, in the form of intergovernmental transfers, the magnitude of this transfer is small relative to the revenue gains in the winning regions. As a result, regions that were more exposed to reduction in the tariff uncertainty experienced relative increases in LG government expenditure. Consequently, regional inequality worsens across multiple dimensions of public infrastructure and services including education, health and paved roads.

In the absence of a well designed redistributive policies, trade liberalization risks exacerbating spatial divergence in both private incomes and public service quality, with potentially long-lasting implications for social cohesion, human capital formation, and balanced national development. Our results thus highlight the importance of carefully designed inter-governmental transfer systems in ensuring that the aggregate welfare gains from globalization are more equitably shared across space.

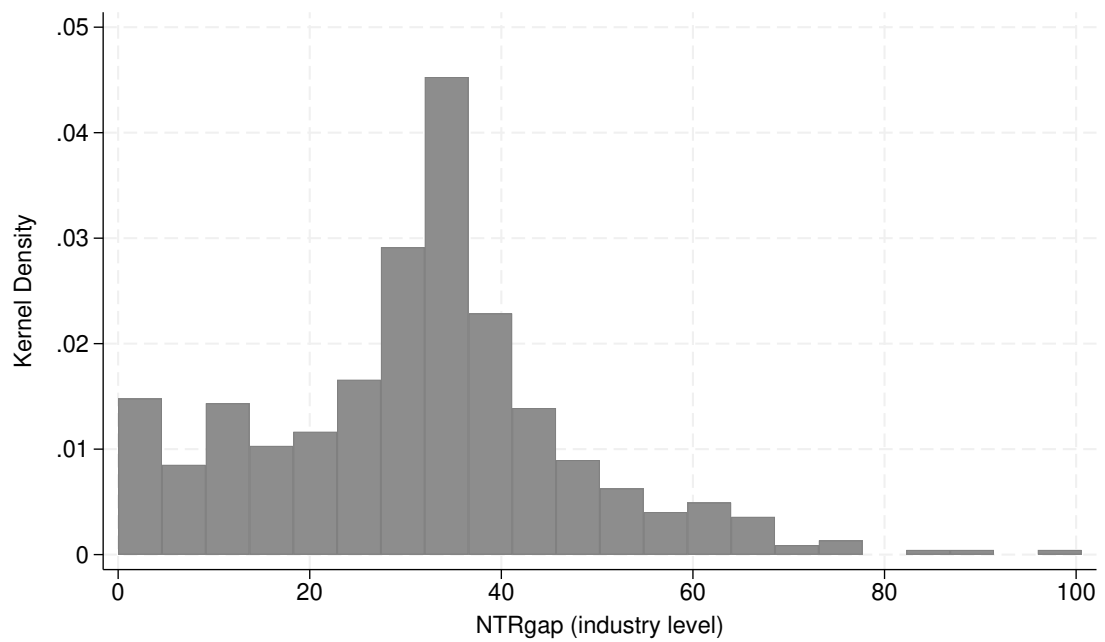
# Figures

Figure 1: Variation in the NTRgap across Prefectures



Notes: This figure presents variation in NTRgap calculated as  $\text{NTRgap}_c = \sum_j \alpha_{jc} \text{NTRgap}_j$  across prefecture cities, where where  $\text{NTRgap}_j$  the difference between the non-NTR and NTR tariff rates for industry  $j$ ;  $\alpha_{jc}$  is industry  $j$ 's employment share in prefecture  $c$  in 1998.

Figure 2: Variation in the NTRgap across Industries



Notes: This figure presents variation in industry level  $\text{NTRgap}_j$  which is the difference between the non-NTR and NTR tariff rates for industry  $j$ .

