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Import competition and domestic transport costs

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Abstract

With China's 2001 WTO accession, trade costs *between* the US and China fell sharply, but the transport costs of Chinese imports *within* the US remained sizable. We argue that domestic transport costs shield local labor markets from globalization. Using a shift-share design for industry-level Chinese imports across 42 ports of entry, we show that US job losses from competing imports occurred near the ports where they arrived. Once accounting for domestic transport costs, import competition affects coastal areas more than inland areas; shows larger impacts in housing markets and indirectly affected jobs; and explains voting, mortality and family formation.

Keywords: import competition, local labor markets, trade infrastructure, China syndrome, transport costs

JEL classification codes: E24, F14, F16, R23, J23, J31, L60, O47, R12

1. Introduction

China's access to the World Trade Organization in 2001 has dramatically reduced trade costs between China and the US. The decade following China's accession saw a surge of Chinese imports into the US. For areas with employment that competed with Chinese products, the

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consequences were substantial. Import competition drove declines in US manufacturing jobs (Autor et al., 2013, Pierce and Schott, 2016, Autor et al., 2021). Import-competing areas also saw declines in local business, increased overall unemployment, discontented voting behavior and deteriorations in mental health, among others (Frieden, 2018; Colantone and Stanig, 2018, Lang et al., 2019). At the same time, export opportunities expanded employment, consumer prices lowered, and competing labor markets increased productivity and changed functional specialization (Bugamelli et al., 2015, Feenstra et al., 2019, Bloom et al., 2019).

However, while trade costs between the US and China declined in 2001, trade costs within the US remained sizable. For instance, shipping a container from the port of Shanghai to the port of Houston costs about $1,100. A container shipped from Shanghai to Denver largely takes the same route: the container is offloaded in the same port of Houston, but then switches modality for the segment from Houston to Denver. The last segment of the trip substantially increases the price, ending up at $4,500, tripling the cost of shipment (prices as quoted from searates.com in 2020). Accordingly, domestic transport costs plausibly represent large shares of the overall trade costs for Chinese imports.

This paper argues that the domestic trade costs between port of entry in the US and the local labor markets reduce the effective competition of Chinese imports. Workers in importing-competing industries close to trade infrastructure are highly exposed to imports, but peers in the same industry in more isolated areas are sheltered by domestic transport costs. Consequently, isolation from the infrastructure of international trade leads to less pronounced local impacts of China's entry into the WTO on local wages, rents and economic development.

We estimate a model of import competition that takes domestic transport costs into account. We exploit data on disaggregated imports from China into 42 different points of entry into the US. Using the locations of entry and the local road network, we calculate exposure to imports according to how close the labor market is to the different international entry points. In our measure of competing imports per worker, the employment consequences of a competing imported product fall, as the distance between its US entry point and the local labor market increases. The measure of import competition of Autor et al. (2013) is a special case of our measure: in the limiting case when domestic transport frictions are zero, import competition is exclusively driven by the local employment overlap with national imports by industry. In addition to overlap between the job and the imported product, our measure of import competition explains the severity of import competition from how far an imported product needs to travel to a potentially affected labor market. To estimate the causal impacts of competing imports from China, we use the shift-share potential outcomes framework (Adao et al. 2019) with shifter resampling. We use industry-level shift-share instruments with exposure to 42 different locations of goods entry into the US that produces variation across commuting zones (CZs) in the competition experienced by workers within the local industry.

Once we account for transport costs in goods movement within the US, local workers face substantially changed quantities of competing imports. For instance, the imports per worker in electrical components are around twice as high around L.A. (a port handling large shares of Chinese electrical components), but up to 40% lower around Boston (which has large employment in electrical components, but no nearby port that imports them from China).[4]

Our results show that impacts of import competition concentrate in areas that are geographically exposed to international trade. The measures of import competition based on domestic transport costs outperform other measures on encompassing tests and explanatory power. Once accounting for domestic transport costs, the results show larger losses in manufacturing jobs in the coastal US, but lower losses are identified in the Midwest and the South. Consistent with this result, we show that there is significant heterogeneity in the seminal import competition regression (Autor et al., 2013): local labor markets close to international trade infrastructure face significantly stronger labor market effects than more sheltered labor markets. In the aggregate, our estimate of national job losses is similar to those of seminal import competition estimates; the main difference lies in where the employment losses occur. Moreover, we find considerably stronger local price responses to competing imports and larger impacts on groups that are only indirectly affected,such as college-educated or non-manufacturing workers.

The results revisit our understanding of import competition. Job losses associated with import competition occur in different places than previous results imply: import competition accounts for more of the manufacturing decline in coastal areas, but for less of the declines in the Midwest.

[4] In Appendix A , we map and document examples of the differences in the import per worker measures with and without domestic transport costs.

Hence, national infrastructure is fundamental for understanding the impacts of globalization on local labor markets. As import competition explains less of the inland manufacturing job losses, other explanations play a significant role: we find stronger results for lower-educated workforce and routine-based job shares. Once domestic transport infrastructure is introduced in measures of import competition, the impacts of import competition on house prices and wages, in particular for indirectly affected groups, are more prominent. The vote shares for Democrat presidential candidates (who were more protectionist) also significantly increase in exposure to import competition, as do alcohol and drug related mortality, marriage rates, and the share of children raised in poverty.

We contribute to a growing literature that documents how local infrastructure changes the impacts of international trade. First, better access to trade through transportation infrastructure directly increases the participation of local firms in international trade (Coşar and Demir, 2016). Consequently, and more important for our paper, infrastructure connecting local labor markets to world markets amplifies the local impacts of international trade. Better infrastructure implies increased competition and induces firm specialization, leading to enlarged local welfare gains from trade (Porter, 2000). Fajgelbaum and Redding (2022) argue that Argentinian regions with higher exposure to international trade saw lower prices for internationally traded goods and lower specialization into traded goods when Argentina opened up to world trade. In the US, skill premia induced by exposure to international trade are higher in counties that directly connect to main roads (Michaels, 2008), and in cities that are better connected to international infrastructure (Farrokhi and Jinkins, 2019). More broadly, our results are consistent with a recent literature that shows how domestic transport costs affect wages and employment across the US (Allen and Arkolakis, 2019; 1999; Glaeser and Gottlieb, 2009).

The paper also connects to an established literature on the impacts of China's growing exports on US labor markets (Acemoglu et al 2016; Autor et al, 2013; Pierce and Schott, 2016; Caliendo et al., 2019). This literature models import competition as an area's *industrial* exposure to Chinese trade – i.e., as the similarity in an area's employment across different industries and the Chinese imports in those industries. Our approach, by contrast, limits the impacts of industrial exposure to the areas near where the competing imports arrive. The literature also offers competing explanations for declining manufacturing employment shares, such as robotization (Acemoglu and

Restrepo, 2020), skill polarization (Autor, 2019), and offshoring (Hummels et al., 2018). In our results, the importance of competing explanations changes, once domestic transport costs can soften the job loss impacts in import-competing industries.

We briefly motivate our argument with a stylized model, before explaining the empirical methodology.

2. A stylized model for the role of domestic transport costs in import competition

We discuss a stylized model to understand the role of domestic transport costs in import competition. As a main result, some regions face stronger declines in trade costs with China than others, which causes differences in price index adjustments after liberalization. In the areas most strongly affected, demand shifts away from domestic producers, implying that the labor markets near the most affected consumers adjust their manufacturing employment more strongly.

Domestic transport plays no role in earlier models of import competition. The latter view local labor markets is independent small economies trading with China but not with each other; or as a single, representative integrated economy experiencing general equilibrium trade effects; either case leaves no role for domestic transport or trade.

As incorporating domestic trade reduces the tractability of the model, we simplify along another dimension: we assume that domestic wages are equalized through a freely traded domestic numeraire good. This assumption implies that all adjustment in the model occurs through employment impacts and not wage impacts. Though stylized, this summarizes the intuition behind the channels for adjustment.

We discuss the assumptions and main result of the framework, leaving intermediate results for Appendix B . The model contains two domestic regions: an oceanside (O) region that is highly exposed to international trade and an inland (I) region that is more isolated due to higher trade costs with international markets. The third region is China (C). Region O has lower trade costs τ with China than region I: $\tau_{OC} < \tau_{IC}$, where the subscripts denote the origin and destination region. Both domestic regions employ workers in a CRS industry producing national goods that are freely shipped across domestic markets. Consumers have Cobb-Douglas preferences over the goods types produced by each industry and CES preferences over the manufacturing varieties within an industry with an elasticity-of-substitution parameter σ. As in other models of import competition and in line with empirical results, we assume that workers do not migrate between regions. Workers can move freely between industries which implies that domestic wages equalize across regions, under the assumption that the national goods industry employment is positive. Workers spend their labor income plus any account deficits (which is a ratio b of their labor income) on the two types of goods. The third region, China, is a small market in terms of demand for US producers, but a significant source of supply to US consumers, fueled by a current account deficit. As in Autor et al. (2013), we consider trade costs shocks and the current account shocks as exogenous and derive how local employment responds to the shocks.

