An Econometric Framework for General Equilibrium Analysis of Trade Shocks*

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Abstract

This paper develops an econometric framework that bridges the structural and reduced-form literatures by translating the quantitative trade concept of market access into a tool for causal estimation of general-equilibrium effects on local labor markets. Guided by a multi-region, multi-sector model, we compute region–sector market access that embeds domestic input–output and competition linkages, estimate how it responds to Bartik-style trade shocks, and aggregate the resulting effects across regions and sectors using observed spatial links. Applying this framework to the China Shock, we quantify changes in market access across 722 U.S. commuting zones and 22 sectors, estimating domestic trade costs via infrastructure networks (rail, road, waterways, and air). Accounting for these spillovers reduces the estimated contraction in manufacturing employment by about 60% relative to partial-equilibrium estimates. While upstream contractions amplify the shock, reduced domestic competition redirects demand toward less-affected regions, where producers expand. By embedding general-equilibrium trade theory into a tractable econometric design, this framework offers a new tool for assessing the local labor-market effects of globalization.

JEL codes: F11, F14, F62, H54
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1 Introduction

Over the past three decades, globalization and technological change have profoundly reshaped local labor markets in advanced economies. In the United States, for example, manufacturing employment declined from 14% to 8% of total employment between 1990 and 2010 (Autor et al., 2013). A large literature attributes this contraction to automation, offshoring, and trade integration.[1] Early empirical work on trade shocks relied on reduced-form, partial-equilibrium analyses, overlooking the general-equilibrium and spatial adjustments that propagate shocks across sectors and regions (e.g., Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2016). To overcome these limitations, quantitative trade simulations managed to capture general-equilibrium effects (e.g., Caliendo et al., 2019; Adao et al., 2019), but they depend on strong assumptions and are not directly comparable to reduced-form estimates.

This paper develops an econometric framework that recovers the general-equilibrium effects of international trade shocks on local labor markets, bridging reduced-form and quantitative approaches. The framework highlights two key domestic propagation channels, the input–output linkages and spatial competition, that jointly determine how foreign shocks reshape regional employment and wages. Guided by a multi-region, multi-sector model, we compute region–sector market access, estimate its econometric response to Bartik-style trade shocks, and aggregate the resulting effects across regions and sectors using observed input–output and trade linkages. The method requires fewer structural assumptions than quantitative simulations and yields estimates directly comparable to reduced-form regressions, allowing us to measure the relative magnitude of general-equilibrium effects.

We apply this framework to the China Shock, quantifying changes in market access for 722 U.S. commuting zones and 22 sectors by estimating domestic trade costs using U.S. infrastructure networks (rail, road, waterways, and air) and a least-cost path algorithm. Accounting for these spillovers reduces the estimated contraction in manufacturing employment by roughly 60 percent relative to partial-equilibrium estimates. While upstream contractions amplify local losses through input-output linkages, reduced domestic competition redirects demand toward less-affected regions, where producers expand.

We begin by deriving a measure of market access from the stationary version of Caliendo et al. (2019), which provides region-sector granularity and incorporates input-output and trade linkages. The measure is defined at the labor market level, where a labor market corresponds to a region–sector pair, and consists of two components. The first captures input-ouput spillovers: a labor market's market access increases with the market access of its suppliers, particularly when it

[1] For a review of manufacturing employment trends and their determinants, see Fort et al. (2018); for evidence on automation, see Graetz and Michaels (2017); Acemoglu and Restrepo (2020); and for offshoring, see Boehm et al. (2020).

sources heavily from them, as reflected in input–output linkages. Intuitively, as suppliers gain market access, their production costs decline, benefiting downstream customers. The second component captures spatial-competition and demand spillovers: a labor market's market access increases with the expenditure capacity of its consumers and decreases with the market access of its competitors. These effects are stronger for more central labor markets, as captured by bilateral iceberg trade costs. As competitors gain market access, their production costs fall, enabling them to capture larger market shares, whereas higher expenditure capacity in connected markets benefits the labor market by expanding potential demand. We then isolate local shocks in market access from foreign fundamentals and trace their propagation across regions via domestic trade and input-output linkages, demonstrating that employment responses to trade shocks are fully summarized by this measure of market access.

Building on this structural framework, we next show how to implement it empirically. Under suitable assumptions, shocks to foreign fundamentals can be expressed in a Bartik-style form. We then estimate a regression of market access on this Bartik trade shock to identify local general-equilibrium effects for each labor market. Following the model, we account for spatial spillovers by aggregating the predicted responses of other regions and sectors using observed domestic input–output tables and export shares. This procedure yields a general-equilibrium measure of the shock, which we refer to as the global response. Finally, we exploit the structural link between employment and market access to estimate our main equation, relating changes in employment to the global response. Econometrically, the estimated coefficient decomposes into three components: (i) the local general-equilibrium effect of the shock, (ii) the spatial propagation effect, capturing how the shock diffuses through input–output and trade linkages, and (iii) the partial-equilibrium benchmark, representing the direct effect of the Bartik shock on employment. The standardized coefficient thus measures the impact of a one–standard-deviation increase in import penetration after accounting for domestic propagation, making it directly comparable to the partial-equilibrium benchmark.

We then apply this econometric framework to the China Shock. We numerically compute market access for 722 commuting zones and 22 sectors for the years 2000 and 2007, focusing on the period just before and after China's accession to the WTO. These changes captures the general equilibrium adjustments to all shocks affecting U.S. local labor markets during this period. To quantify market access, we estimate domestic sectoral iceberg trade costs. We micro-found these trade costs adapting the methodology of Allen and Arkolakis (2014). We first compute least cost path using the Fast Marching Method on infrastructure networks, which covers air, railroads, waterways, and highways, for 2000 and 2007. We then map least cost paths to sectoral geographic and non-geographic trade costs with a discrete choice framework. The regression of market access on exogenous import exposure reveals a strong and robust negative relationship. A one–standard-deviation increase in import exposure (≈ USD 430 per worker) reduces market access by 107 units, compared to an average increase of 71 units across U.S. labor markets between 2000 and 2007. This reduction reflects a general-equilibrium effect: although cheaper Chinese imports lower prices for the varieties they displace, import-driven contractions among domestic producers reduce supply and raise prices of other goods in the consumption basket, resulting in a net increase in the aggregate price index.

We then propagate the regression-based projections of market access on import exposure through domestic trade and production linkages to construct the global response. As a benchmark, we first estimate the partial-equilibrium effect of the China shock on manufacturing employment across 12 sectors and 722 U.S. commuting zones. Our estimates closely align with Autor et al. (2013), both with and without controls: a one–standard-deviation increase in decadal Chinese import exposure per worker reduces a CZ-sector's manufacturing employment-to-working-age population ratio by about 0.33 percentage points. Turning to the global response, which incorporates full general-equilibrium adjustments including spatial spillovers, the same increase in import exposure propagated across space leads to a substantially smaller decline of about 0.13 percentage points. This attenuation arises from the spatial propagation effect.

To understand the positive sign of the spatial propagation effect, we decompose it into two components: the input–output channel and the spatial competition channel. The input–output term is negative, amplifying the China Shock.[2] When upstream suppliers contract in response to Chinese import competition, downstream customers face input shortages or higher prices, as cheaper Chinese intermediates do not fully offset the loss of domestic supply. By contrast, the spatial competition term is positive, attenuating the global effect: when competitors in other labor markets contract and Chinese imports fail to fully replace the lost output, local producers absorb the residual demand, partially offsetting the direct negative impact of the China Shock.

Turning to the pooled sample of manufacturing and services, we find that a one–standard-deviation increase in import penetration reduces employment by 0.16 percentage points. The larger effect relative to the manufacturing sample reflects the role of input–output linkages, which transmit contractions from manufacturing into the ten service sectors that source inputs from it. In the paper, we further explore heterogeneity by worker demographics—education, age, gender, and origin—across both manufacturing and services.

This paper is most closely related to the empirical literature on the China Shock and its effects on the U.S. economy (Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2016; Adao et al., 2019).[3] Our main contribution is to develop a granular empirical strategy that quantifies general

[2]This result is consistent with Acemoglu et al. (2016) and Pierce and Schott (2016), who document national-level negative effects of upstream input–output linkages on manufacturing and non-manufacturing employment, though Caliendo et al. (2019) find contrasting results in a quantitative analysis.

[3]More broadly, our paper contributes to the literature on how local labor markets respond to trade shocks, building

equilibrium effects relative to partial equilibrium benchmarks. We benchmark our analysis against Autor et al. (2013), who estimate the partial-equilibrium impact of rising Chinese import competition on manufacturing employment across 722 commuting zones. Using their Bartik instrument, we estimate these effects at a finer level—across 12 manufacturing sectors within each commuting zone—finding similar results in both sign and magnitude. We then show that incorporating general equilibrium adjustments reduces the negative effects of the China Shock by a factor of 2.5.

While Acemoglu et al. (2016) and Pierce and Schott (2016) emphasize amplification of industry-level shock through input-output linkages, we explicitly model spatial propagation through domestic production and trade linkages across commuting and sectors, guided by a quantitative trade model. This allows us to capture additional margins, including adjustments in domestic spatial competition. Adao et al. (2019) provide reduced-form evidence of spatial amplification using distance-weighted exposure measures at the Commuting-zone level, but our framework accounts for both sectoral and regional interactions, including input-output and spatial competition effects. Crucially, we show that once these channels are incorporated at a granular level, the net negative employment effects are substantially mitigated, highlighting the importance of rich general equilibrium spillovers in assessing the full impact of globalization on local labor markets.

This article departs from the quantitative (simulation) literature that evaluates GE effects of trade shocks via counterfactual experiments (Caliendo et al., 2019; Adao et al., 2019). Instead, we develop an empirical strategy to estimate GE effects directly, enabling a transparent comparison with partial-equilibrium estimates.[4] While Caliendo et al. (2019) quantify heterogeneous short-run (2000–2007) manufacturing contractions across U.S. states, our commuting-zone $\times$ sector analysis works at a finer scale and links directly to the Bartik-style partial-equilibrium estimates prevalent in the literature.

We also contribute to the literature on market access (Donaldson and Hornbeck, 2016; Allen and Arkolakis, 2023; Redding and Venables, 2004) by deriving a new, more granular measure of market access, quantified for 2000 and 2007 across U.S. commuting zones and sectors. Building on Donaldson and Hornbeck (2016)'s methodology, we adopt a stationary version of the Caliendo et al. (2019) framework to construct this measure. Unlike existing measures, our is both more granular and uniquely integrates input-output and trade linkages, and we use it for the first time to trace how trade shocks propagate through the economy, affecting wages and employment.[5] Finally, this

on Bartik (1991) and Blanchard et al. (1992) and subsequent studies documenting heterogeneity in local outcomes (Topalova, 2010; Autor et al., 2013; Kovak, 2013; Dauth et al., 2014; Dix-Carneiro and Kovak, 2017; Hakobyan and McLaren, 2016; Yi et al., 2016).

[4] To our knowledge, no previous empirical approach has addressed general-equilibrium effects via market access, largely due to methodological and data limitations, particularly the endogeneity of market access (Allen and Arkolakis, 2023).

[5] While prior studies analyze the relationship between market access and GDP at the country level (Redding and Venables, 2004, Head and Mayer, 2011) or U.S. county-level wages (Hanson, 2005), they do not derive a formal measure of market access. Similarly, Brülhart et al. (2012) examine the effects of improved market access—arising

paper builds on the methodological advancements introduced in Allen and Arkolakis (2014). We micro-found iceberg trade costs and adapt the fast-marching method to our setup, enabling the estimation of these costs across four modes of transport at a more granular level.[6]

The remainder of the paper is organized as follows. Section 2 derives the market-access measure and structural equations. Section 3 explains the empirical strategy used to implement the model. Section 4 describes the data and the construction of CZ–sector–level employment, wages, and market access, and details the steps used to quantify market access and estimate domestic sectoral iceberg trade costs. Section 5.1 provides descriptive evidence on the newly constructed measures, including the global response. Section 6 reports our main findings and robustness checks. Section 7 concludes.

2 Theoretical Framework

This section presents the theoretical framework guiding our empirical analysis. We first outline the stationary version of the Caliendo et al. (2019) model and derive the theoretical measure of market access (Subsection 2.1). Subsection 2.2 develops the structural equations linking changes in market access to changes in wages and employment, and relates market access to the China Shock.

2.1 Theoretical Market Access

We build on the stationary version of Caliendo et al. (2019), which provides region–sector granularity and explicitly incorporates input–output (I–O) and trade linkages—features essential to our analysis of how trade shocks propagate through local labor markets. The economy consists of N regions and J sectors, with nj denoting a specific region–sector market. In each nj, a continuum of firms produces intermediate goods with Cobb–Douglas constant returns to scale technology, combining three inputs: labor, capital, and materials sourced from all sectors. Sectoral productivity follows a Fréchet distribution as in Eaton and Kortum (2002). Each market nj also produces a final good, which is a CES composite of intermediates; they are either consumed by households or used as inputs in intermediate good production, thereby generating I–O linkages. Intermediate varieties are tradable across regions subject to iceberg trade costs, while final goods are non-tradable. Households earn wages and consume final goods from all sectors. At equilibrium, goods, labor, and structures markets clear under perfect competition.

from trade liberalization—on wages and employment using a location discrete-choice model in a spatial framework à la Helpman (1998), but focus on Austria during the fall of the Iron Curtain without constructing a formal market access measure.

[6] Additionally, we leverage Allen and Arkolakis (2023)'s gold medal error strategy to develop a model-based IV that isolates exogenous variation in Market Access. This approach aligns with similar methodologies employed in Monte et al. (2018), Allen et al. (2020), and Adao et al. (2019).

Following Donaldson and Hornbeck (2016), we define Consumer Market Access (CMA) as the inverse of the local price index. Intuitively, a lower price index implies that consumers face cheaper goods, including transport costs, and thus enjoy greater access to other regions' markets. The price index in region–sector nj is

$$P_{nj} = \Gamma_{nj} \left(\sum_{i=1}^{N} \left(x_{ij} k_{nj,ij} \right)^{-\theta_j} \left(A_{ij} \right)^{\theta_j \gamma_{ij}} \right)^{-\frac{1}{\theta_j}} \equiv \Gamma_{nj} \left(CMA_{nj} \right)^{-\frac{1}{\theta_j}}, \tag{2.1}$$

where

$$x_{ij} = B_{ij} \left[\left(r_{ij} \right)^{\xi_i} \left(w_{ij} \right)^{1-\xi_i} \right]^{\gamma_{ij}} \prod_{k=1}^{J} \left(P^{ik} \right)^{\gamma_{ij,ik}}. \tag{2.2}$$

Here, r_{ij} and w_{ij} denote capital and labor prices, P^{ik} is the price of material inputs, $k_{nj,ij}$ are bilateral trade costs between region n and i in sector j, and A_{ij} denotes fundamental productivity. The parameter θ_j is the sector-specific productivity dispersion (also the trade elasticity), and Γ_{nj} is a constant. The production function of intermediate varieties exhibit constant returns to scale: the value-added share γ_{ij} and input shares $\gamma_{ij,ik}$ satisfy $\sum_k \gamma_{ij,ik} = 1 - \gamma_{ij}$. Finally, ξ_i is the share of capital in value added, which is fixed in supply in each labor market.

The expenditure share of region n on good j produced in region i and the labor market clearing condition for market nj are given by:

$$\pi_{nj,ij} = \frac{\left(x_{ij}\, k_{nj,ij} \right)^{-\theta_j} \left(A_{ij} \right)^{\theta_j \gamma_{ij}}}{\sum_{m=1}^{N} \left(x_{mj}\, k_{nj,mj} \right)^{-\theta_j} \left(A_{mj} \right)^{\theta_j \gamma_{mj}}} \tag{2.3}$$

$$w_{nj} = \frac{\gamma_{nj} \left(1 - \xi_n \right)}{L_{nj}} \sum_{i=1}^{N} \pi_{ij,nj} X_{ij} \tag{2.4}$$

where X_{ij} denotes total expenditure of region i on good j, and $\pi_{ij,nj} X_{ij}$ represents the corresponding expenditure on goods produced in region n. Under symmetric bilateral trade costs, Firm Market Access (FMA) is proportional to Consumer Market Access (CMA) up to a constant $\rho > 0$: $MA_{nj} = FMA_{nj} = \rho\, CMA_{nj}$. Consequently, any change in fundamentals that reduces firms' market access will likewise lower consumers' market access.[7] Here, Firm Market Access (FMA) measures the ability of firms in market nj to sell their output competitively across regions. Combining equations

[7] This proportionality is established in Donaldson and Hornbeck (2016) and discussed in Redding (2022). In a broad class of quantitative spatial models, as long as bilateral trade costs are symmetric, FMA and CMA are strictly proportional: the ease with which firms sell across markets mirrors that of consumers sourcing from them.