# Tables

Table 1: Summary statistics

|                                             | Mean    | S.d     |
|---------------------------------------------|---------|---------|
| Log GDP per capita                          | 9.51    | 0.94    |
| Log Nightlight                              | 0.87    | 1.11    |
| Log Exports                                 | 9.52    | 4.00    |
| Per capita budget expenditure               | 2830.95 | 4314.29 |
| Per capita budget revenue                   | 1625.95 | 3059.87 |
| Doctors (per 1000 people)                   | 1.81    | 1.06    |
| Hospital (per 1000 people)                  | 6.53    | 9.52    |
| Hospital beds (per 1000 people)             | 3.20    | 1.68    |
| Primary schools (per 1000 people)           | 31.61   | 22.93   |
| Secondary schools (per 1000 people)         | 6.08    | 1.70    |
| Tertiary schools (per 1000 people)          | 0.15    | 0.19    |
| Primary school teachers (per 1000 people)   | 4.55    | 1.10    |
| Secondary school teachers (per 1000 people) | 3.75    | 0.84    |
| Tertiary school teachers (per 1000 people)  | 0.70    | 1.05    |
| Per capita education expenditure            | 775.25  | 837.44  |
| Per capita science expenditure              | 88.24   | 304.05  |
| Paved road area (1000 square meters)        | 1301.93 | 1909.71 |
| Per capita paved road (in meter squares)    | 9.37    | 6.24    |

Notes: This table presents summary statistics of main outcome variables over the sample period. All monetary values are in constant 2010 Yuan.

Table 2: The effect on government per capita expenditure and revenue

|                                   | (1)<br>Revenue           | (2)<br>Expenditure      | (3)<br>Deficit          | (4)<br>Transfer          | (5)<br>General T        | (6)<br>Specific T      |
|-----------------------------------|--------------------------|-------------------------|-------------------------|--------------------------|-------------------------|------------------------|
| <b>Panel A: Logs and shares</b>   |                          |                         |                         |                          |                         |                        |
| PostNTR $\times$ <i>NTRgap</i>    | 0.104***<br>(0.039)      | 0.008<br>(0.037)        | -0.045***<br>(0.014)    | -0.061***<br>(0.018)     | -0.041***<br>(0.009)    | -0.011*<br>(0.006)     |
| <i>N</i>                          | 5554                     | 5539                    | 5517                    | 4494                     | 3534                    | 3536                   |
| <i>R</i> <sup>2</sup>             | 0.946                    | 0.956                   | 0.424                   | 0.450                    | 0.765                   | 0.506                  |
| <b>Panel B: Per capita levels</b> |                          |                         |                         |                          |                         |                        |
| PostNTR $\times$ <i>NTRgap</i>    | 1591.338***<br>(497.667) | 1228.262**<br>(535.312) | -309.745**<br>(146.600) | -383.705***<br>(112.346) | -199.056***<br>(58.069) | -76.404***<br>(29.072) |
| <i>N</i>                          | 5554                     | 5539                    | 5517                    | 4612                     | 3652                    | 3654                   |
| <i>R</i> <sup>2</sup>             | 0.765                    | 0.829                   | 0.807                   | 0.548                    | 0.839                   | 0.816                  |

Notes: In panel A, revenue and expenditure are measured in logs of per capita measures while Deficit and Transfers are measured as shares of expenditure. In Panel B, all the outcome variables are measured in real per capita Yen. The estimation is based on Prefecture-level data between the 1996 and 2019 for the first three columns. Transfer data (columns 4-6) are based on available between 2000-2019. Discrepancies in number of observations between panels A and B across columns 4-6 are due to missing values. All regressions include Prefecture and year fixed effects and control variables discussed in the paper. Standard errors are clustered at Prefecture level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 3: The effect on education (logs of measure per 1000 people)

|                                    | (1)<br>Primary School | (2)<br>Secondary School | (3)<br>Tertiary School |
|------------------------------------|-----------------------|-------------------------|------------------------|
| <b>Panel A: Number of schools</b>  |                       |                         |                        |
| PostNTR $\times$ <i>NTRgap</i>     | 0.019<br>(0.031)      | 0.056**<br>(0.022)      | 0.010<br>(0.103)       |
| <i>N</i>                           | 5326                  | 5150                    | 5148                   |
| <i>R</i> <sup>2</sup>              | 0.851                 | 0.831                   | 0.851                  |
| <b>Panel B: Number of teachers</b> |                       |                         |                        |
| PostNTR $\times$ <i>NTRgap</i>     | 0.067***<br>(0.018)   | 0.049**<br>(0.021)      | -0.022<br>(0.132)      |
| <i>N</i>                           | 5333                  | 5332                    | 5135                   |
| <i>R</i> <sup>2</sup>              | 0.795                 | 0.716                   | 0.899                  |