The region-specific log-linearized harmonized price index for industry j, Φ_j (with hats to denote relative change) are:

$$(1-\sigma)\widehat{\Phi_{JI}} = \pi_{jOI}\widehat{L_{JO}} + \pi_{iII}\widehat{L_{JI}} + (1-\sigma)\pi_{jCI}\widehat{\tau_{CI}}\,,$$
$$(1-\sigma)\widehat{\Phi_{JO}} = \pi_{jOO}\widehat{L_{O}} + \pi_{jIO}\widehat{L_{JI}} + (1-\sigma)\pi_{jCO}\widehat{\tau_{CO}}\,, \tag{1}$$

which uses that the manufacturing firm size is constant under CES demand. The weights π_{jik} are the shares of product *j* expenditure of region *k* consumers on producers from region *i*: for instance, π_{jCO} is the expenditure share of the Oceanside consumer on Chinese products. Eq. (1) shows that trade costs reductions with China drive down the harmonized price index and/or employment in the competing domestic manufacturing industries. Clearing on the local labor markets pins down the price index relative to the current account deficits to the local trade cost changes (see Appendix B). Solving for manufacturing employment by substituting the price indices gives:

$$\widehat{L_{JO}} = \frac{\pi_{iII}\left((\sigma-1)\pi_{jCO}\widehat{\tau_{CO}} + \widehat{b_I}\right) - \pi_{IO}\left((\sigma-1)\left(\pi_{jCI}\widehat{\tau_{CI}}\right) + \widehat{b_O}\right)}{\pi_{jOO}\pi_{jII} - \pi_{jOI}\pi_{jIO}},$$
$$\widehat{L_{JI}} = \frac{\pi_{jOO}\left((\sigma-1)\pi_{jCI}\widehat{\tau_{CI}} + \widehat{b_I}\right) - \pi_{OI}\left((\sigma-1)\pi_{jCO}\widehat{\tau_{CO}} + \widehat{b_O}\right)}{\pi_{jOO}\pi_{jII} - \pi_{jOI}\pi_{jIO}}. \tag{2}$$

Oceanside manufacturing employment in industry j, L_{jO}, declines with reductions in trade costs with China ($\widehat{\tau_{CO}}$ is negative); with the expenditure share on Chinese firms in the *Oceanside* (π_{CO}); and with smaller accommodations in the current account deficits (as then, they substitute domestic products for Chinese products). *Oceanside* manufacturing employment may fall faster in the shock than in *Inland*: consumers in *Oceanside* have a higher propensity to spend on Chinese products, as they are relatively cheap ($\pi_{CO} > \pi_{CI}$); *Oceanside* trade costs with China may fall sharper in relative terms ($\widehat{\tau_{CO}} < \widehat{\tau_{CI}}$). In addition, the result shows a dampening effect of the trade cost shock from the other domestic region: as firms in the other region exit, the local price index increases, reducing local competition and firm exit. The higher the trade among domestic regions, the lower the region's own Chinese trade cost shock translates into lower employment (but the more exposed it is to the other region's trade cost shock with China). The impact of trade costs declines is amplified by the elasticity of substitution reflected in σ: high substitutability implies that consumption shifts faster towards Chinese goods.

The overall change in a region's manufacturing share of employment (in all $j \in J$ industries) after a reduction in China's trade costs is:

$$\frac{\sum_j dL_{ji}}{L_{\mathrm{i}}} = \sum\nolimits_j \frac{L_{ji}}{L_i} \widehat{L_{ji}}\,, \tag{3}$$

where $\widehat{L_{ji}}$ is the sector-specific adjustment based on its trade costs with China (as eq. (2) details), and $\frac{L_{ji}}{L_i}$ is the region-specific exposure, familiar from Autor et al. (2013). Equation (3) suggests that, all else being equal, regions specialized in import-competing industries will see stronger manufacturing employment losses, but particularly so if *i)* their region-specific trade costs with China reduce more strongly than in other regions; and *ii)* their local industry price harmonized price indices in the competing industry gives large weights to Chinese products. The latter plausibly occurs if Chinese imports are shipped at relatively lower prices. The response is also stronger if the other domestic region is relatively isolated (as it purchases larger shares from its own producers or experience weaker exit in the same industry), as that isolates competitors from the trade costs shock.

The import penetration measure in equation (3) is similar to existing measures of import penetration in its prediction that local labor market with large industrial overlap with China are predicted to lose manufacturing employment. However, it differs as it shows that labor markets with higher exposure to the transport cost shock (in $\widehat{\tau_{CO}}$) and a higher propensity to trade internationally (in the expenditure share π_{CO}) lose more manufacturing employment as the international trade costs decline.

3. Empirical strategy

A transport-based measure of import penetration

We propose a measure of import competition that allows the impacts to fade with transport costs between the imported good's point of entry in the US and the affected local labor market. We model domestic transport costs as a friction in the impact of competing imports. The transport friction causes imports into a specific port to weigh more heavily on its nearby local labor markets, in line with Ramondo et al. (2016), Fan (2019), or Xu and Yang (2021). Following Autor et al. (2013), we use commuting zones (CZs) to denote local labor markets. CZs are defined on the basis of high within-area commuting flows, to approximate the geography of a common labor market (Fowler et al., 2016).

We apportion the change in the imports in industry j arriving in port d over period t, ΔM_{djt}, across different CZs. The friction of transport between local labor market i and port d is given by s_{id}. Thus, the CZ-specific exposure to imports in industry j arriving in port d is $s_{id}\Delta M_{djt}$. Aggregating across all possible ports of import d, CZ i's exposure to changes in imports in industry j is given by $\sum_d s_{id}\Delta M_{djt}$.

Using this transport-based exposure to a specific product, we follow Autor et al. (2013) to construct the imports per worker. We calculate each CZ's employment share in industry j, multiply the employment share by the (transport-based) imports per national worker in the industry L_{ujt}, and then aggregate across industries. This produces a transport-based import penetration measure:

$$IPW_{uit}^{transport\&ind} = \sum_j \frac{L_{ijt}}{L_{it}} \frac{\sum_d s_{id}\Delta M_{djt}}{L_{ujt}}, \qquad (4)$$

Where the superscript "*transport&ind*" signals that industrial employment overlap as well as domestic transport costs explain the import penetration. This measure of imports per workers allows competing imports to be given more weight if they arrive in nearby ports. Transport frictions are normalized to sum to 1 across labor markets: $\sum_i s_{id} = 1, \forall d$. This condition ensures that every dollar of imports in a given port is attributed at rate 1 to the national level of imports, so that the measure is comparable to other import-per-worker measures at the national level.

Our measure of imports per workers $IPW_{uit}^{transport}$ nests the original measure in Autor et al. (2013), $IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{ujt}} \frac{\Delta M_{ujt}}{L_{it}}$, as a special case. It arises under the assumption that transport frictions are zero, so that s_{id} is uniform (i.e. if there are D ports of entry, $s_{id} = 1/D$). On the other hand, the measure reverts to a term based entirely on proximity to ports and not on industrial employment exposure if we impose that the area's employment specialization perfectly overlaps with the national average. In that case, $L_{ijt}/L_{it} = L_{ujt}/L_{ut}$, and the import penetration measure simplifies to $\frac{\sum_d s_{id} \Delta M_{dt}}{L_{ut}}$, in which $\Delta M_{dt} = \sum_j \Delta M_{djt}$. In this polar opposite formulation, the competing import per worker is only explained by proximity to the arrival point of imports of any kind, irrespective of whether workers are employed in industries that compete with the import.

Once accounting for domestic transport costs, a CZ is only assigned large imports per worker if the products that form its competition enter the country in a nearby port. Hence, if Chinese imports rise in an industry that Seattle specializes in, Seattle is projected to be exposed to competition if those imports enter near Seattle, but not if they enter through the port of New York.

We estimate the labor market effects of rising Chinese imports on 722 US CZs over the period 1990-2000 and 2000-2007, following Autor et al. (2013) and many ensuing studies. Our estimates are based on the following reduced form equation:

$$\Delta y_{it} = \beta \Delta IPW_{it} + \gamma \Delta x_{it} + u_{it} \quad (5)$$

in which y_{it} is a labor market outcome of interest, IPW_{it} is a measure of imports per worker and x_{it} are controls, including state and year fixed effects.

Transport between the port and the commuting zone

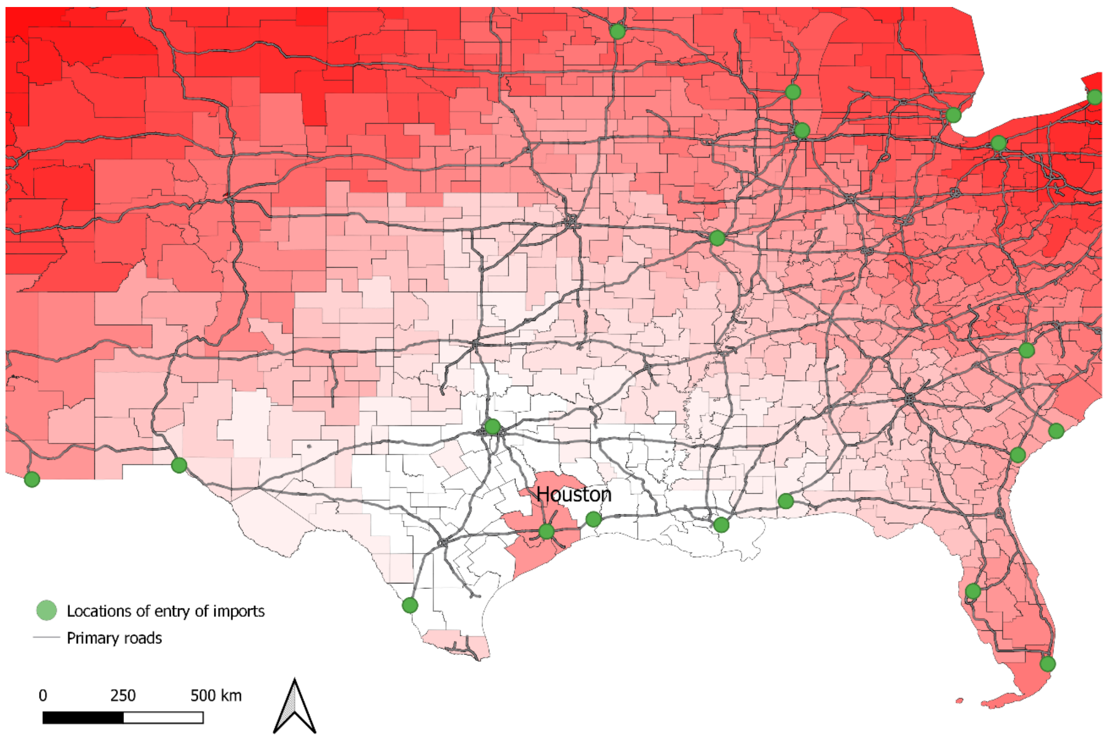
The central change of the import competition measure relative to those in the literature is that the importance of competing imports is smaller when there are higher costs of moving goods from the port of entry to the CZ.