(2.1), (2.3), and (2.4), we obtain our main measure of market access:

$$MA_{nj} = \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} \left(\frac{MA_{nk}}{\rho}\right)^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \cdot \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}}{\rho}\right)^{-1} X_{ij} \tag{2.5}$$

Proof. see appendix A.2. □

where $\varrho = \rho^{-1} \cdot \prod_{k=1}^{J} \rho^{\frac{\gamma_{nj,nk}\theta_j - \alpha_k}{\theta_k}}$ and $M_{ij} \equiv \left[\gamma_{ij}(1-\xi_i) \prod_{k=1}^{J} (\alpha_k)^{\alpha_k}\right]^{-1}$. Equation (2.5) highlights four distinct channels through which shocks affect market access. First, the I-O effect: market access in sector j of region n rises with the market access of all the local sectors, as cheaper intermediate inputs lower production costs. Second, the Competition effect: market access in nj falls when competing region–sectors improve their market access, lowering their prices and diverting demand away from nj. Third, the Consumption effect: the market access of nj increases with the expenditure capacity of nearby regions. Fourth, Centrality / trade-cost effect: the market access of nj decreases with bilateral trade costs $k_{ij,nj}$. Higher trade costs increase the price of nj products, reducing competitiveness and raising the price index, which worsens consumer welfare. Also, how much the twin effects of the destination markets ij - competition effect and consumption effect - will affect market nj depends upon the inverse of the trade cost between ij and nj.

There are two key differences between our measure of market access and the standard formulation in the literature, as shown in the market access in Allen and Arkolakis (2023) ($MA_i = \sum_j T_{ij} \frac{Y_j}{MA_j}$). First, our measure is defined at the region–sector level, whereas the literature typically adopts a region-level measure. This greater granularity allows us to capture a more localized affect of a trade shock. Second, our measure incorporates an additional term (highlighted in green in equation 2.5) that captures inter-sectoral linkages. This extension enables us to distinguish labor market effects operating through cross-sectoral linkages from those operating through inter-regional trade linkages.

2.2 Structural equations

We now establish the link between market access and labor demand. Combining the price index (2.1), the expenditure share (2.3), and the labor market clearing condition (2.4), we derive the following relationship between wages and market access:

$$(w_{nj})^{1+\theta_j\gamma_{nj}} = \varkappa_1 \frac{(H_{nj})^{\theta_j\gamma_{nj}\xi_n} (A_{nj})^{\theta_j\gamma_{nj}}}{(L_{nj})^{1+\theta_j\gamma_{nj}\xi_n}} \cdot MA_{nj}. \tag{2.6}$$

Proof. see appendix A.1. □

where $\varkappa_1 \equiv \gamma_{nj}\xi_n (B_{nj})^{\theta_j}$ is a constant. The wage in region-sector nj is increasing in its own market access. Log-differentiating equations (2.6), (2.5), and defining $\hat{x} \equiv \Delta \log x = \frac{\Delta x}{x}$, we obtain the labor demand equation:

$$\hat{w}_{nj} = \frac{\theta_j \gamma_{nj}}{1+\theta_j\gamma_{nj}}\hat{A}_{nj} - \frac{1+\theta_j\gamma_{nj}\xi_{nj}}{1+\theta_j\gamma_{nj}}\hat{L}_{nj} + \frac{1}{1+\theta_j\gamma_{nj}}\hat{MA}_{nj} \tag{2.7}$$

$$\hat{MA}_{nj} = \underbrace{\sum_{k=1}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k}\hat{MA}_{nk}}_{\text{Input-Ouput}} + \underbrace{\sum_{i=1}^{N} \alpha_{ij,nj}\left(\hat{X}_{ij} - \hat{MA}_{ij} - \theta_j \hat{k}_{ij,nj}\right)}_{\text{Spatial Competition \& Demand}} \tag{2.8}$$

Proof. see appendix A.1 and A.3. □

where $\alpha_{ij,nj} \equiv \frac{\pi_{ij,nj}X_{ij}}{\sum_l \pi_{lj,nj}X_{lj}}$ denotes the share of shipments in sector j produced in region n and sold to region i, relative to total shipments of sector j produced in n (i.e., exports from n to i relative to all exports from n). Equation (2.7) represents the labor demand schedule, which implies a negative relationship between wages and labor demand, and includes both local and global shifters. The change in the fundamental productivity term $\hat{A}_{nj}$ shifts the labor demand curve outward, as workers in market nj become more productive. However, this is a *local* shifter, since higher productivity in market nj affects only the demand for labor in that specific market. In contrast, changes in market access act as a *global* shifter: an increase in market access raises labor demand through sectoral and regional interlinkages within the economy. The Input–Output term in equation (2.8) corresponds to the green term in equation (2.5), while the spatial competition and demand effects correspond to the competition, centrality, and consumption components in equation (2.5). Hence, changes in market access shift labor demand not only through local mechanisms but also through global spillovers from connected labor markets. Using equations (2.7) and (2.8), the labor demand in region n and sector j can be written as:

$$\hat{L}_{nj} = -\frac{1+\theta_j\gamma_{nj}}{1+\theta_j\gamma_{nj}\xi_n}\hat{w}_{nj} + \frac{\theta_j\gamma_{nj}}{1+\theta_j\gamma_{nj}\xi_n}\hat{A}_{nj} + \frac{1}{1+\theta_j\gamma_{nj}\xi_n}\hat{MA}_{nj} \tag{2.9}$$

Equation (2.9) and (2.8) show that an aggregate shock affect employment through changes in market access. These effects operate both directly, within the region-sector, and indirectly, via inter-regional and inter-sectoral spillovers. In the model, the elasticity of employment in sector j and region n with respect to market access is decreasing in the share of immobile structures ξ_n, in the trade elasticity θ_j, and in the sector's value-added share γ_{nj}. Intuitively, market access expands the effective market for local firms, raising labor demand, but this effect is dampened when production is constrained by fixed structures, larger value added share, or higher trade sensitivity. Overall, this elasticity summarizes how sectoral structure, trade responsiveness, and frictions jointly shape labor adjustments to exogenous changes in market access. When either $\xi_n = 0$ or $\gamma_{nj} = 0$ the elasticity equals one, reflecting full adjustment of employment to market access in the absence of fixed assets.[8]

At last, we derive how a direct trade shock affects market access in each region–sector. To do so, we temporarily abstract from spatial linkages and solve equation (2.8) such that only the market access of region nj responds to the Chinese import shock.[9] The resulting expression is:

$$\hat{MA}_{nj} = \frac{1}{c'_{nj}} \underbrace{\alpha_{Cj,nj} \left(\hat{X}_{Cj} - \hat{MA}_{Cj,mj} - \theta_j \hat{k}_{Cj,nj} \right)}_{\text{Chinese Import Shock}} + \underbrace{\alpha_{nj,nj} \left(\hat{X}_{nj} - \theta_j \hat{k}_{nj,nj} \right)}_{\text{Change in Home Consumption}} \tag{2.10}$$

Proof. see appendix A.4. □

where the subscript C refers to China, and c'_{nj} is a constant.

3 From Theory to Empirics

We now describe the construction of our global response measure of the China Shock and specify the estimating equations. First, we predict changes in labor markets' Import Penetration per Worker (IMW) from China to the U.S. using changes in imports from China to other developed countries, computing Autor et al. (2013)'s measure at the region-sector level:[10] The estimating equation is

$$\Delta IMW_{nj}^{US} = \eta_1 \cdot \Delta IMW_{nj}^{Other} + \epsilon_{nj} \tag{3.1}$$

where IMW_{nj}^{US} denotes Chinese imports to the U.S. per worker, and IMW_{nj}^{Other} is the instrumental variable based on imports to other developed countries, as detailed in Section 4. This captures the effect that has been well known in the literature at the level of the commuting zone. Since our objective is to capture how labor demand shifts effect employment through movements in the market access - as theoretically shown in the previous section - we will estimate the link between the china shock and market access first. After imposing the assumption of constant trade imbalances

[8]The final change in the employment level will depend upon the shape of labor supply curve. If the supply curve is flat, then any increase in market access which shifts the labor demand curve outward will one to one translate into higher employment. This would happen if the labor is perfectly mobile across sectors and regions (indicating wage equalization). If however the labor supply curve is upward sloping, then an outward shift in labor demand curve will not entirely translate to an increase in employment. Rather some of it will be arrested by wage increase. In the extreme case of inelastic aggregate labor supply for a given market nj, all the shift will be absorbed by wages and no change in employment. In Caliendo et al. (2019), the model dynamics introduced via frictional labor market results in an upward sloping labor supply. In our paper, we will empirically measure how much actual employment response to shifts in market access induced by the China shock.

[9]We adapt the methodology from the Online Theory Appendix of Autor et al. (2013) to our market-access framework. While Autor et al. (2013) focus on the price index, we instead use its inverse—market access.

[10]Note that Autor et al. (2013) run regression at the CZ level for the aggregate manufacturing sector and hence an additional subscript j will appear in all our regressions indicating sector for each commuting zone.

and constant export margins,[11] equation (2.10) results in the following estimating equation:

$$\Delta MA_{nj} = \gamma_1 \cdot \widehat{\Delta IMW}_{nj} + \epsilon_{nj} \tag{3.2}$$

where $\widehat{\Delta IMW}_{nj} \equiv \widehat{\eta}_1 \Delta IMW^{Other}_{nj}$ are the predicted values from equation (3.1). The predicted change in market access in equation (3.2), $\widehat{\Delta MA}_{nj}$, captures only the *local* effect of the trade shock. However, the total change in demand in a local labor market also reflects *regional* and *sectoral* spillovers. To account for these spillovers, we incorporate (i) *spatial linkages* across regions—through domestic trade connections—and (ii) *input–output linkages* across sectors, through production interdependencies. Using the expression for changes in market access from equation (2.8), we structurally capture the indirect effects on region n and sector j arising from changes in market access in all other regions and sectors. The resulting *Global Response (GR)* variable—constructed under the assumption of constant export margins and domestic trade costs—is therefore:

$$GR_{nj} = \underbrace{\sum_{k}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{\Delta MA}_{nk}}_{\substack{\equiv IO_{nj} \\ \text{Input-Output term} \\ \text{Same region, other sectors}}} - \underbrace{\sum_{i}^{N} \alpha_{ij,nj} \widehat{\Delta MA}_{ij}}_{\substack{\equiv SC_{nj} \\ \text{Spatial Competition term} \\ \text{Other Regions, same sector}}} \tag{3.3}$$

where $\widehat{\Delta MA}_{nk} \equiv \widehat{\gamma}_1 \widehat{\Delta IMW}_{nk}$ and $\widehat{\Delta MA}_{ij} \equiv \widehat{\gamma}_1 \widehat{\Delta IMW}_{ij}$ are the predicted changes in market access from equation (3.2). The constructed global response term in equation (3.3) for region n and sector j depends positively on the change in market access summed across all other sectors that provide material inputs (IO_{nj} term). This positive relation reflects that lower input prices in upstream sectors reduce the production costs in sector j, weighted by the input shares in the production function ($\gamma_{nj,nk}$). The second term captures the competition effect within the same sector j. When market access in other regions for sector j increases, it intensifies competition, which reduces domestic labor demand in that sector. This effect is weighted by the share of region n's exports going to region i relative to total exports from n ($\alpha_{ij,nj}$). Consequently, if region i represents a large share of region n's exports, any changes in market access in region i have a greater impact on region n's sales.

We distinguish between the following three estimating equations, which together with equation 3.2 allow us to derive the general equilibrium (GE) effect of the China Shock:

$$\textit{Partial Equilibrium (PE):} \quad \Delta L_{nj} = \delta_1 \cdot \widehat{\Delta IMW}_{nj} + \delta_2 X'_{nj} + \epsilon_{nj} \tag{3.4}$$

[11] Here again we adapt the methodology in the Online Theory Appendix of Autor et al. (2013) to our Market Access environment.

$$\textit{GE without spillovers:} \quad \Delta L_{nj} = \phi_1 \cdot \widehat{\Delta MA}_{nj} + \phi_2 X'_{nj} + \epsilon_{nj} \tag{3.5}$$

$$\textit{GE with spillovers:} \quad \Delta L_{nj} = \beta_1 \cdot GR_{nj} + \beta_2 X'_{nj} + \epsilon_{nj} \tag{3.6}$$

The first equation (3.4) estimates the partial equilibrium effect of the China Shock, with δ_1 capturing the reduced-form impact—equivalent to the approach of ADH, but at a more granular level.[12] The partial equilibrium effect captures changes in employment directly induced by the China Shock. To move beyond these direct effects, we first estimate how the China Shock affects local market access (equation 3.2). Since market access in a given market also influences connected regions and sectors, we then estimate the resulting general equilibrium effects, including both local and spillover impacts with equation (3.6).

Since market access is a sufficient statistics for equilibrium employment and wages, ϕ_1 in equation (3.5) reflects the local GE effect (i.e., the effect of changes in local goods and factor market prices) of the China Shock. It is however only local as we are not yet accounting for the spatial propagation of the shock. The vector X'_{nj} contains a rich set of controls for CZs-sector's start-of-decade labor force and demographic composition that might independently affect manufacturing employment. Standard errors are clustered at the state level to account for spatial correlations across CZ.

Coefficient Interpretation: PE vs. Local GE Past studies have focused on estimating variants of equation (3.4) which captures the partial-equilibrium effect of import competition on local employment (δ_1). As a first step in capturing the general equilibrium effect, Equation (3.5) estimates the *local GE effect* ϕ_1, i.e., the employment response to the China shock but before spatial spillovers. In Appendix A.5 we show the econometric link between the local general equilibrium effect and partial equilibrium effect -

$$\phi_1 = \frac{\delta_1}{\gamma_1}, \tag{3.7}$$

where γ_1 is the first-stage coefficient relating the import shock to market access (equation 3.2). This ratio corresponds to the standard indirect least squares (ILS) representation of 2SLS with a single instrument—the reduced-form effect divided by the first-stage effect—which holds even in the presence of co-variates (Angrist and Pischke, 2009, Chapter 4, fn. 6).

Proposition 1. *Once the regressors are standardized, the absolute value of the magnitudes of the reduced-form and 2SLS coefficients are identical :* $\delta_1^{\text{std}} = \phi_1^{\text{std}}$.

Proof. See Appendix A.5 □

Economically, ϕ_1 measures the employment response per unit of market access induced by the shock, rather than per unit of import penetration. The equality in equation (3.7) implies that ϕ_1

[12] Commuting-zone × sector instead of Commuting zone only

is mechanically determined by δ_1 and γ_1, though the latter two coefficients have distinct interpretations - the first captures the effect of the china shock on employment and the second captures the effect of the china shock on market access. Since both are driven by the same exogenous variation in Chinese exports, the choice of metric does not affect the substantive interpretation of the standardized coefficients for PE and local GE effects.