Notes: The estimation is based on Prefecture-level data between the 1996 and 2019. All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 4: The effect on expenditure on education and science (in per capita terms)

|                         | (1)                    | (2)                    |
|-------------------------|------------------------|------------------------|
|                         | Educational expense    | Expenditure on science |
| PostNTR $\times$ NTRgap | 393.116***<br>(90.278) | 176.351***<br>(59.802) |
| $N$                     | 3496                   | 3495                   |
| $R^2$                   | 0.818                  | 0.522                  |
| Mean of d. v            | 775.25                 | 88.24                  |

Notes: The estimation is based on Prefecture-level data between the 1996 and 2013. All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 5: The effect on health care facilities (logs of measure per 1000 people)

|                         | (1)                | (2)               | (3)                |
|-------------------------|--------------------|-------------------|--------------------|
|                         | Doctors            | Hospitals         | Hospital beds      |
| PostNTR $\times$ NTRgap | 0.094**<br>(0.046) | -0.012<br>(0.032) | 0.068**<br>(0.034) |
| $N$                     | 5345               | 5078              | 5345               |
| $R^2$                   | 0.773              | 0.693             | 0.865              |

Notes: The estimation is based on Prefecture-level data between the 1996 and 2019. All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 6: The effect on paved roads

|                         | (1)                                     | (2)                                                |
|-------------------------|-----------------------------------------|----------------------------------------------------|
|                         | Paved road area<br>(1000 meter squares) | Paved road per capita<br>(meter square per person) |
| PostNTR $\times$ NTRgap | 1085.366***<br>(181.758)                | 3.327***<br>(1.022)                                |
| $N$                     | 3440                                    | 3440                                               |
| $R^2$                   | 0.868                                   | 0.883                                              |
| Mean of d. v            | 1301.93                                 | 9.37                                               |

Notes: The estimation is based on Prefecture-level data between the 1996 and 2013. All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 7: The effect on real GDPPC and night time light

|                         | (1)                 | (2)                    |
|-------------------------|---------------------|------------------------|
|                         | Log Real GDPPC      | Log Average Nightlight |
| PostNTR $\times$ NTRgap | 0.049***<br>(0.012) | 0.065***<br>(0.013)    |
| $N$                     | 3791                | 3751                   |
| $R^2$                   | 0.967               | 0.930                  |

Notes: The estimation is based on Prefecture-level data between the 1997 and 2013.

All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 8: Industrial Production, Sales Revenue, Profit and VAT

|                         | (1)                   | (2)                 | (3)                 | (4)                |
|-------------------------|-----------------------|---------------------|---------------------|--------------------|
|                         | Industrial production | Sales Revenue       | Profit              | VAT                |
| PostNTR $\times$ NTRgap | 0.180***<br>(0.025)   | 0.110***<br>(0.022) | 0.132***<br>(0.044) | 0.067**<br>(0.028) |
| $N$                     | 3254                  | 2733                | 3866                | 3937               |
| $R^2$                   | 0.931                 | 0.932               | 0.947               | 0.915              |

Notes: The estimation is based on Prefecture-level data between the 1997 and 2013.

All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level. Industrial production is gross value of industrial production by firms owned by private, state and foreign entities. Profit is total before tax profit of businesses. Sales revenue is total revenue from sales of products and VAT is value-added tax collected. All dependent variables are converted to real values using CPI and are measured in log units.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 9: Employment and wage growth

|                         | (1)                 | (2)                 |
|-------------------------|---------------------|---------------------|
|                         | Employment          | Total wages         |
| PostNTR $\times$ NTRgap | 0.151***<br>(0.054) | 0.089***<br>(0.018) |
| $N$                     | 3944                | 3937                |
| $R^2$                   | 0.864               | 0.930               |

Notes: The estimation is based on Prefecture-level data between the 1997 and 2015.