To model how trade declines with domestic transport distance, we use a standard gravity specification. For our baseline results, based on a log-linear specification, we use a distance decay coefficient of -1. This assumption is close to transport cost elasticity estimates and is also commonly used in the geographical literature (Harris 1952). Moreover, when estimating a gravity model on internal trade of goods for the US using *Commodity Flow Survey* data, we find a coefficient of log distances on log trade flows close to -1 (Appendix C). Effectively, employing the condition that exposures sum to one, $\sum_i s_{id} = 1 \forall d$, the baseline transport friction is $s_{id} = distance_{id}^{-1} / \sum_{i'} distance_{i'd}^{-1}$. This implies that the impact of trade is approximately half as large, when the distance to the port of entry is twice as large. We relax this assumption in a robustness check, exploring a range of distance decay parameters. We also report results for an alternative specification of transport-based imports per worker, more closely related to the Autor et al. (2013) specification, that does not require specifying the transport cost function.

For the measure of distance, we use the minimum distance covered on the primary roads network (US TL, 2016) between the commuting zone and the location of the trade district authority of each of 42 reported points of entry of imports into the US. We snap commuting zone centroids to the nearest point on the road network for the calculation of road distances. This does not produce meaningful differences compared to using commuting zone centroids. We winsorize the lowest 1% of the calculated minimum distances to ensure that arbitrarily close trade authorities and commuting zone centroids do not dominate the distribution.

Figure 1 shows an example of the primary road distances of every commuting zone to the port of Houston. It shows that commuting zones nearby, and those connected to the primary road network have lower travel distances to the port.

Figure 1. Map of the shortest route distance of the commuting zone to the port of Houston over the primary road network. Darker colors indicate longer distances.



Internal shift-share and estimation

A concern when explaining local labor market outcomes from the exposure to imports from China is that local demand or other shocks may also cause changes in imports. That can obscure the causal impact of the import exposure. For instance, industries in decline may let workers go, thereby causing rises in imports to replace local production, which causes a correlation between employment and imports that should not be interpreted as a causal impact of import competition.

To rule out alternative interpretations, we instrument imports through a port-specific generalization of the instrument of Autor et al. (2013). We exploit that ports specialize in specific products: for instance, as a proportion of total shipment value handled in 2000, the port of San Francisco handled around 8 times more computer terminals and electrical components than New York, while New York handled around 10 times more in almost all fashion-related product classes than San Francisco. With domestic transport costs, all CZs have a different exposure to imports from each port. Therefore, port-industry specific projections of Chinese imports lead to variation in the instrument for import exposure across CZs, even if CZs have similar industrial employment patterns: some CZs will be nearer the location of import than others.

We construct the instrument in two steps. First, we project the import changes of Chinese product flows to advanced economies other than the US using the port-level industry import averages and the development of industry-level exports from China to other countries. The projection yields a prediction of imports by industry by port of entry by year. Next, we allocate the predicted imports according to the proximity of CZs to the ports of entry, s_{id}, to construct a prediction for the imports per worker in every CZ. More formally, the instrument is constructed as follows. We calculate the growth rate of Chinese imports in non-US destinations for every industry as: $g_{oc,j} = \Delta M_{ocj,t}/M_{ocj,t-1}$. The port-level absolute change in imports in an industry, $\Delta M_{djt} = M_{dj,t} - M_{dj,t-1}$, is then projected as $\widetilde{\Delta M_{djt}} = g_{oc,j} * M_{dj,t-1} - M_{dj,t-1}$. The instrument for ΔIPW_{uit}^{gen} is then $\Delta IPW_{ocit}^{gen} = \sum_j \frac{L_{ijt}}{L_{it}} \frac{\sum_d s_{id} \widetilde{\Delta M_{djt}}}{L_{ujt}}$.

The instrumentation isolates variation in the data arising from the interaction among China's exports to third countries in specific industries, ports' specialization of handling in those industries, and CZs' differences in proximity to each of the ports of entry. The argument that China's exports to other countries capture a supply shock in China is akin to that of Autor et al. (2013), although the interaction with port-level industrial specialization generates prediction for 42 different locations of entry in the US.

A threat to inference when using CZs is that the observations are not independent. When unobserved variation in labor market outcomes correlates across CZs with the industrial employment specialization, standard errors may be considerably underestimated (Adao et al., 2019). We employ the Adao et al. potential outcomes framework because of its robustness to cross-CZ correlations, by resampling shifters conditional on shares and residuals. Our dataset has relatively many sector shares (at three- or four-digit industry levels) which makes individual industries unlikely to dominate the inference (for the year 2000, the mean share of imports for an industry is 0.2%, with a maximum of 8%). As some of the earlier studies in this literature cluster standard errors at the state level, we report those standard errors too for comparability.

In the shift-share analysis, the exposure to import growth in a Chinese product varies by location. In our generalized import penetration measure, an area's exposure to a specific industry import change is different from the non-spatial measure, as the generalized measures includes distance to the port of entry in addition to the area's industrial employment overlap with the imported product. For the weighting of exposure in the Adao et al. potential outcome framework we factor weights by rewriting the import penetration measure from eq. (4) as:

$$\Delta IPW_{ocit}^{gen} = \sum_j \frac{L_{ijt}}{L_{it}} \left(\frac{\sum_d s_{id} M_{dj,t-1}}{L_{ujt}} \right) \left(g_{oc,j} - 1 \right), \tag{6}$$

in which the weights can be summarized as $IPW_{ocit}^{gen} = \sum_j w_{ijt} \left(g_{oc,j} - 1 \right)$, with $w_{ijt} = \frac{L_{ijt}}{L_{it}} \left(\frac{\sum_d s_{id} M_{dj,t-1}}{L_{ujt}} \right)$. In the case without domestic transport costs, the term $\sum_d s_{id} M_{dj,t-1}$ is substituted for national import changes for the industry. Using the weighted exposure shares w_{ijt}, we report standard errors conditional sector shares.

Data

For the labor market outcomes, we follow Autor et al. (2013) in the construction of employment data, estimates for weekly (log) earnings to proxy for wages and population composition. The data on house prices are from the 1990, 2000 and 2010 US Censuses via NHGIS, converted to CZs using the original crosswalks (Autor et al., 2013).

The data on Chinese imports disaggregated by point of entry are from the US Census bureau (the USA Trade Online portal at USAtradeonline.gov). The imports are encoded at 6-digit harmonized system (HS6) codes by origin country from 1992 onward. We transform the HS6-level imports from China into the US into SIC (Standard Industrial Classification) classes using the crosswalk from UN Comtrade. Data are classified into 42 different customs districts across the US (other forms of entry are minor or not registered). We take the largest infrastructure point of entry by freight value in the customs district as the geographical point of entry of the imports.

Import data from the US Census Bureau may differ from the import data reported in the UN Comtrade datasets that most related literature uses. However, the two datasets are aggregated from the same raw data sources. District-level Census data are more disaggregated and may have more cells missing because of data sensitivity concerns. Nevertheless, the overlap between the Comtrade and the Census datasets is substantial, as documented in Appendix D . In order to ensure that our results are driven by geographical variation in points of entry and not by other differences between the Comtrade and Census data, we also verify that when aggregated similarly as the Comtrade data, the Census data give us the same results in the baseline regressions.

4. The spatial impact of trade shocks on local manufacturing employment

Our main results compare regressions of manufacturing employment decline on different import competition measures. Subsequently, we consider other outcomes affected by manufacturing decline, while also documenting how the model's predictions change once domestic transport costs are accounted for.

Results on manufacturing shares from the transport-based import penetration measure

Column 1 of Table 1 shows the coefficient for the impact of the transport-based import per worker measure on manufacturing share changes. It implies that $1,000 in competing imports is associated with around half a percentage point decline in the manufacturing employment share of CZ. The estimate is significantly different from zero, both when considering the state-clustered and Adao et al. (2019) standard errors. The regressions report first-difference estimates of decadal change and include the full set of controls as well as time and Census region fixed effects. The controls include the percentage of employment in manufacturing; the percentage of college-educated population; the percentage of foreign-born population; the percentage of employment among women; the percentage of employment in routine occupations; and the average offshorability index of occupations.

Columns 2 to 4 show the estimates from related approaches for comparison. Column 2 replicates the estimation of Autor et al. (2013), which shows marginally stronger reductions in the share of manufacturing jobs (around 10%). These coefficients can be compared directly as the two

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Change in manufacturing employment share						
IPW (transport&industry)	-0.54***						-2.06
	(0.12)						(1.73)
IPW (industry only)		-0.60***				-1.88***	
		(0.06)				(0.61)	
IPW (aggr. industry only)			-0.62***	-0.64***			
			(0.06)	(0.11)			
IPW (spatial only)					-0.24**		
					(0.10)		
Prediction with transport costs						-1.81*	
						(0.93)	
Prediction no transport costs							-3.25
							(2.19)
Obs.	1,444	1,444	1,444	1,444	1,444	1,444	1,444
R-squared	0.26	0.34	0.34	0.33	0.43	-0.27	-1.23
controls	yes	yes	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes	yes	yes
region FE	yes	yes	yes	yes	yes	yes	yes
State-clustered s.e.	0.15***	0.10***	0.10***	0.16***	0.19	0.61***	1.42
Kleibergen Paap Fstat	14.88	47.64	50.01	88.85	133.5	6.418	1.893

Table 1. Impacts on manufacturing employment shares. Import penetration measures and artificial nested model estimates of impacts of import competition on changes in commuting zone manufacturing employment shares

*Notes. IPW refers to imports per worker. IPW (transport&industry) is the import penetration measure based on unit elastic decay in domestic transport costs. IPW (industry) is the import penetration measure based on Comtrade data as in Autor et al. (2013). IPW (aggr.) is the import penetration measure based on US Census aggregated data. Column 2 is instrumented with Comtrade data, Column 3 is instrumented with Census data. IPW (spatial only) is the aggregate import per worker based on unit elastic decay in domestic transport costs, irrespective of the industrial overlap. "Prediction with transport costs" is the predicted outcome from model 4. "Prediction no transport costs" is the predicted outcome from model 2. Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1*

measures of import penetration represent the same quantity of assigned imports. Both coefficients are statistically significantly different from zero. Column 3 shows the results when estimating the model with aggregated Census trade data but instrumenting with UN Comtrade data, showing somewhat larger declines in manufacturing jobs. In Column 4, both the instrument and the import per worker measure are from aggregated Census data, revealing a slightly larger reduction in manufacturing employment shares than other measures do. Although the data nearly overlap, the estimates based on the Census data suggest slightly larger, but not significantly different coefficients for manufacturing job reductions.