Coefficient Interpretation: Local GE vs. GE with spillovers Equation (3.6) captures the full general-equilibrium effect of the China shock, including both local adjustments and spatial spillovers. The coefficient β_1 therefore measures the employment response to the shock when (i) local goods and factor prices adjust and (ii) spillovers from other regions and sectors are accounted for. This global effect can be written as

$$\beta_1 = \frac{\phi_1 \cdot SPE}{\delta_1}, \tag{3.8}$$

where it is a composition of SPE (*Spatial Propagation Effect*) which summarizes how exogenous variation in imports elsewhere translates into local labor-market outcomes, local GE and PE effects. Formally,

$$SPE \equiv \frac{\mathrm{Cov}\big(\Delta L_{nj},\, SP_{nj}\big)}{\mathrm{Var}\big(SP_{nj}\big)}, \qquad SP_{nj} \equiv \sum_{k=1}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{\Delta IMW}_{nk} - \sum_{i=1}^{N} \alpha_{ij,nj} \widehat{\Delta IMW}_{ij},$$

and Appendix A.6 provides the derivation. Intuitively, SP_{nj} aggregates direct and indirect exposure to the China shock through input–output and trade linkages, while SPE measures the strength of the transmission from that indirect exposure into local employment. Equation (3.8) highlights the three-step ladder from partial equilibrium to global GE. The numerator, $\phi_1 \times SPE$, captures the local GE effect per unit of propagated exposure; dividing by δ_1 provides a mechanical rescaling to relate the global effect to the original partial-equilibrium exposure. Thus β_1 equals the local GE effect (market-access channel) amplified or attenuated by the spatial-propagation mechanism.

Finally, in standardized terms the scale differences drop out and the coefficients δ_1^{std} and β_1^{std} are directly comparable:

$$\begin{aligned} \beta_1^{std} &= \frac{\phi_1 \cdot SPE}{\delta_1} \cdot \sigma_{GR} = \\ &= \pm\, SPE \cdot \sigma_{SP|\sigma_{\Delta IM}} \end{aligned} \tag{3.9}$$

since $\sigma_{GR} = \left|\frac{\delta_1}{\phi_1}\right| \cdot \sigma_{SP|\sigma_{\Delta IM}}$ as shown in Appendix A.7. Hence β_1^{std} and the reduced-form analogue δ_1^{std} are directly comparable: the former measures the effect of a one–standard-deviation import shock propagated across space on local employment, while the latter measures the non-propagated localized partial e effect.

4 Data and Variable Construction

The unit of analysis for the regressions is the 722 US commuting zones by 22 broad sectors. The commuting zone boundaries are a cluster of counties created by Tolbert and Sizer (1996) based on the commuting data in the 1990 census. We use the 722 of the 741 clusters which are used in Autor et al. (2013). The 22 sectors are classified according to the North American Industry Classification System (NAICS) which includes 12 tradable sectors and 10 non-tradable sectors as used by Caliendo et al. (2019) (see Appendix C for the list of sectors included). We use the years 2000 and 2007 for the two periods in our analysis which allows us to study the market access and labor market outcomes before and after China's entry into WTO in the year 2002.

4.1 Labor Market Outcomes and the China Shock

The County Business Pattern 2000 reports employment by county and industry for 6-digit NAICS codes and the distribution of firm sizes over 9 establishment size classes[13]. CBP is an annual data series that provides information on employment, firm size distribution, and payroll by county and industry. It covers all U.S. employment except self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees. We impute employment by county by 4-digit SIC code using the procedure outlined in the online appendix of Autor et al. (2013) (page 3-4). In order to map NAICS to SIC codes, we use a weighted crosswalk based on the Census "bridge" file (available for download from David Dorn's webpage here). Our empirical analysis also uses data on changes in commuting zone's population, employment, and wage structure by education, age, and gender. Their measures are based on data from the Census Integrated Public Use Micro Samples for the year 2000 and the American Community Survey (ACS) for 2006 through 2008[14]. The 2000 Census samples include 5 percent of the U.S. population while the pooled ACS for 2006 through 2008 uses 3 percent of the U.S. population which we use for our measure of 2007. Our sample of workers consists of individuals who were between age 16 and 64 and who were working in the year preceding the survey. Residents of institutional group quarters such as prisons and psychiatric institutions are dropped along with unpaid family workers. Labor supply is measured by the product of weeks worked times usual number of hours per week. For individuals with missing hours or weeks, labor supply weights are imputed using the mean of workers in the same education-occupation cell, or, if the education-occupation cell is empty, the mean of workers in the same education cell. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight. The computation of wages excludes self-employed workers and individuals with missing wages, weeks or hours. Hourly wages

[13]Available at https://www.census.gov/programs-surveys/cbp.html

[14]Available at https://www.census.gov/programs-surveys/acs/microdata.html

are computed as yearly wage and salary income divided by the product of weeks worked and usual weekly hours. Top-coded yearly wages are multiplied by a factor of 1.5 and hourly wages are set not to exceed this value divided by 50 weeks times 35 hours. Hourly wages below the first percentile of the national hourly wage distribution are set to the value of the first percentile. Wages are inflated to the year 2007 using the Personal Consumption Expenditure Index. We map these data to CZs using the matching strategy that is described in detail in **?**. We aggregate the corresponding county and census data at the level of 722 commuting zones for each of the 22 sectors.

We construct the import shock as in Autor et al. (2013) except that our shock is at the sectoral level. For that, we use the 3-digit SIC level trade flow between China and the US and aggregate it to the 12 NAICS level industries. The import shock per worker (IMW) in sector j and commuting-zone n thus constructed is represented as

$$\Delta IMW_{nj}^{US} = \frac{L_{njt-1}}{L_{ujt-1}} \frac{\Delta M_{ucjt}}{L_{nt-1}} \tag{4.1}$$

where n is the commuting zone, j is the NAICS industry, M_{uc} indicates imports from China to the US. As in Autor et al. (2013), we instrument it using imports by other rich countries from China such that

$$\Delta IMW_{nj}^{Other} = \frac{L_{njt-1}}{L_{ujt-1}} \frac{\Delta M_{ocjt}}{L_{nt-1}} \tag{4.2}$$

and we source the import data from Autor et al. (2013)'s paper.

4.2 Estimation of Trade costs

To quantify the theoretical measure of market access from equation (2.5), we solve the model in levels, implying the knowledge of the trade costs parameter matrix, which is of $N \times N \times J$ dimension (with $N = 722$ being the total number of US CZs and $J = 22$ being the broad sectors). To reduce computational issues, we micro-found the geographic component following Allen and Arkolakis (2014). We use the highway, railroad and waterway networks for the years 2000 and 2010.[15] To run gravity regressions at the CZ-sector by mode to estimate region-sector trade costs, we use the Commodity Flow Survey (CFS), which offer bilateral trade flows across CFS areas. However, the CFS does not provide information on trade flow data at the CZ-sectoral level by mode of transport (train, air, boat, truck). To overcome this issue, and after mapping CFS to CZ, we approximate the share by mode of each CZ with the one for the US, keeping it constant across CZs.[16]

We briefly outline the procedure used to estimate sectoral iceberg trade costs here, while Ap-

[15]We use infrastructure data from 2010 because data for 2007 are not available. Furthermore, since the waterway network remained essentially unchanged between 2000 and 2010, we also use the 2010 data for the year 2000 in order to account for ports in both years.

[16]To test how strong this assumption is, we plan to aggregate estimated sectoral flows of each CZ by sector and compare them to the CZ flows by mode available in the CFS data.

pendix B provides additional details and compares our estimates to the aggregate estimates in Allen and Arkolakis (2014). First, we create PNG images of the infrastructure networks of the US for the years 2000 and 2010.[17] For the year 2000, we use the infrastructure network images created by Allen and Arkolakis (2014). They estimate trade costs using the railroad, highway, and waterway networks, to which we add ports. We create our own images for the year 2010 (see images B.1a and B.1b). The image size is 1452×991[18] pixels.

Second, we estimate the bilateral trade costs function $k_{ij,nj}$ corresponding to equation (B.2) in Appendix B.2. To do so, we first estimate the bilateral mode-specific distance $d_m(i, j)$ using the FMM algorithm.[19] We upload the geographic coordinates of the centroid of US CZs. We then convert the longitude and latitude of the network images to coordinates of the pixels to overlap the centroid and infrastructure network images. Then, we estimate the cost via each mode of travel from every origin to every destination, which we refer to as the normalized mode-specific distance $d_m(i, j)$. To do so, we assign an instantaneous cost function τ_m to each mode m. This involves assigning a relative speed value to each transport mode, so that a pixel containing a specific infrastructure will have a specific instantaneous trade cost (see details in appendix). Second, we apply the FMM algorithm for any origin-destination pair to compute the normalized mode-specific distance $d_m(i, j)$, which consists of the sum of instantaneous trade costs along the shortest path between i and j across different modes of transport. It is normalized since we assume that the width of the US in a straight line is equal to one using mode m.

Using estimates of mode-specific bilateral distances, we determine the relative cost of trade across different modes of transport by sector, and compute the average sectoral geographic iceberg trade costs, $k_g^{ij,nj}$, incurred when shipping goods from region i to region j, based on the discrete choice framework developed in Allen and Arkolakis (2014) which we apply to each sector. We then define total iceberg trade costs, $k_{ij,nj}$, as the sum of geographic trade costs ($k_g^{ij,nj}$)—estimated using infrastructure networks—and non-geographic trade costs ($k_g^{ij,nj}$), such as linguistic or ethnic similarity. To estimate the sectoral shape parameters in equation (B.2), we employ a gravity model using CFS trade flow data from 2007. Due to data availability, we use this to estimate trade costs for both the year 2000 and 2010. This allows us to estimate total iceberg trade costs, $k_{ij,nj}$, for both 2000 and 2007.

Appendix B provides plots of our estimated trade costs and the sectoral shape parameters, as well as kernel density estimates of $k_{ij,nj}$, which we use to compute market access in the next section 4.3.

[17]Despite CFS flows are for 2007, we take infratructures from 2010 as they are not available for year 2007.

[18]Allen and Arkolakis (2014) use pixel images of size 1032×760.

[19]Allen and Arkolakis (2014) provides a code which we modify to fit our analysis. While they compute trade costs at the county level for the year 2000, we estimate them at the CZ-sector level for the years 2000 and 2010.

4.3 Estimation of Market Access

Having the estimates of the trade costs, we can construct market access using equation 2.5, reported here for simplicity

$$MA_{nj} = \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} \left(\frac{MA_{nk}}{\rho}\right)^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \times \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}}{\rho}\right)^{-1} \boldsymbol{X_{ij}}$$

which require information on trade costs ($k_{ij,nj}$) and sectoral expenditures $X_{ij} = \frac{w_{ij}L_{ij}}{\gamma_{ij}(1-\xi_i)}$ which we compute using wage earnings. The parameters we need are the trade elasticity (θ^k) which we take from Caliendo et al. (2019), the share of value added in gross output (γ_{nj}), material input shares ($\gamma_{nj,nk}$) which is constructed using data on value-added, gross output, and intermediate good consumption from the US Input-Output tables. We have 722 x 22 equations for commuting zone and sector combination and we use them to solve for 722 x 22 market access of each commuting zone and sector. We start by solving non-linear set of equations using an iterative algorithm. After we have parameterized the above equation for a given year (2000 or 2007), the algorithm starts with an initial guess of market access ($\text{MA}_{nj}{}^0$), which we set equal to observed wages. This initial guess is then used to update the market access values in the subsequent iteration $\text{MA}_{nj}{}^1$ such as

$$MA_{nj}{}^{1} = \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} \left(\frac{MA_{nk}{}^{0}}{\rho}\right)^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \times \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}{}^{0}}{\rho}\right)^{-1} \boldsymbol{X_{ij}}$$

If the max distance between new MA and the old MA is close enough such that $\max(|\text{MA}_{nj}{}^1 - \text{MA}_{nj}{}^0|) < \text{tol}$ where tol is set to $1e^{-5}$, we stop the iteration in the algorithm. However if this inequality doesn't hold, then the initial guess of market access ($\text{MA}_{nj}{}^0$) is updated such that

$$\text{MA}_{nj}{}^0 = \text{MA}_{nj}{}^0 + \nu(\text{MA}_{nj}{}^1 - \text{MA}_{nj}{}^0)$$

where ν is a small positive number which represent the step iteration parameter and we set it to 0.05. We gain convergence for the system of equations in under 150 iterations.

5 Descriptive Evidence

5.1 Spatial Representation of Market Access and the China Shock

We begin by analyzing our measure of Market Access estimated in Section 4.3. Panels (a) and (b) of Figure 1 display the spatial distribution of U.S. commuting zones (CZs) in 2000 and 2007, respectively. Although our measures are at the CZ–sector level, the figures show averages across sectors for each CZ. According to our estimates, CZs with the highest market access in 2000 are concentrated along the West Coast, particularly in California, as well as in major metropolitan areas on the East Coast such as New York and Florida. The Midwest, including metropolitan areas like Chicago, also exhibits relatively high market access. A distinct geographic boundary extends from San Antonio, Texas, to western Minnesota. Market access is relatively high to the east of this line—including the Midwest—but decreases immediately to the west of it, before rising again toward the West Coast, where California and other coastal areas reach peak market access. Perhaps not surprisingly, Market Access in 2007 (Panel b) is visually highly correlated with Market Access in 2000 (Panel a). Figure 2 confirms this persistence, with values closely aligned along the black dashed 45-degree line. Notably, the estimated correlation slightly exceeds 1, indicating that inequality in market access across CZs increased during this period.

Despite the strong persistence of market access over the period, Figure 3 maps the average change in market access at the CZ level between 2000 and 2007. Since our data are at the CZ–sector level, we first average market access changes across sectors within each CZ to construct this spatial map. Red areas indicate CZs where market access contracted on average, while green areas show expansions. Most commuting zones experienced an expansion in market access during this period, with contractions concentrated primarily in the Midwest, Northeast, and South. Importantly, this measure captures general equilibrium adjustments to the full range of shocks affecting U.S. labor markets over the period, including the China Shock. As shown in panel (a) of Figure 4, the CZs experiencing the largest contractions in market access correspond closely to those most directly exposed to the China Shock. This maps show predicted exogenous changes in import penetration per worker between 2000 and 2007, estimated from equation (3.1) and averaged across sectors at the CZ level. The regions with the greatest market access contractions largely overlap with those experiencing the highest import penetration increases, notably around the Rust Belt and the South. However, this relationship is not one-to-one; some regions heavily exposed to import penetration nonetheless saw expansions in market access over the period.

Panel (b) presents our estimated global response function to the China Shock from equation (3.3). As detailed in Section 2, this global response isolates the overall change in market access induced by the China Shock during the period. The figure shows that, on average, the general equilibrium effect of the China Shock led to an expansion of market access across U.S. commuting zones (CZs). However, this aggregate picture conceals important sectoral heterogeneity (see Panels A and B in Table 1), where some sectors within CZs contract while others expand. Crucially, although the China Shock induces an overall increase in China-Shock-induced changes in market access (the global response), this does not necessarily translate into increased employment, as we will show in the result Section 6.

Panels (a) and (b) of the figure 5 decompose the global response into its two components: the input-output (IO) and spatial competition (SC) effects, respectively. Table 1 shows that the IO component is on average negative across the pooled sample, as well as in manufacturing and non-manufacturing sectors. This indicates that IO linkages generate negative spillovers across regions, contracting market access. This finding aligns with the downstream IO propagation mechanism: when suppliers lose market access due to the China Shock, their goods become less competitive, which in turn harms their customers. Figure (3.1) panel (a) illustrates that this negative transmission is concentrated in regions directly affected by the shock, with pronounced effects in the Rust Belt. Conversely, the spatial competition component in panel (b) is consistently positive on average across commuting zones, suggesting that as domestic competitors lose market access due to the China Shock, a given CZ experiences an expansion in its own market access. The Southern U.S. benefits most from this channel.[20] This preliminary analysis highlights that the global response reflects the net effect of these two components, with the spatial competition effect generally outweighing the negative IO spillovers. In Section 6, we further investigate whether these general equilibrium expansions in market access correspond to contraction, mitigation, or expansion in manufacturing, non-manufacturing, and aggregate employment at the sector–CZ level.