All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level. Total wages is converted to real values using CPI. All dependent variables are measured in log units.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 10: Investment in fixed assets

|                                | (1)                 | (2)                           | (3)                                     |
|--------------------------------|---------------------|-------------------------------|-----------------------------------------|
|                                | Total Assets        | Investment in<br>fixed assets | Investment in<br>residential realestate |
| PostNTR $\times$ <i>NTRgap</i> | 0.141***<br>(0.026) | 0.089**<br>(0.036)            | 0.189***<br>(0.044)                     |
| <i>N</i>                       | 3937                | 3943                          | 3931                                    |
| <i>R</i> <sup>2</sup>          | 0.924               | 0.933                         | 0.856                                   |

Notes: The estimation is based on Prefecture-level data between the 1997 and 2015.

All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level. All dependent variables are converted to real values using CPI and are measured in log units.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 11: Trade shock and revenue from land sales

|                                | (1)               | (2)               | (3)              |
|--------------------------------|-------------------|-------------------|------------------|
|                                | Log Area          | Log Revenue       | Log Profit       |
| PostNTR $\times$ <i>NTRgap</i> | -0.063<br>(0.090) | -0.121<br>(0.112) | 0.033<br>(0.118) |
| <i>N</i>                       | 2660              | 2553              | 1716             |
| <i>R</i> <sup>2</sup>          | 0.725             | 0.850             | 0.739            |

Notes: The estimation in columns 1-2 are based on Prefecture-level data between the 1999 and 2013. Column 3 is based on data for 1999-2007. All regressions include Prefecture and year fixed effects. Standard errors are clustered at Prefecture level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 12: Trends in regional inequality