The transport-based measure of import competition comprises the interaction of two explanations for competitive pressure: overlap in the industrial patterns of local employment and imports; and proximity to the locations of imports. Our measure $IPW_{uit}^{transport\&ind}$ reverts the Autor et al. (2013) measure if we assume domestic transport costs to be zero. Reversely, there is a special case in which all CZs' employment patterns overlap equally with imports, so only the transport costs towards the ports of import matter.

Column 4 shows the coefficient when modeling import penetration solely based on transport costs to the port, disregarding the industry overlap of employment. Again, this import penetration measure ("*spatial only*") accounts for all imports and has similar averages to the previous measures, so the coefficient can be directly compared to the others. The coefficient is significantly different from zero but reduces to less than half the impacts estimated before. Hence, the purely spatial component of the Chinese import penetration measure has a significant impact on manufacturing employment by itself, but the impact is smaller than when taking the overlap of employment specialization with competing imports into account.

To evaluate the relative explanatory power of the import penetration with and without domestic transport costs, we report an artificial nesting J-test. As the two import penetration measures are not strictly nested, we test whether the predicted values of one model have additional explanatory power in the competing model (Davidson and MacKinnon, 1981). Column 3 shows that the predictions of the transport-based model has a significant coefficient as explanatory variable in the non-spatial model. The reverse is not true: the transport-based model statistically encompasses the other model and adds significant explanatory power to it. Second, we report the generalized R-squared statistics for the models (Pesaran and Smith, 1984), as the regular R-squared carries a problematic interpretation for instrumental variable models. The results suggest a better fit for the transport-based model (0.36 vs. 0.28).

Finally, the entrance of China into the WTO may have offered confounding export opportunities. If export opportunities correlate with import competition experienced per CZs, the estimate of job losses may be biased. To investigate this, we estimate the manufacturing employment impacts of net exposure. We take the change in Chinese imports by product by port net of the change in exports towards China in that same port and product. Then, we allocate this net product-by-port exposure to CZs using the domestic transport cost function. The results are in Appendix E . We find that the estimated job loss coefficient is slightly more pronounced for the change in net imports than for the change in imports. However, the two coefficients are less than a standard error apart.

The location and origin of job losses

Our estimates using transport-and-industry-based import exposure imply different locations of manufacturing job losses than do exposure measures based on industrial exposure only. In 0, we map the where the job losses occur as implied by our estimates. While the aggregated national manufacturing job losses are not significantly different between the two models, their locations differ considerably. The transport-and-industry-based import exposure accounts for large job losses Florida, the North-East and the West Coast, but less so in the Midwest.

If import competition does not account for large job losses in the remaining parts of the US, our specification may leave room for other explanations in remote areas. Moreover, our transport-based measure plausibly correlates differently with the controls: the routineness or the offshorability of local jobs may be high neat trade infrastructure, for instance. In Appendix G we document how the coefficients for controls once we introduce a transport-based measure of expose, once not filtering for regional fixed effects. In that case, the impact of import competition is estimated to be larger than in the original specification; and college education, foreign born population and lower shares of routine jobs are linked to significantly smaller manufacturing decline.We also find that when either removing the control variable or the regional fixed effects from the specification, the coefficients for transport-based import penetration measures are considerably larger while the coefficient for the original measures changes far less. That is the result of a higher correlation of the transport-based measure with either type of controls (as the controls are common between specifications, and the two import penetration measures have similar variances, differences in the coefficients for the controls are driven by the correlation between the respective import penetration measure and the controls).

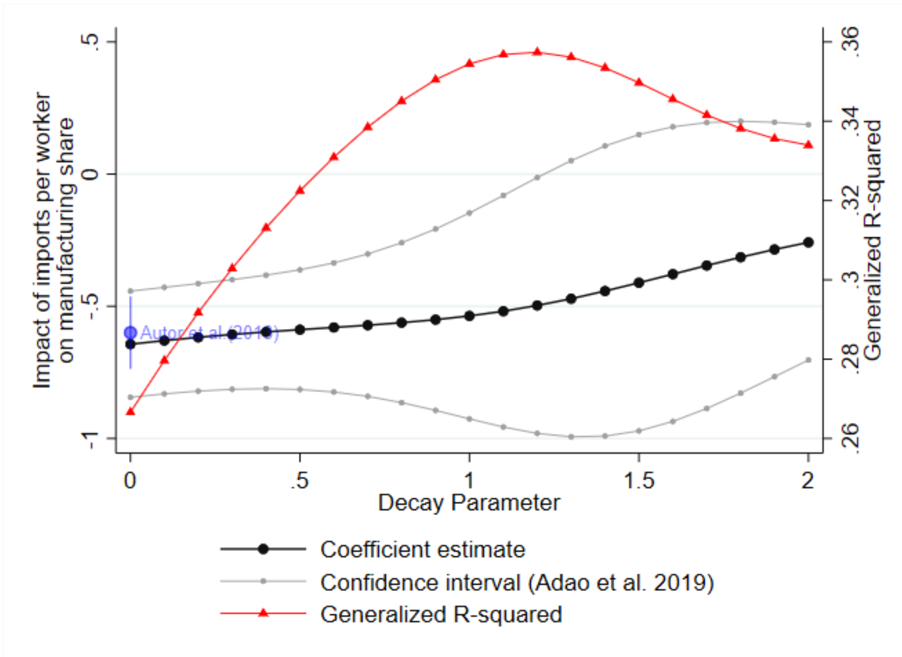
Sensitivity to assumptions on the transport costs parameter

The construction of the import penetration measure based on domestic transport costs requires an assumption: how the competitive effects decay as a function of the transport distance from the CZ to the port. Following US gravity models for domestic trade (see also Appendix C), we used a distance decay parameter of 1 in our main results. To check the sensitivity of that assumption, we re-estimate the model with decay parameters from 0 (effectively the original import penetration measure as there is no distance decay) to 2.

Figure 2 shows the evolution of the estimated coefficient on manufacturing share declines, for different levels of the distance decay parameter. Higher decay parameters imply that the presumed impacts of imports competition are allocated closer to ports. As the weights are normalized, the coefficients using different decay coefficients can be compared directly. The development of the coefficient shows that the estimated impact of import competition declines when assuming the competition takes place closer to the point of entry – with the impact becoming statistically insignificant for higher levels of decay.

Figure *2* also shows how the generalized R-squared of the model (right Y-axis) develops with the assumptions on the decay parameter, on the right Y-axis. The generalized R-squared peaks at a distance decay parameter of 1.2. That suggests that the best fit model has slightly stronger decay than our assumed decay.

Figure 2. Estimates of manufacturing share decline coefficients and goodness of fit when varying assumed parameter of distance decay. The original estimate of Autor et al. (2013) is plotted in blue. Estimates conditional on the full set of controls and fixed effects. Confidence intervals are based on the Adao et al. (2019) shift share estimates of standard errors.



Coefficient stability in a standard import competition framework

A simpler prediction of our argument, and of Eq. (3), is that industrial employment overlaps with Chinese imports lead to more job losses, when a labor market is closer to the infrastructure of international trade. In statistical terms, the prediction is that the import penetration constant in the standard import competition framework (Autor et al., 2013) is not constant. The coefficient is arguably closer to zero for labor markets that are more isolated from international trade.

A test for the stability of the import penetration coefficient does not capture the idea that similar imports need to arrive in a nearby port to compete: workers near New York might qualify as highly exposed due to their simultaneous proximity to a large port and their import competing industry, although the competing imports arrived in Los Angeles. Nevertheless, there are two advantages to this approach. First, it preserves the direct comparability to the (tried and tested) instrumental variable strategy of Autor et al. (2013), by instrumenting changes in the imports of Chinese products in different industries with changes in exports from China of the same products to other countries. Second, allowing for coefficients by quintile of exposure requires only few assumptions on the functional form of exposure, except that commuting zones can be ordered in their shelteredness from international trade.

We allow the coefficient for import penetration to vary across commuting zone quintiles ordered by shelteredness from international trade as:

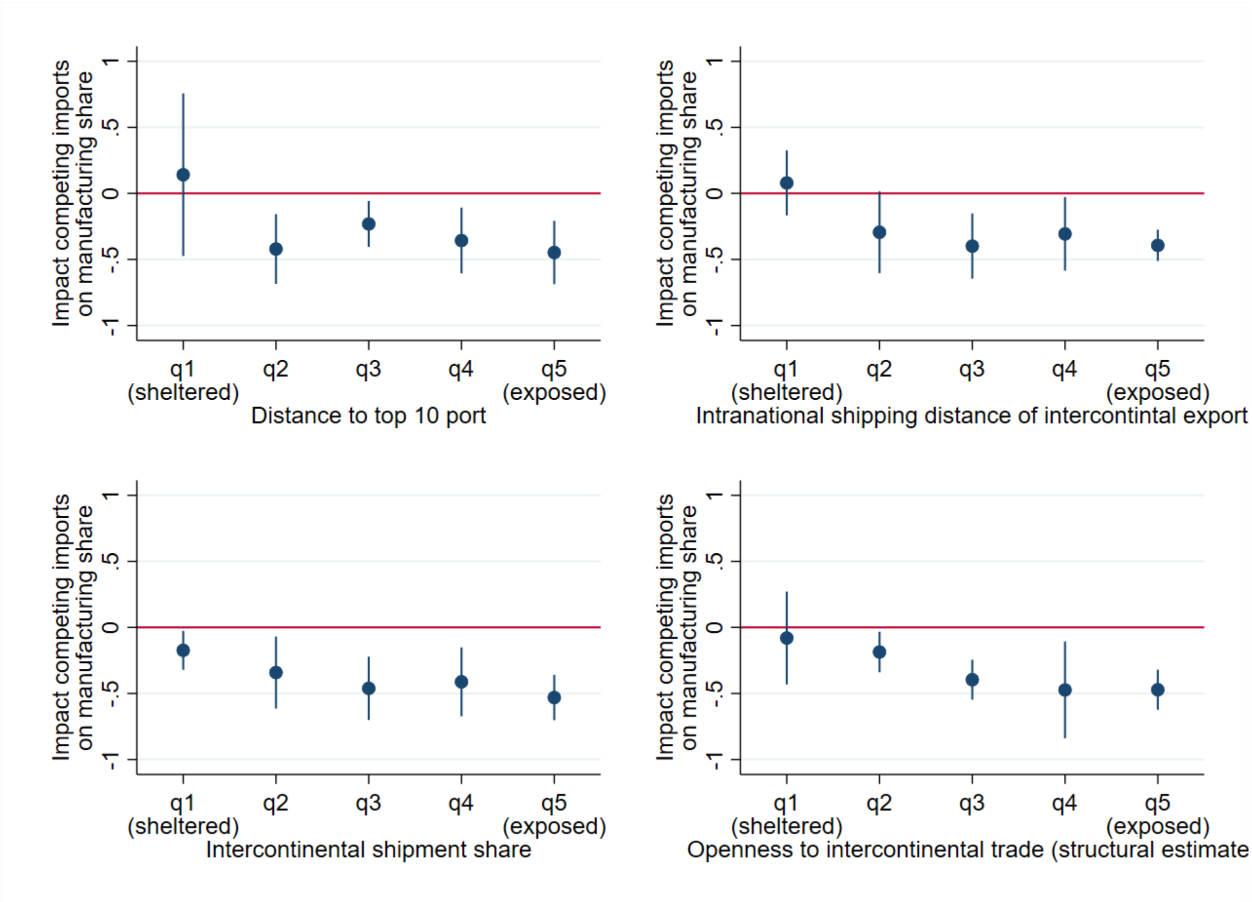
$$\Delta L_{it}^{m} = \sum_{q} \beta_q \, D_q \Delta IPW_{uit} + \sum_{q} \delta_q \, D_q + \gamma X_{it} + \alpha_t + \varepsilon_{it}. \tag{7}$$

where D_q is a dummy for the quintile of a proxy for domestic transport costs of international trade, and β_q is the quintile-specific coefficient for the impact of competition with Chinese imports on manufacturing employment shares.

We use four different measures to quantify commuting zone's level of shelter from imports, each detailed in Appendix H . First, we calculate each commuting zone's road distance over the principal road network to the nearest of the 10 largest ports by value of imports. Second, we measure the average domestic distance that a commuting zone's exports cover up to the location of export (i.e. to the port of international shipment) from the Commodity Flow Survey. Third, we include the share of a commuting zone's total sales that is destined for intercontinental shipment, as a revealed measure of the ease of international shipment. Fourth, we estimate a gravity model of trade to domestic and international destinations and take each commuting zone's estimated intercontinental trade friction as a measure of shelteredness from trade. This measure controls for the commuting zone's own general propensity to trade and that of rivalling origins and destinations, when identifying the estimate of trade costs with respect to other countries.

Figure *3* shows the coefficients of the IV. In the quintile of the most sheltered areas (q1), the impact of import penetration is closest to zero (on the left-hand side of the graphs). The estimated impact is not significantly different from zero among the most sheltered commuting zones in three of the four measures of shelter (only for shipment shares is the estimated impact negative and significant). For all definitions of shelteredness from international trade, the estimated negative impact of competing imports on local manufacturing employment is larger in areas that are less sheltered. To test whether less sheltered areas see structurally stronger manufacturing decline from import competition given their employment overlap with imports, we calculate Wald statistics for the equality of the coefficients. For all definitions, the test rejects (at 10% for distance to top 10 ports, 5% for the structural trade openness estimates, and 1% for the distance routed to international ports and international shipment shares): for all measures, higher exposure to international trade is associated with significantly stronger impacts of import competition.

Figure 3. Impact of import penetration on manufacturing employment shares by quintile of CZ isolation from international trade (IV estimates)



An alternative way to separate the location-specific impacts from the industrial overlap, is to exploit within-industry across-CZ variation in outcomes. In Appendix I , we regress industry-location specific employment on the (instrumented) product-specific distance to ports of import, controlling for industry-year and commuting zone year fixed effects. The regression uses variation within the industry to estimate employment correlations with exposure to imports that arrive nearby. However, the approach is more likely to suffer SUTVA violations if workers move across industries in response to trade cost shocks. Our main regression implies around one job lost per $37,000 in competing imports.

Impacts of import competition on employment, wages, and housing prices

We estimate the impacts of Chinese import competition on manufacturing employment, unemployment levels, and subsidies (Table 3); overall employment levels (with a breakdown by college education and age bracket; Table 4); wages (Table 5); and housing prices (Table 6). For reference, all tables report the estimates of import competition with domestic transport costs in panel a and the regular import competition measures (as in Autor et al. 2013) in panel b. [5]

Table 2 shows the main employment outcomes. Although the transport cost-based import competition measure shows somewhat lower estimates of manufacturing employment decline (-0.54 vs -0.60), it shows larger estimated impacts in all other reported segments of the labor market. We find significant and substantial declines in non-manufacturing employment (of around -0.54 percentage point per $1,000 in competing imports). The impact in non-manufacturing employment is significant and around three times as large as the original estimate (-0.54 vs. -0.18). The estimated declines in employment for non-college educated workers are significantly larger than for college educated workers. The pattern is similar to the original import competition measure but more pronounced, as the estimated impacts are around 50% higher. Other outcomes are comparable between the original and transport-based measures, with the exception of workers not in the labor force, which see stronger responses to import competition when using the transport-based import penetration measure.

Table 3 shows the impact of import competition on wages. Within the manufacturing sector, we find no evidence of overall wage changes with competing imports – both in the transport based and the original import penetration measures. The transport cost-based import penetration suggests considerably stronger wage reductions for the overall population and outside the manufacturing sector. For non-manufacturing non-college educated workers, the transport cost measure implies around 70% higher wage losses (-1.39 vs. -0.82). The transport cost-based measure also suggests considerably higher wage losses for non-college educated workers relative to college-educated workers, than the original estimates suggest.

[5] We find no impact on the labor force (segments) in either measure of import competition. The results are reported in 0.

Lastly, Table 4 shows the impacts on housing market outcomes. Most strikingly, once accounting for domestic transport costs (panel a), the estimated impact of import competition is around three times as large: per $1,000 in competing imports, house price decline around 9%, instead of 3%. This suggests that in areas where the transport-cost based import measures predict the strongest competition, house prices reduced at faster rates than where the original import competition measure allocates competition. The transport-based import competition measure also shows a significant (at the 10% level) reduction of 2% in rents per $1,000 in competing imports per worker, while the effect is smaller and insignificant when employing industry-only variation. By contrast, industry variation predicts decreases in vacancy rates, though at minor magnitude (0.14% decline per $1,000 competing imports per worker; the sample standard deviation is 2.8%).

Impacts on non-economic outcomes

The import competition literature on the Chinese trade shock extends beyond labor market outcomes. We examine how measures of impact competition based on domestic transport costs affect three main sets of results: voting in presidential elections, mortality and gender mortality gaps, and family formation choices (Autor et al. 2019). We discuss the main results, leaving the regression tables in 0.

Table K1 shows regressions explaining presidential electoral outcomes from import competition measures. The dependent variable is the share of Republican votes in the total Democrat and Republican votes across counties within the CZ (Amlani and Algara, 2021). We consider elections around the decades for which we calculated import competition shifts, both for the period 1988-2012 (George H.W. Bush – George W. Bush- Obama) and 1992-2008 (Clinton – Bush - Obama). Once considering domestic transport cost in import competition, an increase by $1,000 in competing import per worker reduces the Republican vote by 1.6 percentage point (1988-2012), and 1.3 percentage point (1992-2008), respectively. The import competition measure based on industrial exposure only shows no significant effects on electoral outcomes.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variables	Manufacturing employment	Non-manufacturing employment	College degree employment	Non- college degree employment	Unemployed	NILF	SSID
Panel a							
IPW (transport & industry)	-0.54***	-0.54*	-0.62**	-1.54**	0.24**	0.83**	0.10***
	(0.20)	(0.31)	(0.29)	(0.69)	(0.11)	(0.39)	(0.03)
State clustered se	0.15***	0.31*	0.26**	0.61**	0.12**	0.33**	0.03***
Kleibergen Paap Fstat	14.88	14.88	14.88	14.88	14.88	14.88	14.88
Panel b							
IPW (industry only)	-0.60***	-0.18	-0.42***	-1.11***	0.22***	0.55***	0.08***
	(0.07)	(0.10)	(0.08)	(0.19)	(0.06)	(0.10)	(0.01)
State clustered se	0.10***	0.14	0.12***	0.25***	0.06***	0.15***	0.03***
Kleibergen Paap Fstat	47.64	47.64	47.64	47.64	47.64	47.64	47.64
Observations	1,444	1,444	1,444	1,444	1,444	1,444	1,444
controls	yes	yes	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes	yes	yes
region FE	yes	yes	yes	yes	yes	yes	yes

Table 2. Employment outcomes

*Notes: Regression across 722 commuting zones over two time period. Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. Regressions are weighted to start-of-period CZ population. Controls include percentage of employment in manufacturing; Percentage of college-educated population; Percentage of foreign-born population; Percentage of employment among women; Percentage of employment in routine occupations: Average offshorability index of occupations. Outcomes are relative changes in the employment of groups denoted where NILF is not in labor force and SSDI indicates disability benefits. *** p<0.01, ** p<0.05, * p<0.1*