5.2 Market Access, Trade Costs, and Labor Market Outcomes

Table 3 summarizes market access across industries in the year 2000 and the change between 2000 and 2007, as estimated in Section 4.3. On average, industries in the manufacturing sector have higher market access, whereas service-related industries have lower market access. This is largely because manufacturing consists of tradable industries which, through regional trade links, achieve substantially greater access to markets. By contrast, the non-tradability of most service sector industries results in lower market access. Table 3 also reports the change in market access across sectors between 2000 and 2007. For most manufacturing industries, market access contracts, while it expands for most service-based industries. Textiles, Computers, Plastics, Wood, and Machinery experience the largest contractions. Although these variations in market access are not due solely to the China shock, it is worth noting that the goods most exposed to Chinese competition include luggage, rubber and plastic footwear, games and toys, apparel, textiles, furniture, leather goods, electrical appliances, and jewelry. Unsurprisingly, these goods belong to the three industries that experienced the largest decrease in market access during the reference period. By contrast, Education, Finance, Accommodation and Food, Health, and Wholesale Trade services expanded the most in the service sector. Part of this expansion may reflect the relocation of workers displaced by trade-related shocks. For instance, as shown in (Ferriere et al., 2018), households more exposed

[20]Note that the domestic competition component is identical for all CZs within the same state because it is computed using state-level export shares from 2000. This approach averages exposure across input sectors with identical weights, resulting in uniform exposure for sectors within CZs of the same state. An alternative would be to use export shares from the CFS data, but these are only available for 2007, which introduces endogeneity concerns.

to the China shock tend to spend additional years in college as the wage premium for high-skilled jobs rises. Moreover, given the growing importance of trade (both domestic and international), it is consistent that the largest expansion in market access is observed for the wholesale trade industry.

We next examine the correlations between our estimates of market access and the average trade costs computed in Section 4.2. Columns 1 and 2 of Table 4 report the coefficients from a regression of market access on average trade costs in each commuting zone. A negative coefficient confirms that commuting zones with higher trade costs exhibit lower estimated market access. Equation 2.5 illustrates that when a region is farther from other regions (higher κ), its access to those markets is limited, thereby lowering overall market access. Thus, more remote regions, characterized by higher bilateral trade costs, experience reduced market access. These negative relationships hold for both years in our analysis. Our estimated measure of market access is also correlated with employment across commuting zones, indicating that our estimates are robustly associated with labor market outcomes. Columns 3 and 4 of Table 4 report the correlations between market access and employment. The positive coefficients suggest that commuting zones with larger labor markets are also those with higher estimated market access. These relationships are consistent in both 2000 and 2007, reinforcing that our market access measure passes a basic validity check through positive correlations with employment.

6 Results

In this section, we examine the empirical relationships among our key variables, focusing first on 12 manufacturing sectors across 722 U.S. commuting zones. We first document a strong negative relationship between market access and exposure to the China shock. We then estimate the partial equilibrium effect of the China shock on manufacturing employment as a benchmark, before turning to our global response measure, which captures the full general equilibrium adjustment including spatial spillovers. Finally, we explore heterogeneity in the effects by extending the analysis to the pooled sample (manufacturing and services), the service sector alone, and worker characteristics.

6.1 Market Access and the China Shock

Before analyzing the relationship between market access and the China shock, we first establish the validity of our instrument. Table 5 reports the relationship between U.S. imports from China and Chinese exports to other developed economies using equation (3.1). The two series are strongly correlated: an increase of about USD 350 in Chinese exports to other developed economies is associated with a USD 432 increase in Chinese exports to the United States.

We then estimate the effect of the China shock on the market access of U.S. local labor markets. Specifically, we estimate equation (3.2) for 722 commuting zones across 12 tradable sectors, with results reported in Table 6. Column 1 presents the OLS estimate: a one–standard-deviation increase in local exposure to Chinese imports (≈ USD 440 per worker) reduces market access by approximately 109 units. The IV results, reported in column 2, imply that a one–standard-deviation increase in exogenous import exposure (≈ USD 430 per worker) leads to a 107-unit decline in market access. To put this in perspective, the average change in market access across U.S. labor markets between 2000 and 2007 was 71 units (SD = 483, see Table 1). A one–standard-deviation increase in exposure to Chinese imports reduces market access by 107 units, exceeding the typical change, highlighting a substantial first-order effect on local market access.

This decline in market access reflects a general-equilibrium effect. Although Chinese imports lower the price of directly competing goods, the contraction of domestic suppliers raises prices for other goods in the consumption basket, especially when imports and local varieties are imperfect substitutes. Since market access is inversely related to the aggregate price index, the net effect of import competition is an increase in local price indices, even though imported goods themselves are less expensive.

6.2 The Partial vs. General Equilibrium Effect of the China Shock on Manufacturing Employment

We begin with tradable industries directly affected by the China shock—the manufacturing sectors. Column 1 of Table 7 reports the effect of the shock on the U.S. labor market (CZ-sector pair), corresponding to the estimation of equation (3.4). A one–standard-deviation increase in exogenous imports per worker (≈ USD 430) reduces the manufacturing employment share by 0.33 percentage points. This magnitude is very similar to the estimates reported by Autor et al. (2013) at the commuting-zone level.[21]

In column 2, we report the estimate of equation (3.5), which isolates the local GE effect ϕ_1, i.e., the employment response to the China shock after local goods and factor prices adjust but before spatial spillovers. Because Table 7 reports results using standardized regressors, the coefficients in columns 1 and 2 have the same magnitude (see Section 3).[22] A one–standard-deviation increase in China-shock-induced changes in market access reduces employment by 0.33 percentage points. Since a one–standard-deviation increase in Chinese imports per worker actually reduces market access by roughly 103 units, even a positive coefficient on market access translates into a net contraction in employment. In raw units, the non-standardized ϕ_1 coefficient is 0.0032, implying that a one-unit decrease in market access induced by the China shock reduces employment by 0.0032 percentage points; multiplied by 103, this yields roughly 0.33. Economically, this does not imply that the

[21] In column 2 of their Table 2, ADH report a coefficient of 0.72 for a USD 1000 increase in Chinese imports (2000–2007). Scaling to a USD 430 increase yields roughly 0.31 p.p., consistent with our estimate both with and without controls.

[22] Unstandardized coefficients would, of course, differ in magnitude.

partial-equilibrium and local general-equilibrium effects are identical: the similarity in magnitudes is an artifact of how market-access changes are constructed and scaled. Conceptually, the local GE effect captures the response to changes in market access per unit of exposure, not a direct one-to-one mapping from imports to employment.

We next move to column 3, our main specification. As illustrated in equation 3.3, changes in market access can propagate across labor markets through input–output linkages or trade linkages. Hence, when we regress employment shares on the global response term, we capture both the partial effect and the spatial propagation effect of the China shock. Accounting for spillovers, the effect on employment shares falls by 2.5 times—from 0.33 p.p. (δ_1) to 0.13 p.p. (β_1^{std}). Since our coefficients are standardized, the coefficient β_1^{std} estimated correspond to equation 3.9, that is, minus the spatial propagation effect (SPE) multiplied by the standard deviation of the spatial propagation term. The bottom panel of Table 7 reports the SPE. Under this specification, the employment decline is substantially attenuated—by 0.13 percentage points. This suggests that, despite the strong and negative direct effect of the shock, general equilibrium adjustments and spatial propagation mitigate contractions in manufacturing employment shares. Overall, this reduces the employment losses predicted in Autor et al., 2013 from 1.5 million to about 0.7 million.

6.3 Mechanism: Input–Output vs. Domestic Spatial Competition

To understand the mechanisms mitigating losses from the China shock, we decompose the global response into two components: the input–output (I–O) effect and the trade spillover effect. Propagation through I–O linkages occurs when upstream suppliers contract in response to rising Chinese import competition, their downstream customers face higher prices or input shortages. Trade spillovers operate differently: when firms in one commuting zone exit due to import competition, demand shifts either to Chinese imports or to close domestic substitutes. With incomplete substitution toward Chinese goods, firms in less-exposed zones expand sales to replace lost output, dampening aggregate employment losses.

We separate these channels empirically and report the standardized coefficients β_1^{std} in the top panel of Table 8. Translating them into spatial propagation effects (bottom panel), we find that trade spillovers mitigate manufacturing employment losses by 0.105 p.p., while I–O linkages exacerbate them by 0.107 p.p. The I–O result echoes Acemoglu et al. (2016), who show that upstream linkages in particular amplified contractions, while downstream effects were ambiguous. Since the aggregate spatial propagation effect is positive (Table 7), trade spillovers dominate I–O spillovers. The similarity in magnitude across the two channels also points to potential nonlinearities: when a labor market is simultaneously exposed through both channels, positive trade spillovers can offset I–O–induced losses. For example, if firms face reduced demand for their inputs, they might expand into other commuting zones affected by the China shock. This is feasible when inputs are combined in a Cobb–Douglas fashion (fixed proportions). However, if goods across commuting zones have CES-type substitution elasticities, changes in relative prices alter consumption shares. Thus, demand contraction due to I–O spillovers may be more than offset by demand expansion elsewhere. Thus, demand contraction due to I–O spillovers may be more than offset by demand expansion elsewhere.

6.4 Non-Tradable Sectors and Local Labor Markets

We now extend the analysis to service-sector industries to estimate their general equilibrium effects. In the service sector, the partial equilibrium effect (δ_1) originates only indirectly, through input–output linkages from manufacturing. Thus, in terms of the global response term in equation 3.3, we focus solely on the input–output component. We report β_1^{std} in the top panel of Table D.7 and the spatial propagation effect in the bottom panel. We find that a one-standard-deviation decline in the global response contracts employment shares in the service sector by 0.10 p.p. This finding contrasts with the counterfactual predictions in Caliendo et al., 2019, which suggest I–O linkages insulate against foreign productivity shocks. Instead, our results show they amplify employment losses. Pooling manufacturing and services (Table D.8), we find the spatial propagation effect remains positive overall, as the employment gains from weakened spatial competition in manufacturing outweigh the losses from I–O linkages.

We further examine heterogeneity by education, sex, nativity, and age demographics. Table 11 reports β_1^{std} and the spatial propagation effect for subsamples in manufacturing and services. In columns 1–2 for manufacturing, the spatial propagation effect mitigates losses for non-college-educated workers twice as much as for college-educated workers (0.05 p.p. vs. 0.024 p.p.). As shown in Autor et al. (2013), non-college workers are more adversely affected initially, but some of their losses are attenuated by weakened spatial competition.

When splitting by sex (columns 3–4), we find little difference: male and female workers experience similar mitigation (0.038 p.p. vs. 0.037 p.p.). Splitting by nativity (columns 5–6), however, reveals large differences: natives see far greater mitigation than immigrants (0.06 p.p. vs. 0.007 p.p.). This is consistent with Autor et al., 2021, which shows that foreign-born workers were less affected by the China shock initially, so mitigation through spatial linkages is concentrated among natives.

Turning to the service sector, I–O linkages amplify losses. In columns 1–2 of the bottom panel of Table 11, non-college-educated workers lose more than twice as much as college-educated workers (0.23 p.p. vs. 0.22 p.p.). Downstream services face reduced demand when upstream manufacturing contracts, and less-educated workers are most affected. Splitting by gender (columns 3–4), male workers are hit 60% more than female workers, consistent with gender differences in wages found in manufacturing (Autor et al., 2013, Table 6). Splitting by nativity (columns 5–6), natives are hit

15 times more than immigrants.

Finally, in Table 12, we analyze heterogeneity by age. In manufacturing, differences are negligible. In services, however, younger workers are affected almost three times more adversely than older workers, underscoring the importance of experience in resilience to trade shocks.

7 Conclusion

This paper investigates the general equilibrium effects of international trade shocks on U.S. local labor markets, with a focus on the China Shock and its impact on market access. By leveraging a model-based measure of market access and constructing a novel instrumental variable to account for exogenous variations in Chinese import exposure, we isolate the causal effect of market access changes on sectoral employment and wages. Our results reveal that increases in market access, driven by the China Shock, are positively associated with employment in manufacturing labor markets and negatively in service labor markets.

The findings underscore the importance of considering general equilibrium effects when assessing the impact of trade shocks. This research contributes to the growing literature on the labor market consequences of globalization, highlighting the complex interplay between trade shocks, market access, and local economic outcomes. Understanding these dynamics is crucial for policymakers seeking to design effective labor market interventions that address the unequal distribution of the benefits and costs of trade liberalization.

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A Theoretical appendix

A.1 Wages and Market Access

Starting from the equilibrium Labor Market Clearing (LMC) condition:

$$w_{nj} = \frac{\gamma_{nj}(1-\xi_n)}{L_{nj}} \sum_{i=1}^{N} \pi_{ij,nj} X_{ij}, \tag{A.1}$$

and using (2.3) along with the definition of CMA (2.1), we can write:

$$w_{nj} = \frac{\gamma_{nj}(1-\xi_n)}{L_{nj}} \sum_{i=1}^{N} \left(x_{nj} k_{ij,nj}\right)^{-\theta_j} \left(A_{nj}\right)^{\theta_j \gamma_{nj}} (CMA_{ij})^{-1} X_{ij}. \tag{A.2}$$

Using the unit price equation (2.2), grouping the "nj" terms outside the sum, and taking wages to the left-hand side with the definition of CMA, we obtain:

$$(w_{nj})^{1+\theta_j\gamma_{nj}(1-\xi_n)} = \varkappa_1 \frac{(r_{nj})^{-\theta_j\gamma_{nj}\xi_n}(A_{nj})^{\theta_j\gamma_{nj}}}{L_{nj}} \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \times \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} (CMA_{ij})^{-1} X_{ij},$$

where $\varkappa_1 \equiv \gamma_{nj}(1-\xi_n)(B_{nj})^{\theta_j}$.

Substituting the structure price $r_{nj} = \frac{\xi_n}{1-\xi_n}\frac{w_{nj}L_{nj}}{H_{nj}}$, we obtain:

$$(w_{nj})^{1+\theta_j\gamma_{nj}} = \frac{\varkappa_1\xi_n}{1-\xi_n} \frac{(H_{nj})^{\theta_j\gamma_{nj}\xi_n}(A_{nj})^{\theta_j\gamma_{nj}}}{(L_{nj})^{1+\theta_j\gamma_{nj}\xi_n}} \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \times \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} (CMA_{ij})^{-1} X_{ij}.$$

The last two terms are defined as Firm Market Access (FMA):

$$FMA_{nj} = \underbrace{\prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}}}_{\text{I-O effect}} \times \underbrace{\sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} (CMA_{ij})^{-1} X_{ij}}_{\text{Competition effect}}.$$

- FMA in region-sector nj is positively related to the CMA of all other sectors k in the same region n (I-O effect): as prices of other sectors' goods decrease, materials for producing good j become cheaper.

- FMA in region-sector nj is negatively related to the CMA of sector j in all other regions (competition effect).