|                                         | Budget |      | Health |         | Schools |      |      | Teachers |      |      |
|-----------------------------------------|--------|------|--------|---------|---------|------|------|----------|------|------|
| Year                                    | Expe.  | Rev  | Beds   | Doctors | Prim    | Sec  | Ter  | Prim     | Sec  | Ter  |
| <b>Panel A: Inter-quartile ranges</b>   |        |      |        |         |         |      |      |          |      |      |
| 2000                                    | 1.00   | 1.00 | 1.00   | 1.00    | 1.00    | 1.00 | 1.00 | 1.00     | 1.00 | 1.00 |
| 2001                                    | 1.30   | 0.92 | 0.96   | 0.92    | 0.96    | 1.04 | 1.04 | 1.00     | 1.07 | 1.02 |
| 2002                                    | 1.56   | 0.84 | 0.94   | 0.92    | 0.92    | 1.07 | 1.13 | 1.01     | 1.17 | 1.35 |
| 2003                                    | 1.54   | 0.99 | 0.93   | 0.92    | 0.90    | 0.95 | 1.14 | 1.04     | 1.21 | 1.36 |
| 2004                                    | 1.88   | 1.15 | 0.96   | 0.90    | 0.91    | 1.01 | 1.14 | 1.10     | 1.19 | 1.64 |
| 2005                                    | 2.21   | 1.48 | 0.93   | 0.97    | 0.95    | 0.99 | 1.15 | 1.01     | 1.16 | 1.60 |
| 2006                                    | 2.88   | 1.90 | 0.96   | 1.02    | 0.91    | 0.90 | 1.34 | 1.07     | 1.08 | 1.94 |
| 2007                                    | 3.21   | 2.33 | 0.95   | 1.01    | 0.88    | 0.89 | 1.32 | 1.08     | 1.06 | 1.95 |
| 2008                                    | 3.93   | 2.77 | 0.94   | 1.14    | 0.92    | 0.83 | 1.33 | 1.04     | 1.08 | 2.13 |
| 2009                                    | 4.98   | 3.05 | 1.01   | 1.22    | 0.89    | 0.88 | 1.53 | 1.02     | 1.19 | 2.27 |
| 2010                                    | 5.80   | 3.54 | 1.11   | 1.19    | 0.83    | 0.86 | 1.42 | 1.05     | 1.18 | 2.34 |
| 2011                                    | 6.00   | 4.33 | 1.06   | 1.16    | 0.74    | 0.81 | 1.51 | 0.95     | 1.20 | 2.45 |
| 2012                                    | 6.42   | 4.88 | 1.09   | 1.14    | 0.74    | 0.78 | 1.48 | 1.01     | 1.23 | 2.29 |
| 2013                                    | 7.25   | 5.08 | 1.07   | 1.22    | 0.70    | 0.80 | 1.42 | 0.89     | 1.30 | 2.13 |
| <b>Panel B: 90th - 10th percentiles</b> |        |      |        |         |         |      |      |          |      |      |
| 2000                                    | 1.00   | 1.00 | 1.00   | 1.00    | 1.00    | 1.00 | 1.00 | 1.00     | 1.00 | 1.00 |
| 2001                                    | 1.20   | 1.07 | 1.04   | 1.04    | 0.99    | 1.04 | 1.08 | 0.99     | 0.97 | 1.12 |
| 2002                                    | 1.17   | 1.04 | 0.95   | 0.88    | 0.99    | 1.06 | 1.07 | 1.07     | 0.99 | 1.31 |
| 2003                                    | 1.32   | 1.07 | 0.95   | 0.88    | 1.06    | 1.05 | 1.13 | 1.10     | 0.97 | 1.24 |
| 2004                                    | 1.45   | 1.35 | 0.95   | 0.85    | 1.05    | 1.03 | 1.12 | 1.13     | 1.06 | 1.61 |
| 2005                                    | 1.84   | 1.80 | 0.92   | 0.90    | 0.96    | 1.03 | 1.23 | 1.10     | 1.03 | 1.44 |
| 2006                                    | 2.17   | 2.16 | 0.96   | 0.93    | 0.90    | 0.99 | 1.25 | 1.16     | 1.00 | 1.64 |
| 2007                                    | 2.64   | 2.40 | 1.02   | 1.02    | 0.87    | 0.99 | 1.18 | 1.21     | 1.00 | 1.44 |
| 2008                                    | 2.97   | 2.67 | 1.04   | 1.02    | 0.80    | 0.97 | 1.19 | 1.09     | 1.00 | 1.55 |
| 2009                                    | 3.45   | 3.15 | 1.04   | 0.98    | 0.76    | 0.96 | 1.36 | 1.08     | 1.00 | 1.53 |
| 2010                                    | 3.76   | 3.51 | 1.20   | 1.03    | 0.73    | 0.87 | 1.36 | 1.06     | 0.97 | 1.44 |
| 2011                                    | 4.07   | 3.89 | 1.19   | 1.05    | 0.67    | 0.85 | 1.17 | 0.98     | 1.08 | 1.30 |
| 2012                                    | 4.48   | 4.27 | 1.20   | 1.06    | 0.72    | 0.86 | 1.34 | 1.03     | 1.09 | 1.38 |
| 2013                                    | 4.87   | 4.86 | 1.35   | 1.19    | 0.62    | 0.78 | 1.31 | 0.95     | 1.02 | 1.33 |

Notes: This table reports inequality across prefectures of public good measures for each year relative to the values in 2000. Budgets are defined in per capita terms. All other variables are defined as numbers per 1000 people.

## Appendix A Diagnosis of distribution of the shocks and industry shares

In this subsection we provide diagnosis of key assumptions in our identification strategy following [Borusyak et al. \(2021\)](#). A key assumption of identification in the shift-share research design where identification comes from the exogeneity of the shifts or quasi-random “shocks” is that the number of shocks should be sufficiently large and should not be highly concentrated. Using our notations, these would mean that in the shocks  $\text{NTRgap}_j, j \in \{1, \dots, J\}$ : (i)  $J$  is sufficiently large, and (ii) there is sufficient variation in  $\text{NTRgap}_j$  across  $j \in \{1, \dots, J\}$ . In our setting,  $J = 487$  (the number of industries in four-digit industry classification of China in 2002) and the distribution of  $\text{NTRgap}_j$  across industries is given in figure 2. The standard deviation and inter-quartile ranges of the distribution show that our industry shocks show sufficient variation.