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Average			Manufacturing			Non-manufacturing	
Dep. Variables: wages	All	College	Non-college	All	College	Non-college	All	College	Non-college
Panel a									
IPW (transport & industry)	-0.93	-0.99	-1.20*	-0.79	-0.26	-0.88	-1.05*	-1.03	-1.39**
	(0.58)	(0.63)	(0.63)	(0.68)	(0.42)	(0.57)	(0.63)	(0.67)	(0.71)
State clustered se	(0.47)**	(0.49)**	(0.52)**	(1.03)	(0.59)	(0.82)	(0.44)**	(0.45)**	(0.52)***
Kleibergen Paap Fstat	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88
Panel b									
IPW (industry only)	-0.76***	-0.76***	-0.81***	0.15	0.46	-0.10	-0.76***	-0.74**	-0.82***
	(0.26)	(0.29)	(0.21)	(0.34)	(0.28)	(0.21)	(0.24)	(0.29)	(0.20)
State clustered se	0.25***	0.31**	0.24***	0.48	0.34	0.37	0.26***	0.30**	0.25***
Kleibergen Paap Fstat	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64
Observations	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444
R-squared	0.49	0.44	0.41	0.15	0.20	0.27	0.52	0.45	0.37
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. Wage effects

*Notes: Regression across 722 commuting zones over two time period. Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. Regressions are weighted to start-of-period CZ population. Controls include percentage of employment in manufacturing; Percentage of college-educated population; Percentage of foreign-born population; Percentage of employment among women; Percentage of employment in routine occupations: Average offshorability index of occupations. The outcomes are log wage changes split for all workers (manufacturing and non-manufacturing workers); and split across college and non-college educated workers. *** p<0.01, ** p<0.05, * p<0.1*

Model	(1)	(2)	(3)
Dep. Variables:	Log house price	Log rent	% Vacant
Panel a			
IPW (transport & industry)	-0.09**	-0.02*	-0.09
	(0.03)	(0.01)	(0.14)
State clustered se	0.03***	0.02	0.19
Kleibergen Paap Fstat	13.42	13.42	13.42
Panel b			
IPW (industry only)	-0.03***	-0.01	-0.14*
	(0.00)	(0.01)	(0.08)
State clustered se	0.02*	0.01	0.07**
Kleibergen Paap Fstat	49.03	49.03	49.03
Observations	1,444	1,444	1,444
R-squared	0.49	0.44	0.41
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 4. House price effects

*Notes: Log house price is the log of the median house value of owner-occupied homes. Log rent is the log of median rent of renter-occupied homes. % vacant is the percentage of dwellings out of total that is vacant on average. Regression across 722 commuting zones over two time period. Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. Regressions are weighted to start-of-period CZ population. Controls include percentage of employment in manufacturing; Percentage of college-educated population; Percentage of foreign-born population; Percentage of employment among women; Percentage of employment in routine occupations: Average offshorability index of occupations. *** p<0.01, ** p<0.05, * p<0.1*

This result is in line with county-level evidence (Che et al, 2016), bearing in mind that Republican candidates were less protectionist over this time period. It also agrees with the results on increased polarization from import competition (Autor et al. 2016) that suggest that when faced with import competition, majority white areas are more likely to vote Republican, and majority minority areas are more likely to vote Democrat. As the transport-cost based import competition measure plausibly assigns more of the competitive pressure on majority minority CZs, the results are consistent with the suggestion that Democrat candidates gained votes with import competition.

Tables K2 and K3 reports regressions on cumulative mortality by cause for young population (age 20-39, calculated from Autor et al. 2019). Table G2 explains aggregate mortality. It reports that mortality from (drug and alcohol-related) poisoning is substantially higher under the import competition measure that accounts for domestic transport, as opposed to a measure that considers industrial exposure only. It also suggests that the other causes of death (which also include cardio- and weight related causes of death) are significantly higher when domestic transport is accounted for, but suicide is significantly lower. Table G3 explains the male-to-female mortality gap form import competition. Once domestic transport cost are accounted for, the import competition model, implies almost twice as high gender mortality gaps from poisoning due to import competition, but smaller suicide gender gaps and residual mortality.

Table K4 shows results on family formation, suggesting significant differences between models of import competition with and without domestic transport costs. When accounting for domestic transport costs, increased import competition is associated with more married couple households and fewer single households. By contrast, when considering an industry-only measure of exposure, females are less likely to be married and live with a spouse as import competition rises. Under both measures, birth rates decline with import competition. However, the estimated import competition impact on the share of children living below poverty is twice as large when accounting for domestic transport cost, and the share of women with children is significantly higher, despite the impact on birth rates being very similar. Hence, the transport cost-based import competition measure suggests that more children stay in areas affected by import competition and grow up in poverty, as compared to the measure based on industrial exposure only.

5. Conclusions

This paper argues that local labor markets with low domestic trade costs to international markets are more exposed to the impacts of international trade. Domestic transport costs, like international trade costs, isolate the area and reduce the competition experienced from foreign producers.

We generalize the most common measure of import competition – imports per worker in the competing industry – to allow domestic transport costs between the imports' points of entry into the country and the local CZ to affect the intensity of competition. In a local labor market, the import exposure is higher, if *i)* workers are employed in industries that see rising imports, and *ii)* those imports arrive in ports that connect closely to the local labor market via the main road network.

The model of import competition has stronger explanatory power once domestic trade costs are accounted for. We also find that given a region's employment overlap with Chinese imports, isolation from trade infrastructure shelters their labor force, and that employment in the same industry is more likely to decline, the closer the jobs are to the location of entry of the imports.

Compared to earlier studies, the results account for job losses on the coasts of the US but less so in areas traditionally suspected to suffer, such as the Midwest. The national manufacturing job loss estimates are similar. Once domestic transport is accounted for, import competition shows stronger price responses in terms of wage and house prices and larger negative impacts for groups indirectly impacted, such as lower educated non-manufacturing workers. In addition, import competition measures accounting for domestic transport show significant roles of the rise of China in presidential voting patterns and changed impacts on mortality and family formation. Our results suggest that policies to deal with local impacts of globalization may need to account for trade infrastructure and the location of workers; and that some of the manufacturing decline in inland and rural US may have different causes than exposure to international trade.

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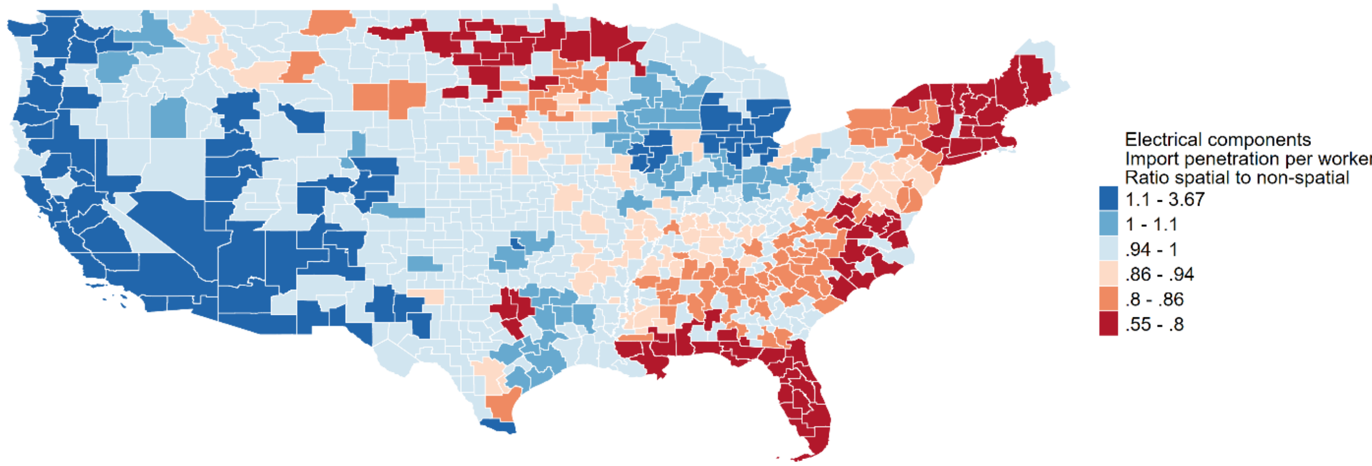
Appendix A Measures of import competition with and without domestic transport costs

Figure A1 maps a comparison of the import competition measure for Chinese electrical components that uses domestic transport frictions, and an import competition measure that assumes no domestic transport cost.

Figure A 1. Ratio of import penetration in the electrical components industry of a measure with domestic transport cost relative to a measure without domestic transport costs.



Notes: Import penetration is defined as $1,000 of imports per worker in the industry of employment. For the transport cost-based measure, imports experience a transport costs elasticity of -1, which is normalized so that the aggregate exposure equals that of the non-spatial measure. Mapping based on a 5 quintiles scale. Sources: Autor at al. (2013), US Census, transport costs on U.S primary roads.