Substituting the definition of Market Access (MA, see Section A.2):

$$(w_{nj})^{1+\theta_j\gamma_{nj}} = \frac{\varkappa_1 \xi_n}{1-\xi_n} \frac{(H_{nj})^{\theta_j\gamma_{nj}\xi_n}(A_{nj})^{\theta_j\gamma_{nj}}}{(L_{nj})^{1+\theta_j\gamma_{nj}\xi_n}} \cdot MA_{nj}. \tag{A.3}$$

The wage in region-sector nj is increasing in its own market access. Given that structures are fixed, taking logs and differentiating gives:

$$\hat{w}_{nj} = \frac{\theta_j\gamma_{nj}}{1+\theta_j\gamma_{nj}}\hat{A}_{nj} - \frac{1+\theta_j\gamma_{nj}\xi_n}{1+\theta_j\gamma_{nj}}\hat{L}_{nj} + \frac{1}{1+\theta_j\gamma_{nj}}\hat{MA}_{nj}. \tag{A.4}$$

Solving for employment:

$$\hat{L}_{nj} = -\frac{1+\theta_j\gamma_{nj}}{1+\theta_j\gamma_{nj}\xi_n}\hat{w}_{nj} + \frac{\theta_j\gamma_{nj}}{1+\theta_j\gamma_{nj}\xi_n}\hat{A}_{nj} + \frac{1}{1+\theta_j\gamma_{nj}\xi_n}\hat{MA}_{nj}. \tag{A.5}$$

A.2 Market Access (equation 2.5)

We derive Market Access $MA_{nj} = FMA_{nj} = \rho CMA_{nj}$.

$$\begin{aligned} MA_{nj} &= FMA_{nj} \\ &= \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \times \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} (CMA_{ij})^{-1} X_{ij} \\ &= \prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} \left(\frac{MA_{nk}}{\rho}\right)^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \times \sum_{i=1}^{N} (k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}}{\rho}\right)^{-1} X_{ij} \end{aligned} \tag{A.6}$$

Recall $X_{ij} = \frac{w_{ij}L_{ij}}{\gamma_{ij}(1-\xi_i)}$, use $C_{ij} = \frac{w_{ij}}{P^i}$, and recall that $P^i = \prod_{k=1}^{J}\left(\frac{P^{ik}}{\alpha_k}\right)^{\alpha_k} = \prod_{k=1}^{J}\frac{(\Gamma^{ik})^{\alpha_k}(CMA^{ik})^{-\frac{\alpha_k}{\theta_k}}}{(\alpha_k)^{\alpha_k}}$, we get:

$$\begin{aligned} MA_{nj} &= \left(\prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}}\right) \times \sum_{i=1}^{N} (k_{nj,ij})^{-\theta_j} (CMA_{ij})^{-1} \frac{w_{ij}L_{ij}}{\gamma_{ij}(1-\xi_i)} \\ &= \left(\prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}}\right) \times \sum_{i=1}^{N} (k_{nj,ij})^{-\theta_j} (CMA_{ij})^{-1} \frac{P^i C_{ij} L_{ij}}{\gamma_{ij}(1-\xi_i)} \\ &= \left(\prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (CMA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}}\right) \times \sum_{i=1}^{N} (k_{nj,ij})^{-\theta_j} (CMA_{ij})^{-1} \prod_{k=1}^{J} (CMA^{ik})^{-\frac{\alpha_k}{\theta_k}} \frac{C_{ij}L_{ij}\prod_{k=1}^{J}\Gamma^{ik}}{\gamma_{ij}(1-\xi_i)} \\ &= \varrho \left(\prod_{k=1}^{J} (\Gamma_{nk})^{-\gamma_{nj,nk}\theta_j} (MA_{nk})^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}}\right) \times \sum_{i=1}^{N} \left(M_{ij}\prod_{k=1}^{J}\Gamma^{ik}\right) (k_{nj,ij})^{-\theta_j} C_{ij}L_{ij} (MA_{ij})^{-1} \prod_{k=1}^{J} (MA^{ik})^{-\frac{\alpha_k}{\theta_k}} \end{aligned} \tag{A.7}$$

where $\varrho = \rho^{-1} \times \prod_{k=1}^{J} \rho^{\frac{\gamma_{nj,nk}\theta_j - \alpha_k}{\theta_k}}$ and $M_{ij} \equiv \frac{1}{\gamma_{ij}(1-\xi_i)\prod_{k=1}^{J}(\alpha_k)^{\alpha_k}}$.

A.3 Log differentiation to obtain equation (2.8)

We start with equation (2.5) and proceed as follow:

$$MA_{nj} = \prod_{k}^{J}(\Gamma_{nk}) \left(\frac{MA_{nk}}{\rho}\right)^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \sum_{i}^{N} (k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}}{\rho}\right)^{-1} X_{ij}$$

$$MA_{nj} = \prod_{k=1}^{J}(\Gamma_{nk}) \left(\frac{MA_{nk}}{\rho}\right)^{\frac{\gamma_{nj,nk}\theta_j}{\theta_k}} \sum_{i}^{N} (k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}}{\rho}\right)^{-1} X_{ij}$$

We now take the log, and differentiate, to obtain (with $\hat{x} = \Delta log(x) = \frac{dx}{x}$):

$$\widehat{MA}_{nj} = \sum_{k=1}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{MA}_{nk} + \sum_{i}^{N} \frac{(k_{ij,nj})^{-\theta_j} \left(\frac{MA_{ij}}{\rho}\right)^{-1} X_{ij}}{\sum_{l}^{N} (k_{lj,nj})^{-\theta_j} \left(\frac{MA_{lj}}{\rho}\right)^{-1} X_{lj}} \left(\widehat{X}_{ij} - \widehat{MA}_{ij} - \theta_j \widehat{k}_{ij,nj}\right)$$

$$\widehat{MA}_{nj} = \sum_{k=1}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{MA}_{nk} + \sum_{i}^{N} \alpha_{ij,nj} \left(\widehat{X}_{ij} - \widehat{MA}_{ij} - \theta_j \widehat{k}_{ij,nj}\right)$$

where in line three we use the fact that , and the export share is $\alpha_{ij,nj} \equiv \frac{\pi_{ij,nj}X_{ij}}{\sum_l \pi_{lj,nj}X_{lj}}$. To go from line 3 to 4, we substitute in for $\frac{MA}{\rho} = CMA = \sum_{i=1}^{N} (x_{ij}\, k_{nj,ij})^{-\theta_j} (A_{ij})^{\theta_j \gamma_{ij}}$ and multiply and divide by the unit cost $((x_{nj})^{-\theta_j})$ and productivity $((A_{nj})^{-\theta_j \gamma_{ij}})$ terms. This way we get the expenditure shares (π) which when multiplied by the total expenditures X, gives us the export shares.

A.4 Market Access and China Shock (equation 2.10)

For sector j, the MA of region n can be directly related to the inverse price index through (see (2.1)):

$$MA_{ij} = \rho CMA_{ij} = \frac{1}{\Gamma_{nj}} \left(\sum_{m=1}^{N} (x_{mj}\, k_{ij,mj})^{-\theta_j} (A_{mj})^{\theta_j \gamma_{mj}} \right)^{-\theta_j} \tag{A.8}$$

Log differentiating (A.8), we get:

$$\widehat{MA}_{ij} = \sum_{m} \phi_{ij,mj} \widehat{\Theta}_{ij,mj} \tag{A.9}$$

where $\phi_{ij,mj} \equiv \frac{\pi_{ij,mj}X_{ij}}{\sum_l \pi^{ij,lj}X_{ij}}$ is the share of region i in purchase of good j produced in m and $\widehat{\Theta}_{ij,mj} \equiv (\theta_j \gamma_{mj}) \left(-\xi_m \widehat{r}_{mj} - (1-\xi_m)\, \widehat{w}_{mj} + \widehat{A}_{mj}\right) - \theta_j \sum_{k}^{J} \gamma_{mj,mk} \widehat{MA}^{mk} - \widehat{L}_{mj} + \theta_j \widehat{k}_{ij,mj}$ is the log change in "export capability" of region-sector mj in market ij. The market access (or price index) of market ij increases in the cost of production of mj ($\widehat{r}_{mj}$, $\widehat{w}_{mj}$, $\sum_k^J \gamma_{mj,mk}\widehat{MA}^{mk}$) as mj becomes less competitive, increases in demand of mj ($\widehat{L}_{mj}$), decreases as mj becomes more productive ($\widehat{A}_{mj}$) and more distant ($\widehat{k}_{ij,mj}$). Substituting equation (A.9) in (2.8), and assuming that the changes happen only in China and the CZs nj (as in the Theoretical Appendix of Autor et al., 2013), we obtain:

$$(1-\gamma_{nj,nj}-\alpha_{nj,nj})\left(\widehat{MA}_{nj}\right) = \widehat{S}_{Cj,nj} + \alpha_{nj,nj}\left(\widehat{X}_{nj} - \theta_j \widehat{k}_{nj,nj}\right) \tag{A.10}$$

where $\widehat{S} \equiv \alpha_{Cj,nj}\left(\widehat{X}^{Cj} - \sum_m \phi_{Cj,mj}\widehat{\Theta}_{Cj,mj} - \theta_j \widehat{k}_{Cj,nj}\right)$ is the China Shock.

A.5 Local GE Coefficient & Equivalence between Reduced and 2SLS

We show that, once standardized, the magnitudes of the reduced form and second-stage coefficients are identical, while they can differ in sign. Consider the three equations in our framework:

$$\begin{aligned}
\textit{First stage:}\quad & \Delta MA_{nj} = \gamma_1 \widehat{\Delta IMW}_{nj} + \epsilon_{nj} \\
\textit{Second stage:}\quad & \Delta L_{nj} = \phi_1\left(\gamma_1 \widehat{\Delta IMW}_{nj}\right) + \epsilon_{nj} \\
\textit{Reduced form:}\quad & \Delta L_{nj} = \delta_1 \widehat{\Delta IMW}_{nj} + \epsilon_{nj}
\end{aligned}$$

The corresponding OLS coefficients are:

$$\gamma_1 = \frac{\text{Cov}\left(\Delta MA_{nj}, \widehat{\Delta IMW}_{nj}\right)}{\text{Var}\left(\widehat{\Delta IMW}_{nj}\right)}, \qquad \delta_1 = \frac{\text{Cov}\left(\Delta L_{nj}, \widehat{\Delta IMW}_{nj}\right)}{\text{Var}\left(\widehat{\Delta IMW}_{nj}\right)}, \qquad \phi_1 = \frac{\text{Cov}\left(\Delta L_{nj}, \gamma_1\widehat{\Delta IMW}_{nj}\right)}{\text{Var}\left(\gamma_1\widehat{\Delta IMW}_{nj}\right)}.$$

Since γ_1 is a scalar, we can rewrite ϕ_1 as:

$$\phi_1 = \frac{\gamma_1\,\text{Cov}\left(\Delta L_{nj}, \widehat{\Delta IMW}_{nj}\right)}{\gamma_1^2\text{Var}\left(\widehat{\Delta IMW}_{nj}\right)} = \frac{\delta_1}{\gamma_1}.$$

The variance of the fitted regressor in the second stage is:

$$\sigma^2_{\gamma_1\widehat{\Delta IMW}_{nj}} = \text{Var}\left(\gamma_1\widehat{\Delta IMW}_{nj}\right) = \gamma_1^2\,\sigma^2_{\widehat{\Delta IMW}_{nj}}.$$

Therefore, the standardized second-stage coefficient is:

$$\phi_1^{std} = \phi_1 \cdot \sigma_{\gamma_1\widehat{\Delta IMW}_{nj}} = \phi_1 \cdot \gamma_1\,\sigma_{\widehat{\Delta IMW}_{nj}}$$

$$= \delta_1 \cdot \sigma_{\widehat{\Delta IMW}_{nj}},$$

which is exactly the standardized reduced-form coefficient δ_1^{std}. Hence, the standardized reduced form and second stages have the same magnitude. Back to Section 6.2.

A.6 Decomposition of the Global GE coefficient (equation 3.8)

To show the relationship between the different coefficients and the general equilibrium propagation of the China Shock, I begin by reporting the relevant estimating equations:

$$\Delta MA_{nj} = \gamma_1 \widehat{\Delta IMW}_{nj} + \epsilon_{nj}$$

$$\Delta L_{nj} = \delta_1 \widehat{\Delta IMW}_{nj} + \epsilon_{nj}$$

$$\Delta L_{nj} = \phi_1 \left(\gamma_1 \widehat{\Delta IMW}_{nj}\right) + \epsilon_{nj}$$

$$\Delta L_{nj} = \beta_1 \, GR_{nj} + \epsilon_{nj}$$

where $\widehat{\Delta IMW}_{nj}$ is predicted from equation (3.1), and the regression coefficients are:

$$\gamma_1 = \frac{Cov\left(\Delta MA_{nj}, \widehat{\Delta IMW}_{nj}\right)}{Var\left(\widehat{\Delta IMW}_{nj}\right)}, \quad \delta_1 = \frac{Cov\left(\Delta L_{nj}, \widehat{\Delta IMW}_{nj}\right)}{Var\left(\widehat{\Delta IMW}_{nj}\right)},$$

$$\phi_1 = \frac{Cov\left(\Delta L_{nj}, \gamma_1 \widehat{\Delta IMW}_{nj}\right)}{Var\left(\gamma_1 \widehat{\Delta IMW}_{nj}\right)}, \quad \beta_1 = \frac{Cov\left(\Delta L_{nj}, GR_{nj}\right)}{Var\left(GR_{nj}\right)}.$$

It then follows that:

$$\phi_1 = \frac{Cov\left(\Delta L_{nj}, \gamma_1 \widehat{\Delta IMW}_{nj}\right)}{Var\left(\gamma_1 \widehat{\Delta IMW}_{nj}\right)} = \frac{\delta_1}{\gamma_1}, \tag{A.11}$$

where the second equality follows from the definition of δ_1, using the fact that γ_1 can be group out of the covariance and variance terms. The partial effect is then equal to:

$$\underbrace{\delta_1}_{PE\,effect} = \underbrace{\phi_1}_{\substack{Local\,GE \\ effect}} \cdot \underbrace{\gamma_1}_{\substack{China\,shock \\ on\,MA}} \tag{A.12}$$

Next, we substitute the predicted value $\widehat{\Delta MA}_{nj} = \gamma_1 \widehat{\Delta IMW}_{nj}$ from equation 3.2 into equation (3.3). This yields:

$$
\begin{aligned}
GR_{nj} &= \sum_{k\neq j}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{\Delta MA}_{nk} - \sum_{i\neq n}^{N} \alpha_{ij,nj} \widehat{\Delta MA}_{ij} \\
&= \gamma_1 \cdot SP_{nj},
\end{aligned}
$$

where

$$
SP_{nj} \equiv \sum_{k}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \cdot \widehat{\Delta IMW}_{nj} - \sum_{i}^{N} \alpha_{ij,nj} \cdot \widehat{\Delta IMW}_{ij} \tag{A.13}
$$

is the Spatial Propagation (SP) of the China Shock. Finally, we derive:

$$
\beta_1 = \frac{Cov\left(\Delta L_{nj}, GR_{nj}\right)}{Var\left(GR_{nj}\right)} = \frac{Cov\left(\Delta L_{nj}, \gamma_1 SP_{nj}\right)}{Var\left(\gamma_1 \cdot SP_{nj}\right)} = \frac{Cov\left(\Delta L_{nj}, SP_{nj}\right)}{\gamma_1 Var\left(SP_{nj}\right)} = \frac{SPE}{\gamma_1} = \frac{SPE \cdot \phi_1}{\delta_1},
$$

where

$$
SPE \equiv \frac{Cov\left(\Delta L_{nj}, SP_{nj}\right)}{Var(SP_{nj})}
$$

is the *Spatial Propagation Effect*.

A.7 Standard Deviation of the GR term (equation 3.9)

In this section, we prove that $\sigma_{GR} = |\frac{\delta_1}{\phi_1}| \cdot \sigma_{SP} \cdot \sigma_{\Delta IM}$.

When we standardize the import shock, we shock by a standard deviation $\sigma_{\Delta IM}$.

$$
\begin{aligned}
Var(GR_{nj}) &= Var\left[\sum_{k\neq j}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{\Delta MA}_{nk} - \sum_{i\neq n}^{N} \alpha_{ij,nj} \widehat{\Delta MA}_{ij}\right] \\
&= Var\left[\sum_{k\neq j}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \left(\gamma_1 \widehat{\Delta IMW}_{nj} \cdot \sigma_{\Delta IM}\right) - \sum_{i\neq n}^{N} \alpha_{ij,nj} \left(\gamma_1 \widehat{\Delta IMW}_{nj} \cdot \sigma_{\Delta IM}\right)\right] \\
&= \left(\frac{\delta_1}{\phi_1}\right)^2 \cdot \sigma^2_{SP|\sigma_{\Delta IM}} \qquad \text{(A.14)}
\end{aligned}
$$

with $\delta_1 = \phi_1\gamma_1$ and σ^2_{SP} is the variance of the SP term defined in equation (A.13). Then, it follows that the standard deviation of the global response function is $\sigma_{GR} = |\frac{\delta_1}{\phi_1}| \cdot \sigma^2_{SP|\sigma_{\Delta IM}}$.