Next, the exposure shares  $\alpha_{jt} \propto \sum_c \alpha_{jct}$ <sup>15</sup> should not be highly concentrated. [Borusyak et al. \(2021\)](#) report two important diagnosis statistics to check the concentration of the normalized shares which we follow here. Panel A of Table A.1 reports these statistic. The first is the inverse of the Herfindahl-Hirschman Index (HHI) of the shares calculated as  $1 / \sum_{j,t} \alpha_{jt}^2$ . In our setting this statistics is 1,628, which according to standards set by [Borusyak et al. \(2021\)](#) is sufficiently large. This index is a measure of effective sample size. The second statistics we report is the maximum of the normalized share across industry-years, which is 0.0022. Again this shows that the normalized shares are not concentrated because the largest share is still very small (0.22%). Together, these two statistics suggest that the assumptions required for consistency of the estimator  $\mathbf{E}[\sum_{j,t} \alpha_{jt}^2] \rightarrow 0$ , as  $J \times T \rightarrow \infty$  are satisfied in our setting.

Note that while the shares ( $\alpha_{jc}$ ) are calculated as industry employment relative to *total* employment in a prefecture, we exclude the shares for agriculture and service following [Borusyak et al. \(2021\)](#). This is for two reasons. First, because agriculture and service sectors account for significant share of employment (relative to each of the four-digit industries), including these sectors would lead to concentration of the shares. Second, the trade policy change does not affect services and affects agriculture only marginally since agriculture is not a major export commodity for China. In other words, these two sectors do not have the same treatment probability as the manufacturing industries. Including them in to the identifying variation would lead to serious violation of Assumptions 1 and 2 in [Borusyak et al. \(2021\)](#). Following their suggestion we include manufacturing employment share of prefectures in 1998

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<sup>15</sup> $\alpha_{jt}$  is employment shares aggregated across prefectures and normalized to add up to one across industry-years.

interacted with year fixed effects to account for different trajectories of prefectures with different initial manufacturing presence.

Table A.1: Characteristics of normalized shares

|                      | Inverse HHI<br>(effective sample size) | Maximum share<br>(across-industry years) |
|----------------------|----------------------------------------|------------------------------------------|
|                      | 1,628                                  | 0.0022                                   |
| Number of Industries | 487                                    |                                          |
| Number of Years      | 18                                     |                                          |

Notes: This table reports inverse HHI of the normalized shares ( $1/\sum_{j,t} \alpha_{jt}^2$ ) and the maximum of the shares across industry-years ( $\max_{j,t} \{\alpha_{jt}\}$ ).

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Appendix B Derivation of comparative statics

Recall the three key relationships governing the local public finance equilibrium:

Local Tax Base ( $B_i$ ):

$$B_i = \Phi_i \cdot A_i(\Delta T_i) L_i^\alpha$$

where  $\Phi_i K_i^{1-\alpha}$  In logs:

$$\ln B_i = \ln \Phi_i + \ln A_i(\Delta T_i) + \alpha \ln L_i$$

Total available budget for prefecture  $i$  after central transfers is:

$$E_i = (1 - \lambda)F_i + \bar{T}R + \lambda\bar{F}$$

where  $F_i = (\alpha_{LG}\tau + \delta)B_i$  represents self-generated local fiscal capacity. Optimal public goods:

$$G_i^* = \frac{\theta}{p_g} E_i = \frac{\theta}{p_g} [(1 - \lambda)(\alpha_{LG}\tau + \delta)B_i + \bar{T}R + \lambda\bar{F}]$$

In logs:

$$\ln G_i^* = \ln \left( \frac{\theta}{p_g} \right) + \ln [(1 - \lambda)(\alpha_{LG}\tau + \delta)B_i + \bar{T}R + \lambda\bar{F}]$$

Differentiate  $\ln G_i^*$  with respect to trade exposure  $\Delta T_i$ :

$$\frac{d \ln G_i^*}{d \Delta T_i} = \frac{\partial \ln G_i^*}{\partial B_i} \cdot \frac{dB_i}{d \Delta T_i}$$