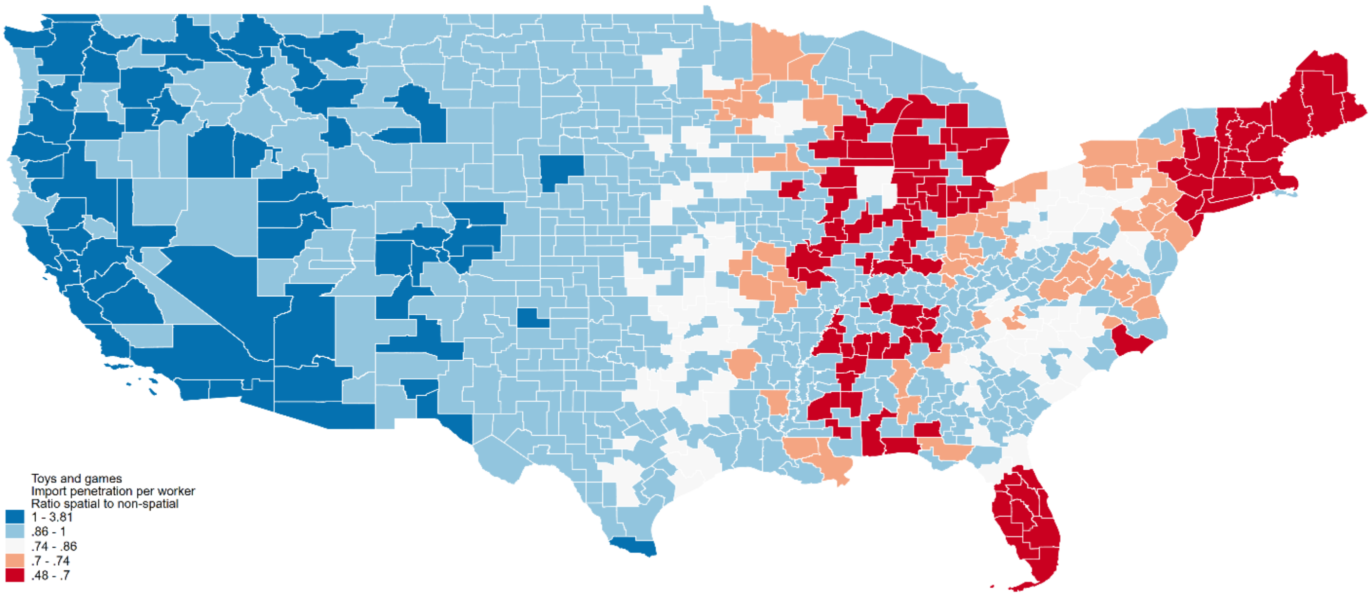
The map plots the ratio of the transport-cost based import penetration to the original import penetration measure to understand when transport-based import penetration is high (in blue) or low (in red) relative to the more commonly used import penetration measure. Labor markets are affected if they simultaneously i) are located near ports that import electrical components and ii) employ workers in that industry. The ports of Los Angeles, San Francisco and Chicago are substantially overrepresented in the handling of Chinese electrical components. When allowing for a standard transport cost specification for internal goods movement from the port of entry[6], the

[6] The specification is a gravity equation with unit-elastic decay of the goods flow in transport costs. The frictions are normalized to that every dollar of import is equally weighted in the aggregate between the two measures. See Section 2 for a more extensive definition.

measure of import penetration changes: when accounting for domestic transport costs, workers in electrical components near L.A. see strong competitive effects, but workers in electrical component firms near Boston (the port of which is underrepresented in Chinese imports) see weaker competitive effects. The experienced imports per worker may be up to twice as high near the importing ports (on the West Coast and Chicago), and up to 45% lower in areas that have electrical component employment but no port that imports the components from China.

The entry of imports through different ports generates spatial differences in the competition of imports that workers experience. Figure A2 shows the ratio of import penetration with and without domestic transport costs, now for toys and games imported from China. Like electrical components, the industry of toys and games saw substantial rises in Chinese import. One striking difference occurs around Chicago. For Electrical Components, the transport-based import penetration is high around Chicago, while for toys and games it is low, relative to the import penetration that does not take transport costs into account. Across the two measures, the employment in the respective industries is the same. However, Chicago's infrastructure is specialized in handling electrical components. After the year 2000, Chicago's customs district saw the second largest rise in electrical components of all districts accounting for nearly 20% of the nationwide change in imports. By contrast, Chicago handled less than 1% of the rise of imports in toys and games. Consequently, the transport cost-based import penetration measure suggests that worker in Chicago faced relatively low competition from Chinese imports.

Figure A2. Ratio of import penetration ($1,000 of imports per worker) in the toys and games industry of a measure with domestic transport cost to a measure without domestic transport costs.



Appendix B A stylized model of two domestic regions and China.

We provide a theoretical motivation for the role of domestic transport costs in the impact of import competition. In import competition models with monopolistically competitive tradables sectors, we have labor market predictions for two geographical settings (Autor et al, 2013; Hsieh and Ossa, 2012). In the first setting, local labor markets are modeled as small economies that trade with China, and sector adjustment in other domestic local labor are treated as constant. However, this ignores that local employment depends on the demand of other domestic areas, where its manufacturing firms compete with Chinese imports too. In the second setting, local economies are aggregated into a large national economy to allow for international general equilibrium effects. However, this implies that domestic trade costs are zero. Introducing positive domestic trade costs generally leads to solutions that are not analytically solvable.

We adapt a standard model of import competition with monopolistically competitive firms with one disciplining assumption: that all impact of import competition is on worker sector choice, and none on wages. Our model features a Krugman (1991) style sector of freely tradable products, which ensures that wages are equalized, and sector choice is the only margin of adaption.

Our stylized model features three locations: Inland (I) (such as Denver), Oceanside (O) (such as Houston), and China (C). The iceberg trade costs between Inland and Oceanside are symmetric at $\tau > 1$; but the trade costs with China are lower for Oceanside than for Inland: $1 < \tau_{CO} < \tau_{CI}$.

In our model, the two domestic regions are large economies relative to the other, but small relative to China (following the small economy model in Autor, Dorn and Hanson, 2013). Hence, one domestic region's sectoral reallocation bears consequences for the other domestic region but not for the Chinese wage. China is a negligible source of demand for the two domestic regions. US Domestic consumers buy Chinese products, leading to shift in the US current account.

Workers in local labor market i can be employed in two sectors. The first is a competitive national sector (N) that ships it goods freely across domestic markets. The number of workers employed in the national sector in location i is L_{Ni}. The second sector is an imperfectly competitive manufacturing sector, which trades its output at iceberg trade costs. Workers can move freely between sectors but not between locations. We assume that all sectors are populated, which equalizes the wages across sectors in the same location.

Workers have Cobb-Douglas preferences over the three sectors, with share γ_j (0,1) of their expenditure on manufacturing ($\sum_j \gamma_j < 1$), and the remainder share $(1 - \sum_j \gamma_j)$ on the national sector. Workers have a CES preferences over manufacturing varieties, such that:

$$U = c_s^{1-\sum_j \gamma_j} \prod\nolimits_j c_j^j \tag{8}$$

With $c_j = \left(\int \quad c(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\sigma/(\sigma-1)}$ where z is a firm identifier and is $\sigma > 1$.

The worker budget is given by income from labor W plus any consumption financed otherwise, B, which reflects the current account deficit (cf. Autor Dorn and Hanson, 2013). We assume that all workers have the same ratio of B to wages, such that $W + B = Wb$

<u>National service industry</u>. Production in the service sector is at constant returns to scale: $X_{Ni} = L_{Ni}$, and the wage is the unit price. Clearing across the domestic markets implies that:

$$\sum_i W_{Ni} L_{Ni} = \left(1 - \sum_j \gamma_j\right) \sum_i E_i$$
$$with\ E_i = L_{Ni}(W_{Ni} b_i) + \sum_j L_{Tij}(W_{Tij} b_i) \tag{9}$$

Manufacturing industries. The production function in every manufacturing firm is given by the labor requirement l to achieve production x: $l = \alpha + \beta x$. As all manufacturing firms in an industry in a location are symmetric, we index them by location-industry. The demand function for a firm in location i implies that the firm sells across destinations k:

$$x_{ij} = \sum_k x_{ikj} = \sum_k \frac{P_{ikj}^{-\sigma}}{\Phi_{jk}^{1-\sigma}} \gamma_j E_k \tag{10}$$

with $\Phi_{jk}^{1-\sigma} = \sum_h M_{jh} {P^*}_{jh}^{1-\sigma}$ where $M_{jh} = \frac{L_{jh}}{\sigma\alpha}$ is the number of manufacturing firms in h and the asterisk on the price denotes a delivered price. Profit maximization implies that the delivered price of a firm in i to a consumer in k is $P_{jik} = \tau_{ik} \frac{\sigma}{\sigma-1} \beta W_{Tji}$. Given the markup price, the firm size is $l = \sigma\alpha$ and the firm output is $x = (\sigma - 1)\alpha/\beta$.

Equilibrium. We assume that the national sector employs workers in both locations. We focus on a setting where the local manufacturing wages are downward-sloping in the number of people employed.[7] As the right-hand side of the manufacturing clearing condition is downward sloping in the local number of firms in the sector, and so in the number of workers in the local sector, we restrict our attention to cases in which $W_{ji} > W_{Ni}$ as $L_{ji} \to 0$ and $W_{ji} < W_{Ni}$ as $L_{Ni} \to 0$

Free trade across the domestic markets implies that the price and the wages in the local production of services are equal across locations. Free mobility in turn implies that wages across the domestic labor market are equalized. Hence, we refer to the common wage level as W.

[7] Total (log) differentiation of the wage condition implies that $\frac{dW_{TO}}{dM_O}\frac{M_O}{W_{TO}} = \frac{(\sigma-1)(s_{OO}\pi_{OO}+s_{OI}\pi_{OI})}{\sigma - s_{oo}\lambda_{TO} - (\sigma-1)(s_{OO}\pi_{OO}+s_{OI}\pi_{OI})}$, where $\lambda_{TO} = \frac{L_{TO}W_{TO}}{L_{TO}W_{TO}+L_{NO}W_{NO}} \leq 1$ is the earnings share of manufacturing workers in all earnings in the O-region and s_{OI} and π_{OI} are sales shares and expenditure from region O to region I (as also defined in more detail below). For the manufacturing wage to be downward-sloping in manufacturing employment, we require that $\sigma - s_{oo}\lambda_{TO} - (\sigma - 1)(s_{OO}\pi_{OO} + s_{OI}\pi_{OI}) < 0$, and the parallel condition for the inland region is obtained by switching the O and I subscripts.

Solving for a shock to trade costs with China. Clearing on the manufacturing market for the two regions implies two per-sector market clearing conditions:

$$\frac{(\sigma-1)\alpha}{\beta} = \gamma_j \left(\frac{\sigma}{\sigma-1}\beta W\right)^{-\sigma} \left[\frac{L_I W b_I}{\Phi_{Ij}^{1-\sigma}} + \frac{\tau^{1-\sigma} L_O W b_O}{\Phi_{Oj}^{1-\sigma}}\right],$$
$$\frac{(\sigma-1)\alpha}{\beta} = \gamma_j \left(\frac{\sigma}{\sigma-1}\beta W\right)^{-\sigma} \left[\frac{\tau^{1-\sigma} L_I W b_I}{\Phi_{Ij}^{1-\sigma}} + \frac{L_O W b_O}{\Phi_{Oj}^{1-\sigma}}\right] \quad (11)$$

with $\Phi_{Ij}^{1-\sigma} = M_{Ij}\left(\frac{\sigma}{\sigma-1}\beta W\right)^{1-\sigma} + M_{Oj}\left(\tau\frac{\sigma}{\sigma-1}\beta W\right)^{1-\sigma} + M_{Cj}\left(\tau_{CI}\frac{\sigma}{\sigma-1}\beta W_c\right)^{1-\sigma}$ and $\Phi_{Oj}^{1-\sigma} = M_{Ij}\left(\tau\frac{\sigma}{\sigma-1}\beta W\right)^{1-\sigma} + M_{Oj}\left(\frac{\sigma}{\sigma-1}\beta W\right)^{1-\sigma} + M_{Cj}\left(\tau_{CI}\frac{\sigma}{\sigma-1}\beta W_{cj}\right)^{1-\sigma}$. In the text, the constant $\psi_j = \frac{(\sigma-1)\alpha}{\beta\gamma_j}\left(\frac{\sigma}{\sigma-1}\beta\right)^{\sigma}$.