A.8 Mechanisms: Input-Output vs Spatial Competition

We now decompose the the global response GR_{nj} term in its component. In particular, we define the Input-Output (IO_{nj})component as:

$$IO_{nj} = \sum_{k}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \widehat{\Delta MA}_{nk} \tag{A.15}$$

and the Spatial Competition (SC) as:

$$SC_{nj} = -\sum_{i}^{N} \alpha_{ij,nj} \widehat{\Delta MA}_{ij} \tag{A.16}$$

To estimate the coefficients β_1^{IO} and β_1^{SC} from the multiple regression

$$\Delta L_{nj} = \beta_1^{IO}\, IO_{nj} + \beta_1^{SC}\, SC_{nj} + \epsilon_{nj}, \tag{A.17}$$

we seek the *partial effects* of each regressor on the outcome, holding the other variable constant. These coefficients do *not* equal the simple ratio of covariances to variances, as in a bivariate regression. Instead, by the *Frisch-Waugh-Lovell* (FWL) theorem, we can derive β_1^{IO} in three steps: (1) regress IO_{nj} on SC_{nj} and obtain the residuals $\widetilde{IO}_{nj}$, which capture the variation in IO_{nj} orthogonal to SC_{nj}; (2) regress ΔL_{nj} on SC_{nj} and obtain the residuals $\widetilde{L}_{nj}$; and (3) regress $\widetilde{L}_{nj}$ on $\widetilde{IO}_{nj}$. The resulting slope coefficient is

$$\beta_1^{IO} = \frac{\mathrm{Cov}(\widetilde{L}_{nj}, \widetilde{IO}_{nj})}{\mathrm{Var}(\widetilde{IO}_{nj})}, \quad \beta_1^{SC} = \frac{\mathrm{Cov}(\widetilde{L}_{nj}, \widetilde{SC}_{nj})}{\mathrm{Var}(\widetilde{SC}_{nj})}.$$

with

$$\begin{aligned}
\widetilde{IO}_{nj} &= IO_{nj} - (\alpha_1' SC_{nj}) \\
&= \sum_{k}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \left(\phi_1\gamma_1 \widehat{\Delta IMW}_{nj}\right) - \alpha_1' \left[-\sum_{i}^{N} \alpha_{ij,nj} \left(\phi_1\gamma_1 \widehat{\Delta IMW}_{ij}\right)\right] \\
&= \delta_1 SP^{IO|_{SC}}
\end{aligned}$$

and similarly

$$\begin{aligned}
\widetilde{SC}_{nj} &= SC_{nj} - (\alpha_1'' IO_{nj}) \\
&= -\sum_{i}^{N} \alpha_{ij,nj} \left(\phi_1\gamma_1 \widehat{\Delta IMW}_{ij}\right) - \alpha_1'' \left[\sum_{k}^{J} \frac{\gamma_{nj,nk}\theta_j}{\theta_k} \left(\phi_1\gamma_1 \widehat{\Delta IMW}_{nj}\right)\right]
\end{aligned}$$

$$= \delta_1 SP^{SC|_{IO}}$$

where α_1' and α_1'' come from regressing IO_{nj} SC_{nj}, and vice-versa, respectively. Intuitively, this captures the effect of changes in input-output linkages (IO_{nj}) on employment changes (ΔL_{nj}), *after removing* the component of variation in both variables that is explained by the SC component (SC_{nj}). A symmetric procedure yields β_1^{SC}. These partial regression coefficients reflect the *marginal effect* of each regressor, net of the influence of the other, and are what OLS estimates in the presence of multiple, potentially correlated covariates.

Then, it follows that:

$$\beta_1^{IO} = \frac{\mathrm{Cov}(\widetilde{\Delta L}_{nj}, \widetilde{IO}_{nj})}{\mathrm{Var}(\widetilde{IO}_{nj})} = \frac{\frac{\mathrm{Cov}\left(\widetilde{L}_{nj}, SP^{IO|_{SC}}\right)}{\mathrm{Var}(SP^{IO|_{SC}})}}{\delta_1} = \frac{SPE^{IO|_{SC}}}{\delta_1} \tag{A.18}$$

$$\beta_1^{SC} = \frac{\mathrm{Cov}(\widetilde{L}_{nj}, \widetilde{SC}_{nj})}{\mathrm{Var}(\widetilde{SC}_{nj})} = \frac{\frac{\mathrm{Cov}\left(\widetilde{L}_{nj}, SP^{SC|_{IO}}\right)}{\mathrm{Var}(SP^{SC|_{IO}})}}{\delta_1} = \frac{SPE^{SC|_{IO}}}{\delta_1} \tag{A.19}$$

B Estimates of iceberg trade costs

B.1 Data to construct the images of US infrastructure networks

We construct a spatial network of trade costs for the year 2010, drawing on geospatial data for the highway, railroad, and waterway networks. Our approach closely follows Allen and Arkolakis (2014), with adjustments based on data availability and updated sources.

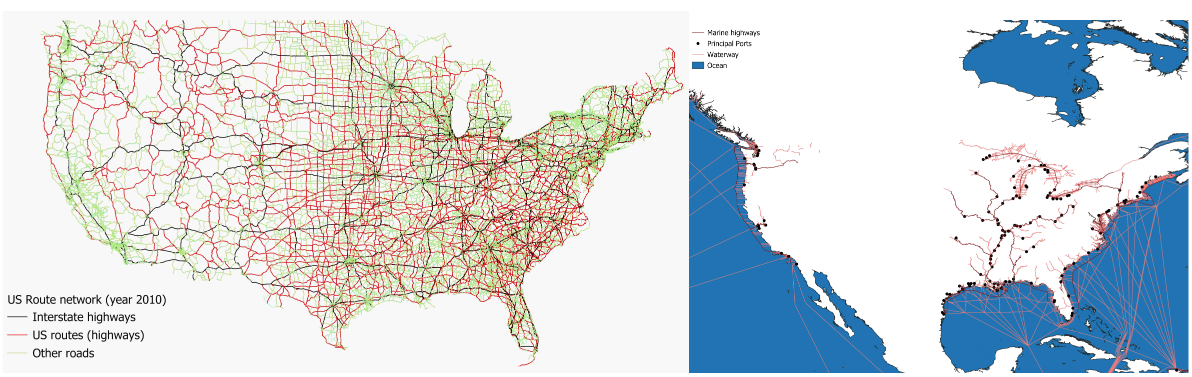
For the highway network, we use the 2010 release of the National Highway Planning Network (NHPN) dataset, available through the U.S. Department of Transportation at link to NHPN. This dataset is available for several years—2000, 2002-2006, 2010, 2012, and 2014. Allen and Arkolakis (2014) rely on the 2005 version; we instead use the 2010 version to align with the timing of our analysis. Following their methodology, we classify roads into three categories: interstate highways, highways, and other roads. We assign instantaneous trade costs based on speed limits across road types. Interstate highways—the fastest road type—are normalized to a cost of 1. Highways are assigned a cost of 70/55, other roads 70/35, and off-road pixels 70/20. The off-road cost is chosen to reflect the speed of transporting goods on foot, relative to the speed of interstate highways.

For the railroad network, we use shapefiles available through Data.gov, the U.S. federal government's open data platform (link to Data.gov). These files provide detailed spatial information on rail infrastructure as of 2010. While Allen and Arkolakis (2014) rely on the Center for Transportation Analysis Railroad Network dataset, that source is no longer publicly available (a point also confirmed in correspondence with Allen and Arkolakis, 2014). An alternative dataset from the

Bureau of Transportation Statistics (BTS) is also unsuitable, as it only provides the most recent rail network as of 2023 and does not offer historical coverage. Moreover, the Allen and Arkolakis (2014)'s dataset allows for classification of railroads into three categories based on speed; our dataset does not contain this information. Consequently, we assign a uniform instantaneous trade cost of 1 to all railroad pixels and a cost of 3 to off-rail pixels, for both 2000 and 2010.

The waterway network is derived from the Bureau of Transportation Statistics (BTS)' dataset on navigable waterways, which includes rivers and oceans (available at: link to BTS). We assume the geography of the waterway network remains constant between 2000 and 2010. Allen and Arkolakis (2014) use data from the U.S. Army Corps of Engineers' Navigation Data Center (1999), which does not account for the presence of ports. We extend their approach by incorporating ports, which significantly reduce trade costs. Specifically, we assign a trade cost of 10 to pixels without water access, 1 to inland waterways, 1 to oceans, and 0.5 to maritime highways (defined as ocean routes and the largest navigable rivers). Pixels containing ports are assigned a much lower trade cost of 0.1, reflecting the substantial reduction in shipping costs for commuting zones with direct port access. Note that the waterway network of Allen and Arkolakis (**to cite**) do not accounts for ports. We assume that the geography of waterways has not changed between 2000 and 2010 and use the instantaneous trade costs of 2010 also for year 2000.

Next, we present the steps to estimate iceberg trade costs.



(a) US route network year 2010 **(b)** US water network

Figure B.1: US infrastructures by mode

[Add railway network image]

B.2 Estimate total iceberg trade costs by sector

To get to our measure of iceberg trade costs, we first estimate the relative costs of trade across different transport modes using a discrete choice framework that is entirely separate from the model in Section 2. This framework is used solely to infer trade costs from mode-specific trade shares, and is useful to exploit the infrastructure networks built in section B.1. As discussed in Allen and

Arkolakis (2014), using a distinct estimation model mitigates endogeneity concerns related to the location of transportation infrastructure—concerns that would arise if we used the theoretical model in Section 2 with variation in bilateral trade flows (e.g., a highway between New York and Chicago may exist because the two cities already trade heavily). By focusing on the relative shares of trade by mode, we effectively control for the total bilateral trade volume. We compare trade shares and distances by mode between a given origin and destination pair (rather than across all pairs), which acts like a fixed-effects approach. This helps reduce endogeneity, though not entirely—since shipment by a specific mode may still reflect the composition of goods traded between the two locations.

Differently from Allen and Arkolakis (2014), we add the sectoral dimension j and apply this framework within sectors since we estimate trade costs for 12 tradable sectors. For every pair of destinations $i, n \in S$, a set of traders choose a mode of transport $m \in \{1, \ldots, M\}$ to minimize the cost of shipping one unit of a good j from i to n. The iceberg trade cost incurred by trader t when using mode m in sector j is given by $e^{\tau_m^j d_m^{ij,nj} + f_m^j + \nu_{tm}^j}$ where $d_m^{ij,nj}$ denotes the distance between i and n by mode m (as computed with the FMM), τ_m^j is the mode-specific variable cost per unit of distance, f_m^j is a mode-specific fixed cost (independent of distance), and ν_{tm}^j is an idiosyncratic cost shock specific to trader t and mode m. We assume that ν_{tm}^j is independently and identically distributed across traders and modes, following a Gumbel distribution with shape parameter ψ^j, i.e., $\Pr\{\nu^j \leq x\} = e^{-e^{-\psi^j x}}$. It follows that e^{ν^j} follows a Fréchet distribution with parameter ψ^j, with cumulative distribution function $Pr\{e^{\nu^j} \leq x\} = e^{-x^{-\psi^j}}$.

Let $\lambda_m^{ij,nj}$ denote the share of trade in sector j between locations i and n that is shipped using mode m. Given the distributional assumption on ν_{tm}^j, the mode choice probabilities take the form:

$$\lambda_m^{ij,nj} = \frac{e^{(-a_m^j d_m^{ij,nj} - b_m^j)}}{\sum_k \left(e^{(-a_k^j d_k^j(i,n) - b_k^j)} \right)} \tag{B.1}$$

where $a_m^j := \psi^j \tau_m^j$ and $b_m^j := \psi^j f_m^j$. Given the set of mode-specific distances $d_m(i,n) : M \times S \times S \to \mathbb{R}_+$ estimated using the FMM, we can estimate the parameters a_m^j and b_m^j so that the predicted mode shares $\lambda_m^{ij,nj}$ match the observed shares in the data using (B.1). To identify the relative scale parameter ψ^j, we normalize by assuming that the fixed cost of road transport is zero, i.e., $f_m^j = 0$ for road, so that no fixed cost is incurred for this mode. We then estimate a_m^j and b_m^j from equation (B.1) using a nonlinear least square routine. To pin down the relative scale, we follow Allen and Arkolakis (2014) and assume that traders do not incur a fixed cost of traveling via road.

Given the estimates of a_m^j and b_m^j, we estimate total iceberg trade costs using the observed level of bilateral trade flows. From the discrete choice framework, the average geographic trade cost between i and n in sector j, up to a scale ψ^j (given $\{\hat{a}^j_m\}\{\hat{b}^j_M\}$), is:

$$k_g^{ij,nj} = \frac{1}{\psi^j}\Gamma\left(\frac{1}{\psi^j}\right)\left(\sum_m e^{(-a^j_m d^{ij,nj}_m - b^j_m)}\right)^{-\frac{1}{\psi^j}} \tag{B.2}$$

Suppose that the total costs k has a geographic and non-geographic component such that $k = k_g + k_{ng}$, with k_{ng} approximated by vector of non geographic bilateral observables $\mathbf{C}(i,n)$ such as similarities in languages and ethnicity. Taking the log of equation (2.3), we estimate the following gravity equation separately for each of the 12 manufacturing sectors (suppressing the time subscript t), using a common trade elasticity $\theta = 8.28$[23] across all sectors:

$$ln(\pi^{ij,nj}) = \frac{\theta}{\psi^j} ln \sum_m \left(e^{(-\hat{a}^j_m d^{ij,nj}_m - \hat{b}^j_m)}\right) - \theta\beta^{j\prime} ln\boldsymbol{C^{ij,nj}} + \delta^{ij} + \delta^{nj} + \epsilon^{ij,nj} \tag{B.3}$$

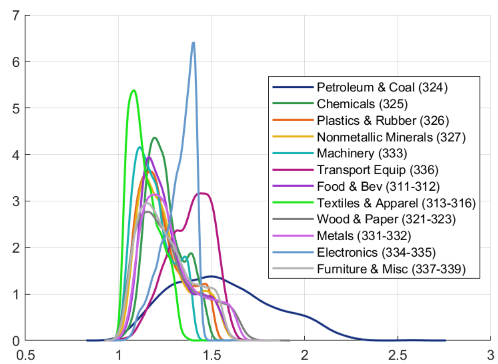
Given this elasticity, we estimate the sector-specific scale parameter ψ^j, which we then use to recover the mode-specific trade cost parameters a^j_m, f^j_m, and τ^j_m, and ultimately to compute geographic iceberg trade costs $k^{ij,nj}$ via equation (B.2).

We repeat this procedure for each tradable sector, using sector- and mode-specific trade shares $\lambda^{ij,nj}_m$ to identify ψ^j and bilateral trade costs $k^{ij,nj}$. We report in panels (a) and (b) of figure B.2 kernel density estimates of our total iceberg trade costs $k^{ij,nj}$, which appear all to be between 1 and 2, except for the oil sector. This compares well with the density function of the total iceberg trade cost of Allen and Arkolakis (2014), as shown in panel (c).

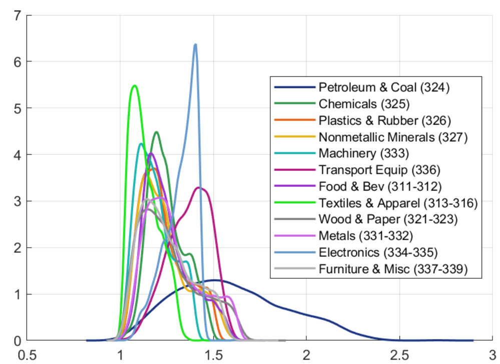
Panels (a) and (b) of Figure B.3 show how the estimated mode-specific trade costs vary with distance across sectors. For comparison, we report the estimated trade costs by mode from a replication of Allen and Arkolakis (2014) in figure B.4.[24] In our estimates, all iceberg trade costs lie between one and two for most sectors, with three exceptions: petroleum and coal (NAICS 324), transport equipment (NAICS 336), and electronics (NAICS 334–335). This likely reflects the specific transport patterns in these sectors. For instance, most U.S. crude oil is transported by pipeline and road, with relatively low trade shares by air, water, or rail. Similarly, transport equipment tends to be shipped primarily by road due to its bulk. For electronics, iceberg costs are much lower than in the aforementioned sectors, but our estimates suggest that road is the dominant transport mode, with air used only over short distances. All other sectors exhibit the

[23] As estimated in the Ricardian framework of Eaton and Kortum (2002).

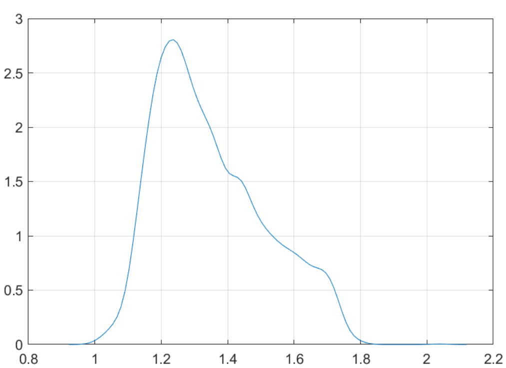
[24] The replication package from Allen and Arkolakis (2014) does not include the code necessary to reproduce panel (b) of their Figure X (equivalent to the figure B.4 here). We plot their available cost estimates against distance but are unable to replicate the original figure exactly. In their estimates in the paper, iceberg trade costs generally range between one and two across modes. However, in our replication, road costs fall slightly below one for short distances. To ensure comparability, we normalize all mode-specific trade costs by the minimum estimated road cost so that all values lie above one. Additionally, waterborne trade costs in their estimates exceed two at longer distances.