Using the chain rule on the log-expenditure term:

$$\frac{d \ln G_i^*}{d \Delta T_i} = \frac{1}{E_i} \cdot \frac{\partial E_i}{\partial B_i} \cdot \frac{dB_i}{d \Delta T_i} = \frac{1}{E_i} [(1 - \lambda)(\alpha_{LG}\tau + \delta)] \cdot \frac{dB_i}{d \Delta T_i}$$

Multiply and divide by  $B_i$ :

$$\frac{d \ln G_i^*}{d \Delta T_i} = \left[ \frac{(1 - \lambda)(\alpha_{LG}\tau + \delta)B_i}{E_i} \right] \cdot \frac{1}{B_i} \frac{dB_i}{d \Delta T_i}$$

Note that  $(\alpha_{LG}\tau + \delta)B_i = F_i$  (local self-generated revenue). Substituting  $F_i$ :

$$\frac{d \ln G_i^*}{d \Delta T_i} = (1 - \lambda) \left( \frac{F_i}{E_i} \right) \cdot \frac{d \ln B_i}{d \Delta T_i}$$

Let  $\Omega_i \equiv \frac{F_i}{E_i}$  denote the local fiscal self-reliance ratio (the proportion of total local

expenditure funded by local tax base vs. central transfers). Thus:

$$\frac{d \ln G_i^*}{d \Delta T_i} = (1 - \lambda) \Omega_i \cdot \frac{d \ln B_i}{d \Delta T_i} \quad \text{--- (Eq. 1)}$$

Decomposing the term  $\frac{d \ln B_i}{d \Delta T_i}$ : The total log-change in tax base  $B_i$  depends on direct productivity gains from trade and endogenous migration/labor influx:

$$\ln B_i = \ln \Phi_i + \ln A_i(\Delta T_i) + \alpha \ln L_i$$

Taking the total derivative with respect to  $\Delta T_i$ :

$$\frac{d \ln B_i}{d \Delta T_i} = \frac{\partial \ln A_i}{\partial \Delta T_i} + \alpha \frac{d \ln L_i}{d \Delta T_i}$$

Where  $\frac{\partial \ln A_i}{\partial \Delta T_i}$  is the direct productivity/scale expansion driven by reduced tariff uncertainty.  $\alpha \frac{d \ln L_i}{d \Delta T_i}$  is the indirect labor agglomeration effect resulting from spatial sorting. Substituting this back into Eq. 1 gives the total elasticity of total public goods provision:

$$\frac{d \ln G_i^*}{d \Delta T_i} = (1 - \lambda) \Omega_i \left[ \frac{\partial \ln A_i}{\partial \Delta T_i} + \alpha \frac{d \ln L_i}{d \Delta T_i} \right] \quad \text{--- (Eq. 2)}$$

Taking logs of per-capita public goods:

$$\ln g_i^* = \ln G_i^* - \phi \ln L_i$$

Differentiating with respect to  $\Delta T_i$ :

$$\frac{d \ln g_i^*}{d \Delta T_i} = \frac{d \ln G_i^*}{d \Delta T_i} - \phi \frac{d \ln L_i}{d \Delta T_i}$$

Substitute Eq. 2 into the expression:

$$\frac{d \ln g_i^*}{d \Delta T_i} = (1 - \lambda) \Omega_i \frac{\partial \ln A_i}{\partial \Delta T_i} + (1 - \lambda) \Omega_i \alpha \frac{d \ln L_i}{d \Delta T_i} - \phi \frac{d \ln L_i}{d \Delta T_i}$$

Factor out the population change derivative  $\frac{d \ln L_i}{d \Delta T_i}$ :

$$\frac{d \ln g_i^*}{d \Delta T_i} = \underbrace{(1 - \lambda) \Omega_i \frac{\partial \ln A_i}{\partial \Delta T_i}}_{\text{Direct tax base expansion effect}} + \underbrace{[(1 - \lambda) \Omega_i \alpha - \phi] \frac{d \ln L_i}{d \Delta T_i}}_{\text{Migration \& congestion spillover}} \quad \text{--- (Eq. 3)}$$

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