(a) Year 2000



(b) Year 2007



(c) Total trade costs from Allen and Arkolakis (2014) (replicated by authors)

Figure B.2: This figure reports, in Panels (a) and (b), the kernel density estimates of iceberg trade costs by sector for the years 2000 and 2007, respectively. For comparison, Panel (c) shows the kernel density estimate of total iceberg trade costs obtained by replicating the estimates of Allen and Arkolakis (2014) using their publicly available code, and plotting the resulting distribution.

expected pattern of increasing costs with distance across modes.[25] Given that the vast majority of trade occurs over roads, it is not surprising that road transport is estimated to have the lowest trade cost across all sectors—except at extreme distances. As the distance between origin and destination increases, the relative cost of air, water, and rail transport declines compared to road, which aligns with the observed decrease in the share of trade carried by road over longer distances. Overall, the magnitude of our estimated trade costs is broadly consistent with previous estimates of domestic trade frictions in the literature. For example, Anderson and Van Wincoop (2004) estimate an iceberg trade cost of approximately 55% for domestic distribution in a representative high-income country.

Table B.1 reports also the estimate of the variable τ_m^j and fixed f_m^j costs for each sector, as well estimates of the shape parameter ψ^j given that we set the trade elasticity $\theta^j = 8.28 \; \forall j$. Excepts for the three sectors mentioned above, the estimates are in line with the ones obtained at the aggregate level in table II of Allen and Arkolakis (2014).

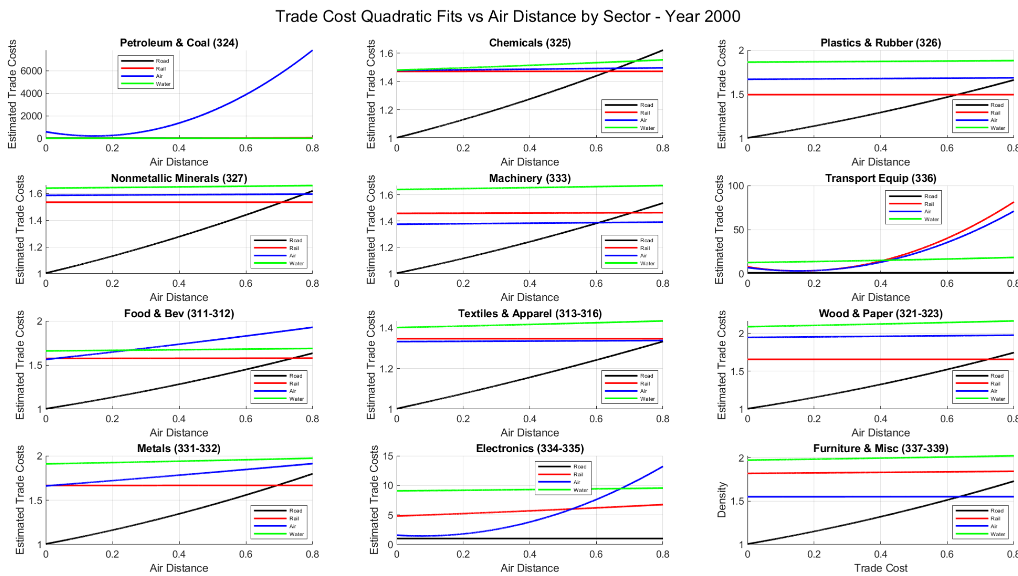
Table B.1: Estimated sectoral mode-specific relative cost of travel

Sector name	ψ^j	Variable cost				Fixed cost		
		Road	Rail	Water	Air	Rail	Water	Air
Petroleum & Coal (324)	1.942	1.030	4.594	0.129	5.149	0.001	0.001	5.149
Chemicals (325)	14.051	0.534	0.001	0.636	0.016	0.423	0.427	0.427
Plastics & Rubber (326)	13.627	0.563	0	0.121	0.013	0.440	0.661	0.550
Nonmetallic Minerals (327)	15.109	0.536	0	0.157	0.008	0.463	0.530	0.496
Machinery (333)	17.154	0.475	0.004	0.243	0.015	0.408	0.525	0.350
Transport Equip (336)	1.342	0.001	4.364	5.054	4.678	0.746	2.609	0.746
Food & Bev (311-312)	16.736	0.543	0.002	0.224	0.262	0.486	0.538	0.478
Textiles & Apparel (313-316)	25.113	0.317	0	0.305	0.005	0.319	0.358	0.309
Wood & Paper (321-323)	10.868	0.617	0	0.478	0.019	0.552	0.782	0.713
Metals (331-332)	10.840	0.649	0.001	0.437	0.176	0.556	0.692	0.554
Electronics (334-335)	2.368	0	0.381	0.678	3.313	1.690	2.323	0
Furniture & Misc (337-339)	12.505	0.607	0.015	0.333	0	0.640	0.720	0.480

Normalized mode-specific distance Note that to obtain the estimates of $k^{ij,nj}$, we first need data on the instantaneous cost function, $\tau_m : S \to \mathbb{R}_{++}$, and then calculate the normalized mode-specific distance, $d_m(i,j)$ presented in section B.2. To define the instantaneous cost function τ_m, we use data on the transportation network constructed in section B.1. We assign low values to pixels on the network and high values to pixels off the network. We map elements of the transportation network into a raster for each transportation mode, resulting in four normalized rasters, each

[25]Because we adapt the Allen and Arkolakis (2014) code to a multi-sector framework, we also observe road costs below one in approximately 600 out of 12,000 observations. As above, we normalize road costs by their minimum to ensure that all estimates lie above one.

(a) Year 2000



(b) Year 2007

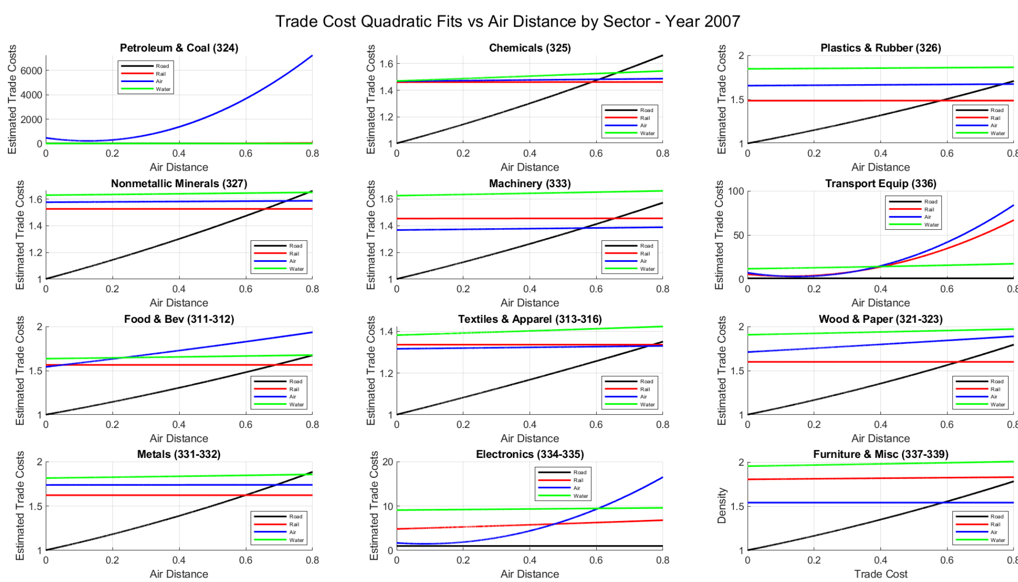


Figure B.3: Sectoral Mode-Specific Estimated Iceberg Trade costs by distance. The figure shows how the sectoral estimated trade costs for each mode of transportation vary with distance for year 2000 and 2007. In both panels, distance is normalized so that the width of the United States has distance of 1.

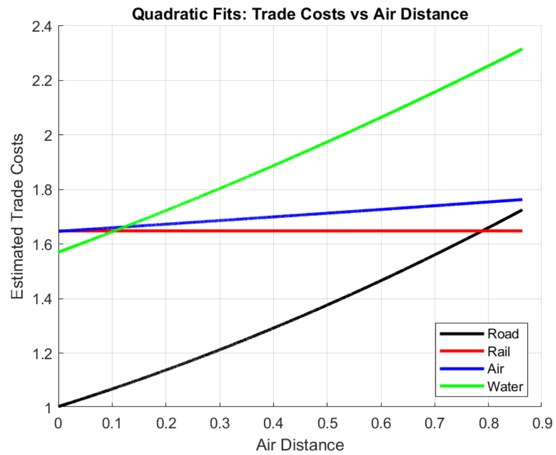


Figure B.4: Replication of Allen and Arkolakis (2014) estimate iceberg trade costs by mode - (Authors computation)

representing one mode of transport. These rasters have a resolution of 1452 by 991 pixels. For highways, the cost is normalized to one, while non-interstate highways are assigned a cost of $\frac{70}{55}$, arterial roads a cost of $\frac{70}{35}$, and other roads a cost of $\frac{70}{20}$. A similar approach is applied to other modes of transport. Once the instantaneous cost function is defined, we apply the Fast Marching Method (FMM) to determine the normalized mode-specific distance $d_m(i, j)$ for any pair of locations i and j for a given transportation mode m. The normalization is done such that the width of the United States, measured in a straight line, is assigned a value of 1.

C Data description

List of sectors. We use a total of 22 sectors, as in Caliendo et al. (2019). The 12 manufacturing sectors considered in this study include Food, Beverage, and Tobacco Products (NAICS 311–312); Textile, Textile Product Mills, Apparel, Leather, and Allied Products (NAICS 313–316); Wood Products, Paper, Printing, and Related Support Activities (NAICS 321–323); Petroleum and Coal Products (NAICS 324); Chemical Products (NAICS 325); Plastics and Rubber Products (NAICS 326); Nonmetallic Mineral Products (NAICS 327); Primary Metal and Fabricated Metal Products (NAICS 331–332); Machinery (NAICS 333); Computer and Electronic Products and Electrical Equipment and Appliances (NAICS 334–335); Transportation Equipment (NAICS 336); and Furniture and Related Products, along with Miscellaneous Manufacturing (NAICS 337–339). The eight service sectors include Transport Services (NAICS 481–488); Information Services (NAICS 511–518); Finance and Insurance (NAICS 521–525); Real Estate (NAICS 531–533); Education (NAICS 61); Health Care (NAICS 621–624); Accommodation and Food Services (NAICS 721–722); and Other Services, which encompass sectors such as NAICS 493, 541, 55, 561, 562, 711–713, and 811–814. Additionally, the analysis incorporates the Wholesale and Retail Trade sectors (NAICS

42–45) as well as the Construction sector.

D Tables

Table 1: Descriptive Statistics

Variables	*Obs*	*Mean*	*St. Dev.*	*Min*	*Max*
Panel A: Pooled sample (12 tradable and 10 non-tradable sectors)					
Δ empl. share (×100)	15884	-0.032	0.940	-25.209	45.986
Δ Unemployment	15884	0.007	0.049	-0.518	0.272
Δ wages	15881	1.110	0.737	-2.868	5.271
Δ population	15884	22435.016	74984.099	-248157.750	1177043.625
MA 2000	15884	894.506	1764.771	0.322	31507.000
MA 2007	15884	935.710	1836.134	0.599	33633.000
Δ MA	15884	41.204	371.919	-5736.500	6200.900
GR_{nj}	15884	569.355	950.214	-603.255	7423.771
IO_{nj} term	15884	-31.878	65.439	-1164.717	3.817
Panel B: 12 Tradable sectors					
US China Shock	8664	0.193	0.439	0.000	7.398
IV China Shock	8664	0.158	0.343	0.000	5.873
Δ empl. share (×100)	8664	-0.155	0.631	-13.288	9.886
Δ Unemployment	8664	0.007	0.049	-0.518	0.272
Δ wages	8661	1.105	0.744	-2.868	5.271
Δ population	8664	22435.016	74986.066	-248157.750	1177043.625
MA 2000	8664	1473.769	2213.779	3.280	31507.000
MA 2007	8664	1544.640	2296.777	2.062	33633.000
Δ MA	8664	70.871	482.530	-5736.500	6200.900
GR_{nj}	8664	1066.426	1053.199	-527.540	7423.771
IO_{nj} term	8664	-35.835	72.561	-1164.717	3.817
SC_{nj} term	8664	1102.261	1068.175	-23.371	7425.347
Panel C: 10 Non-tradable sectors					
Δ empl. share (×100)	7220	0.116	1.194	-25.209	45.986
Δ Unemployment	7220	0.007	0.049	-0.518	0.272
Δ wages	7220	1.116	0.728	0.021	2.910
Δ population	7220	22435.016	74986.931	-248157.750	1177043.625
MA 2000	7220	199.391	291.820	0.322	3926.000
MA 2007	7220	204.994	328.962	0.599	4773.200
Δ MA	7220	5.603	150.344	-2655.519	1092.300
GR_{nj}	7220	-27.130	55.335	-603.255	3.775
IO_{nj} term	7220	-27.130	55.335	-603.255	3.775

Table 2: Parameters to Compute Market Access

Parameter	Source
γ_{ij} (Value Added Shares)	Bureau of Economic Analysis
$\gamma_{ij,ik}$ (Input-Output Shares)	World Input Output Database
$1-\psi$ (Labor Share)	Bureau of Economic Analysis
θ_j (Trade Elasticity)	Caliendo and Parro (2015)
$\kappa_{ij,nj}$ (Sectoral Trade Cost)	Own FMM estimates
η (Elasticity of Substitution)	1 (Set Exog.)
ρ (Relation between CMA and MA)	1 (Set Exog.)

Table 3: Market Access by Sector: Initial Levels and Change, 2000–2007

		Market Access	
Sector	Industry	$\%\Delta_{2007-2000}$	Level in 2000
Manufacturing	Textile, Textile Products, Apparel, Mill	-42.55	6491
	Computer and Electronic Products	-21.58	4864
	Plastics and Rubber Products	-15.97	11005
	Wood Products, Paper, Printing, etc.	-15.09	65699
	Machinery	-14.37	11337
	Furniture and Related Products, and Misc.	-5.76	10412
	Transportation Equipment	-4.77	1314
	Nonmetallic Mineral Products	-3.32	3630
	Chemicals	-3.22	3389
	Primary Metal and Fabricated Metal Products	-2.21	29620
	Food, Beverage, Tobbaco	3.63	17629
	Petroleum and Coal Products	7.21	270
Services	Information Services	-12.18	30
	Construction	1.77	23
	Real Estate	4.41	26
	Transport Services	4.83	29
	Educational	6.59	27
	Finance and Insurance	8.58	35
	Accommodation and Food Services	12.41	39
	Health	16.82	45
	Wholesale and Trade	121.95	23

Table 4: Market Access, Geography, and Labor Market

	log(market access)			
	(1)	(2)	(3)	(4)
	2000	2007	2000	2007
log(average trade cost)	-0.614***	-0.643***		
	(0.011)	(0.011)		
log(employment)			0.172***	0.170***
			(0.007)	(0.007)
N	8664	8664	8664	8664

Standard errors in parentheses

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

Table 5: Exogenous Import Penetration

	ΔIMW_{nj}^{US}
	(1)
ΔIMW_{nj}^{Other}	0.432***
	(0.007)
N	8664
R-squared	0.969

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The Table reports the standardized coefficient from equation (3.1). A one standard deviation increase in Chinese import penetration to other developed economies correspond to about USD 350. The non standardized coefficient, corresponding to an increase of USD 1000, has a magnitude of 1,259, and a standard error of .019

Table 6: China Shock and Change in Market Access

	ΔMA	
	OLS	IV
ΔIMW_{nj}^{US}	-109.51^{***}	–
	(22.33)	
$\Delta \widehat{IMW}_{nj}$	–	-103.82^{***}
		(21.24)
N	8664	8664
F stat	–	4318.51
Cluster	State	State

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. This is a regression of change in market access between 2007 and 2000 on US labor market level import exposure (722 CZ x 12 sectors). In column 2, we report the IV regressions results where the US labor market import exposure is instrumented with import exposure of other rich countries.

Table 7: Regression Results for Manufacturing

	Δ employ share $\times$ 100					
	(1)	(2)	(3)	(4)	(5)	(6)
δ_1 (PE)	-0.334***			-0.340***		
	(0.0309)			(0.0303)		
	[-0.356 (0.032)]			[-0.362 (0.032)]		
ϕ_1 (GE w/o spill.)		0.334***			0.340***	
		(0.0309)			(0.0303)	
		[0.356 (0.032)]			[0.362 (0.032)]	
β_1^{std} (GE w/ spill.)			-0.130***			-0.133***
			(0.0274)			(0.0297)
			[-0.138 (0.029)]			[-0.141 (0.0316)]
Observations	8664	8664	8664	8664	8664	8664
Controls	Yes	Yes	Yes	No	No	No
	Spatial Propagation Effect					
SPE		0.13			0.133	
Controls		Yes			No	
N		8664			8664	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 8: Decomposing Spillovers: Manufacturing

	Δ employ share × 100	
	(1)	(2)
Gen. equilibrium w/ trade spill.	-0.0985***	-0.0958***
	(0.0284)	(0.0303)
	[-0.105 (0.030)]	[-0.102 (0.032)]
Gen. equilibrium w/ I-O spill.	0.107***	0.121***
	(0.0142)	(0.0156)
	[0.113 (0.015)]	[0.128 (0.016)]
	Spatial Propagation Effect	
Through Trade Linkages	0.098	0.095
Through I-O Linkages	-0.107	-0.121
Observations	8664	8664
Controls	Yes	No

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 9: Regression Results for Services

	Δ employ share × 100	
	(1)	(2)
Gen. equilibrium w/ spill.	0.100***	0.102***
	(0.0136)	(0.0153)
	[0.107 (0.014)]	[0.108 (0.016)]
	Spatial Propagation Effect	
SPE	- 0.100	- 0.102
Observations	7220	7220
Controls	Yes	No

Standard errors in parentheses

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 10: Regression Results: All Sectors

	Δ employ share × 100	
	(1)	(2)
Gen. equilibrium w/ spill	-0.156***	-0.157***
	(0.0217)	(0.0229)
	[-0.165 (0.023)]	[-0.165 (0.024)]
	Spatial Propagation Effect	
SPE	0.156	0.157
Observations	15884	15884
Controls	Yes	No

Standard errors in parentheses

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 11: China Shock: Heterogeneity in General Equilibrium Effect

	Change in emp. share × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
	≥ College	≤ H. School	Female	Male	Native	Foreign
Mfg (β_1^{std})	-0.0247***	-0.0509***	-0.0383***	-0.0373***	-0.0679***	-0.00762***
	(0.00583)	(0.0187)	(0.0114)	(0.0101)	(0.0189)	(0.00259)
	[-0.03 (0.007)]	[-0.059 (0.021)]	[-0.043 (0.013)]	[-0.047 (0.012)]	[-0.049 (0.013)]	[-0.035 (0.012)]
N	8664	8664	8664	8664	8664	8664
SPE (M)	0.0247	0.0509	0.0383	0.0373	0.0679	0.00762
	≥ College	≤ H. School	Female	Male	Native	Foreign
Serv (β_1^{std})	0.112***	0.230***	0.134***	0.208***	0.319***	0.0236***
	(0.0244)	(0.0454)	(0.0279)	(0.0413)	(0.0627)	(0.00781)
	[0.146 (0.031)]	[0.267 (0.052)]	[0.154 (0.031)]	[0.267 (0.052)]	[0.231 (0.045)]	[0.111 (0.036)]
N	7220	7220	7220	7220	7220	7220
SPE (Serv)	-0.112	-0.230	-0.134	-0.208	-0.319	-0.0236

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 12: China Shock: Demographics of General Equilibrium Effect

	Change in emp. share $\times$ 100		
	(1)	(2)	(3)
	Age 16-34	Age 35-49	Age 50-64
Manufacturing (β_1^{std})	-0.0268***	-0.0307***	-0.0180***
	(0.00817)	(0.00817)	(0.00485)
	[-0.0366 (0.011)]	[-0.0548 (0.014)]	[-0.0631 (0.017)]
N	8664	8664	8664
Spatial Propagation Effect (Manuf.)	0.0268	0.0307	0.0180
	Age 16-34	Age 35-49	Age 50-64
Services (β_1^{std})	0.184***	0.106***	0.0526***
	(0.0374)	(0.0213)	(0.0105)
	[0.252 (0.051)]	[0.189 (0.038)]	[0.184 (0.036)]
N	7220	7220	7220
Spatial Propagation Effect (Service)	-0.184	-0.106	-0.0526

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 13: Regression Results: Wages

	Δ Log wages			
	Manufacturing		Services	
	(1)	(2)	(3)	(4)
δ_1 (Partial Equilibrium)	-0.000175	-0.000541	-0.000403	-0.000175
	(0.0005)	(0.0006)	(0.000242)	(0.000308)
	[-0.0038 (0.011)]	[-0.0117 (0.014)]	[-0.00875 (0.005)]	[-0.00379 (0.006)]
Observations	8664	8664	7220	7220
Controls	Yes	No	Yes	No

Standard errors in parentheses

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 14: Regression Results: Working Age Population

	Δ Working Age Population	
	(1)	(2)
δ_1 (Partial Equilibrium)	9965.6	-7738.8
	(12700.7)	(7456.8)
	[0.133 (0.169)]	[-0.103 (0.099)]
Observations	722	722
Controls	Yes	No

Standard errors in parentheses

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 15: Regression Results: Unemployment

	Δ Unemployment Share			
	(1)	(2)	(3)	(4)
δ_1 (Partial Equilibrium)	0.035***	0.046***		
	(0.008)	(0.007)		
β_1 (General Equilibrium)			0.036**	0.037
			(0.018)	(0.024)
	[0.714 (0.157)]	[0.952 (0.144)]	[0.748 (0.356)]	[0.756 (0.488)]
Observations	722	722	722	722
Controls	Yes	No	Yes	No

Standard errors in parentheses

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

Table 16: Regression Results: Unemployment

	Δ Unemployment Share			
	(1)	(2)	(3)	(4)
Trade Spillovers	0.030***	0.029**		
	(0.010)	(0.014)		
Input-Output			- 0.028***	-0.039***
			(0.007)	(0.007)
	[0.618 (0.212)]	[0.591 (0.276)]	[-0.572 (0.146)]	[-0.804 (0.135)]
Observations	722	722	722	722
Controls	Yes	No	Yes	No

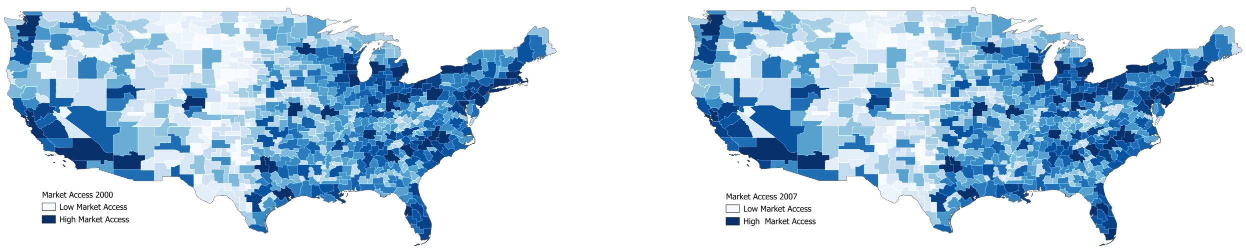
Standard errors in parentheses

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

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Clustering is at the state level. We report the standardized coefficient in square brackets with corresponding standard errors. Control variables include initial employment share of the commuting zone, initial college educated share of the labor force, initial share of male workers, initial share of young workers, and initial share of native workers.

E Figures Discussed in Main Text

Figure 1: Spatial distribution of Market Access in years 2000 and 2007

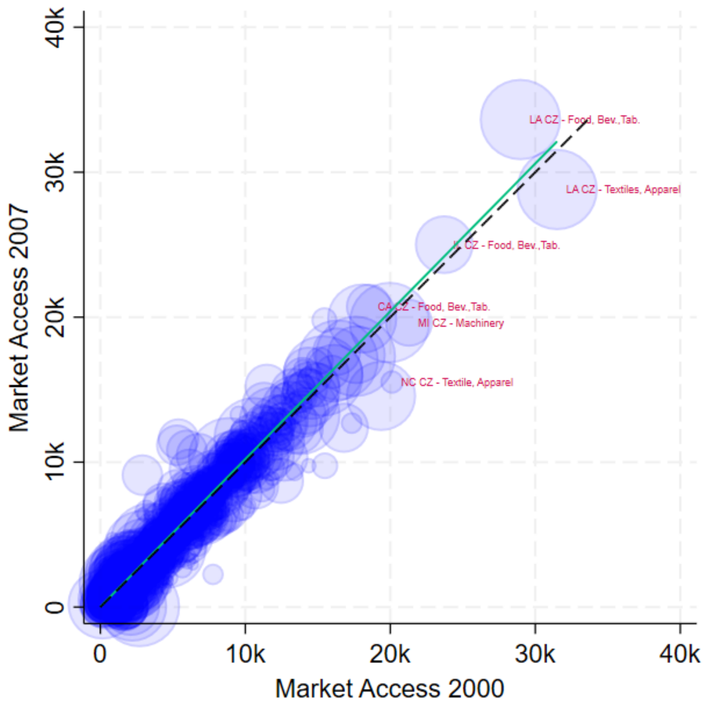


(a) Market Access 2000

(b) Market Access 2007

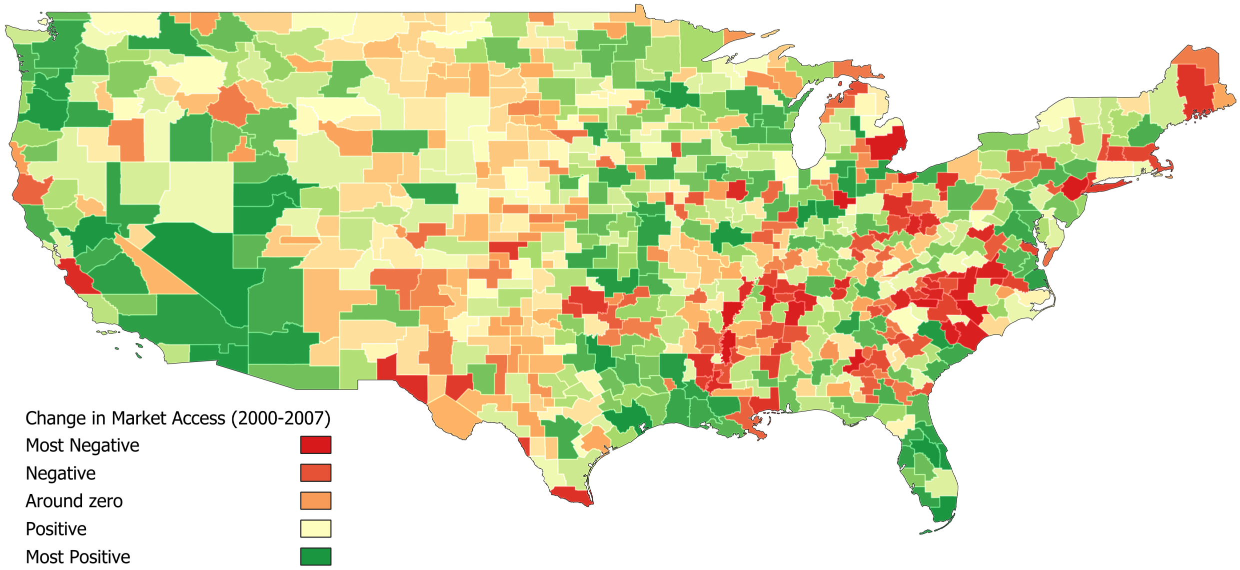
Note: Panel (a) shows the spatial distribution of Market Access in 2000, and Panel (b) in 2007. Values are averaged across sectors within each commuting zone. Back to section 5.1.

Figure 2: Persistence of Market Access



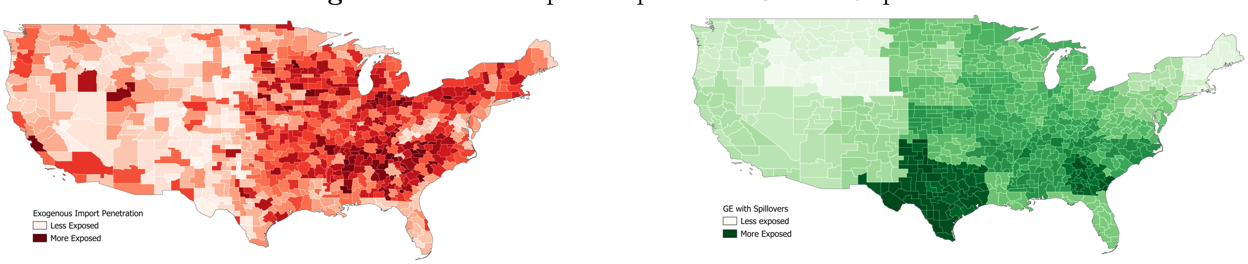
Notes: The figure plots the correlation between U.S. labor markets' market access in 2000 and 2007, as estimated by the authors. Each blue circle represents a commuting zone–sector, with size proportional to its 2000 population. Highlighted labels correspond to CZ–sectors with the highest market access. For example, "LA CZ – Food and Bev, Tab." refers to the Los Angeles metropolitan area in the Food, Beverage, and Tobacco sector; "IL" to Illinois; "MI" to Michigan; "NC" to North Carolina; and "CA" to California (CZs around San Francisco). Back to section 5.1.

Figure 3: Estimated Change in Market Access (2000-2007)



Notes: The figure reports the spatial distribution of the estimated change in market access, computed as described in Section 4.3. We average market access across sectors within each commuting zone. Most commuting zones experienced an expansion in market access during the period 2000–2007. While this measure captures all general equilibrium adjustments in the U.S. labor market over the period, the figure shows that the commuting zones experiencing a contraction in market access are those most exposed—both directly and indirectly—to the China Shock, as shown in panels (a) and (b) of Figure 4. Back to section 5.1.

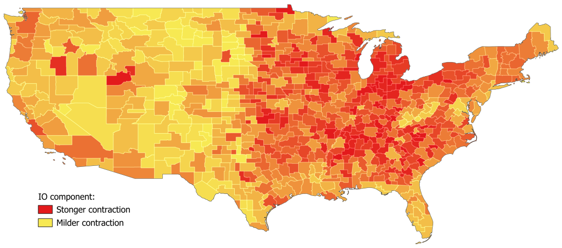
Figure 4: Direct Import Exposure vs Global Response



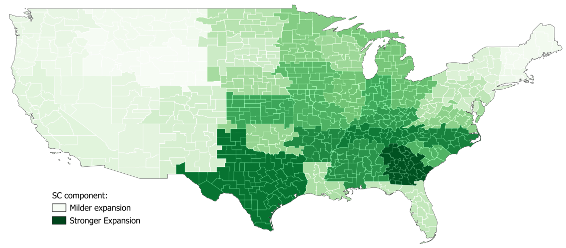
(a) Direct Import Exposure (b) Global Response

Note: Panel (a) reports the spatial distribution of the direct exogenous import penetration, while panel (b) our global response measure. To obtain the figures, we average market access across sector within each commuting zones. Back to section 5.1.

Figure 5: Mechanisms: Input-Output and Spatial Competition components



(a) Input-Output component



(b) Domestic Spatial Competition Component

Note: Panel (a) reports the spatial distribution of the input-output (IO) component, while panel (b) shows the spatial competition term. To construct the figures, we average market access across sectors within each commuting zone (CZ). The component in panel (b) does not vary within states, as the 2000 export shares are measured at the state level. This implies that each CZ within a state is assumed to trade the same amount of goods with other CZs in each sector. Back to section 5.1.