We log-differentiate the equilibrium conditions to derive the impact of a trade shock on the number of firms and workers in the local manufacturing sectors. We denote relative change with hat notation such that $\hat{x} = dx/x$.

Clearing on the market for manufacturing products, along with equal wages among the domestic regions, constant firm size and symmetric current account deficits implies that:

$$0 = s_{jII}((\sigma-1)\widehat{\Phi_{JI}} + \widehat{b_I}) + s_{iIO}((\sigma-1)\widehat{\Phi_{JO}} + \widehat{b_O}),$$
$$0 = s_{iOI}((\sigma-1)\widehat{\Phi_{JI}} + \widehat{b_I}) + s_{iOO}((\sigma-1)\widehat{\Phi_{JO}} + \widehat{b_O}), \quad (12)$$

where $s_{jik} = \frac{P^{*}{}_{jik}^{-\sigma}}{\Phi_{jk}^{1-\sigma}}E_k/(\sum_k \frac{P^{*}{}_{jik}^{-\sigma}}{\Phi_{jk}^{1-\sigma}}E_k)$ denotes the share of a destination in a region's overall sales. The assumption that wages equalize across regions imply that manufacturing price indices compensate for local current account deficits: of regional symmetry on the current account deficits implies that the price indices adjust to satisfy $\widehat{\Phi_I} = \frac{\widehat{b_I}}{1-\sigma}$ and $\widehat{\Phi_O} = \frac{\widehat{b_O}}{1-\sigma}$

The log-differentiation of the price indices in sector i in the Oceanside and Inland regions gives:

$$(1-\sigma)\widehat{\Phi_{JI}} = \pi_{jOI}\widehat{M_{JO}} + \pi_{iII}\widehat{M_{JI}} + (1-\sigma)\pi_{jCI}\widehat{\tau_{CI}},$$
$$(1-\sigma)\widehat{\Phi_{JO}} = \pi_{jOO}\widehat{M_O} + \pi_{jIO}\widehat{M_{JI}} + (1-\sigma)\pi_{jCO}\widehat{\tau_{CO}}. \quad (13)$$

In these equations $\pi_{jik} = M_{ji} {P^*}_{jik}^{1-\sigma} / \sum_h M_{jh} {P^*}_{jhk}^{1-\sigma}$ is the share of total expenditure of region k in industry j on products from region i. Hence, when Chinese supply enters as a reduction in the local price index through lowered trade costs, the price index change is compensated by a mix of adjustment in the current account and in the manufacturing employment.

From the price index derivative and the current account deficits, the region with a stronger trade cost reduction (leading to an increase in $(1-\sigma)\pi_{iCI}\widehat{\tau_{CI}}$) experiences a compensating reduction in supply from the manufacturing sector. That is to say, the change in the domestic part of the price index $\pi_{OI}\widehat{M_O} + \pi_{II}\widehat{M_I}$ needs to reduce more.

Employment changes that satisfy the price indices (solving price index change for $\widehat{M_I}$ and $\widehat{M_O}$) follow:

$$\widehat{M_{JI}} = \frac{(\sigma-1)(\pi_{jOO}\pi_{jCI}\widehat{\tau_{CI}} - \pi_{jOI}\pi_{jCO}\widehat{\tau_{CO}} - \pi_{jOO}\widehat{\Phi_{\iota I}} + \pi_{jOI}\widehat{\Phi_{JO}})}{(\pi_{jOO}\pi_{jII} - \pi_{jOI}\pi_{jIO})}$$
$$\widehat{M_{JO}} = \frac{(\sigma-1)\left(\pi_{jII}\pi_{jCO}\widehat{\tau_{CO}} - \pi_{jIO}\pi_{jCI}\widehat{\tau_{CI}} - \pi_{jII}\widehat{\Phi_{JO}} + \pi_{jIO}\widehat{\Phi_{JI}}\right)}{(\pi_{jOO}\pi_{jII} - \pi_{jOI}\pi_{jIO})} \qquad (14)$$

Local manufacturing employment rises in the region's own trade costs with China but declines in the trade costs with China of the other region. The intuition is that there are two effects. Directly, an increase in trade cost with China reduces the local price index and allows the local manufacturing employment to grow. Indirectly, in the second region, increased trade costs expand the competing manufacturing sector, thus pushing down manufacturing employment in the first region. The price index also implies that the reduced-form sector size needs to decrease as the local price rises, and increase as the price in the other region rises.

The manufacturing employment consequences of a change in Chinese trade costs follow from the system of four unknowns (price index change and manufacturing sector size for both regions) in four equations (manufacturing market clearing and the CES price indices for both regions). The change in manufacturing sector employment simplifies with the assumption that China is a negligible export market for the domestic regions: so $s_{OI} = 1 - s_{OO}$; $s_{IO} = 1 - s_{II}$. Using this, the local changes in manufacturing employment are:

$$\widehat{M_{JO}} = \widehat{L_{JO}} = \frac{\pi_{iII}\left((\sigma-1)\pi_{jCO}\widehat{\tau_{CO}} + \widehat{b_I}\right) - \pi_{IO}\left((\sigma-1)\left(\pi_{jCI}\widehat{\tau_{CI}}\right) + \widehat{b_O}\right)}{\pi_{jOO}\pi_{jII} - \pi_{jOI}\pi_{jIO}}$$

$$\widehat{M_{JI}} = \widehat{L_{JI}} = \frac{\pi_{jOO}\left((\sigma-1)\pi_{jCI}\widehat{\tau_{CI}} + \widehat{b_I}\right) - \pi_{OI}\left((\sigma-1)\pi_{jCO}\widehat{\tau_{CO}} + \widehat{b_O}\right)}{\pi_{jOO}\pi_{jII} - \pi_{jOI}\pi_{jIO}}, \quad (15)$$

where $\pi_{jCO}\widehat{\tau_{CO}}$ is the the product of $\widehat{\tau_{CO}}$, relative change of trade costs between the Oceanside region and China, and π_{jCO}, the weight of Chinese products in the industry price index of the oceanside region. The relative change in the number of firms is equal to the relative change in employment, as firms hire a constant number of workers.

Differences across regions in the manufacturing employment response to a reduction in Chinese trade costs ($\widehat{\tau_{CO}} < 0, \widehat{\tau_{CI}} < 0$) can originate from three broader differences, according to equation (15). (15). First, oceanside regions have larger expenditure shares of manufacturing on Chinese goods $\pi_{jCO} > \pi_{jCI}$, so that the trade costs decline reduces oceanside manufacturing employment in competing industries M_{iO} faster than inland manufacturing employment M_{iI}. This occurs if domestic production is sufficiently similar between the regions.

Second, the trade cost shock itself may differ by region. To take a few examples, suppose that trade costs are additive: for domestic transport, τ is added on top of the ocean transport: $\tau_{CI} = \tau + \tau_{CO}$. Then $\widehat{\tau_{CI}} = \frac{\tau_{CO}}{\tau+\tau_{CO}}\widehat{\tau_{CO}} < \widehat{\tau_{CO}}$, and the decrease in transport costs is weaker in the inland region. Alternatively, if domestic trade costs are multiplicative on the international trade costs, such that $\tau_{CI} = \tau * \tau_{CO}$, then $\widehat{\tau_{CI}} = \widehat{\tau_{CO}}$.

Third, the trade costs impacts on manufacturing employment are weighted by the expenditure shares (resp, π_{OO} for the effect of inland trade costs on inland manufacturing employment; π_{OI} for the effect of ocean-side trade costs on inland manufacturing employment; π_{II} for the effect of ocean-side trade costs on oceanside manufacturing employment; and π_{IO} for the effect of inland trade costs on ocean-side manufacturing employment). If oceanside consumers buy very little inland manufacturing, the net impact of inland trade costs on inland manufacturing is smaller, as the indirect competitive effect is weak – the two regions are communicating vessels in the adjustment of manufacturing employment to the trade costs shock.

Fourth, the impact of the current account deficit plays out differently between the regions. The term $\pi_{OO} - \pi_{OI}$ reflects the difference in expenditure shares on goods from oceanside in oceanside relative to inland.

Aggregate regional changes in manufacturing employment follow from the sum of employment changes in the regions' industries. The change in the share of manufacturing employment in total employment is:

$$d\left(\frac{\sum_j L_{ji}}{L_i}\right) = \frac{\sum_j dL_{ji}}{L_i} = \sum_j \frac{L_{ji}}{L_i}\,\widehat{L_{ji}}\,, \tag{16}$$

As discussed around equation (3).

Appendix C Internal trade and internal distance

Table C1 shows a gravity regression of the form

$$\log flow_{ij} = \beta \log distance_{ij} + \alpha_i + \alpha_j + u_{ij} \tag{17}$$

Where α denotes the origin and destination fixed effects.

The equation is estimated using the Commodity Flow Survey data from the 2012 cross-section with exclusively domestic tradeflows. Origin and destination fixed effects are at the CFS area level, and the distance measures are either the great circle distance or the reported routing distance. The reported estimates are OLS estimates (a Poisson estimators yields similar conclusions). The distance decay coefficient for domestic shipments is estimated to be very close -1, in both measures of domestic distance and both with and without fixed effects.

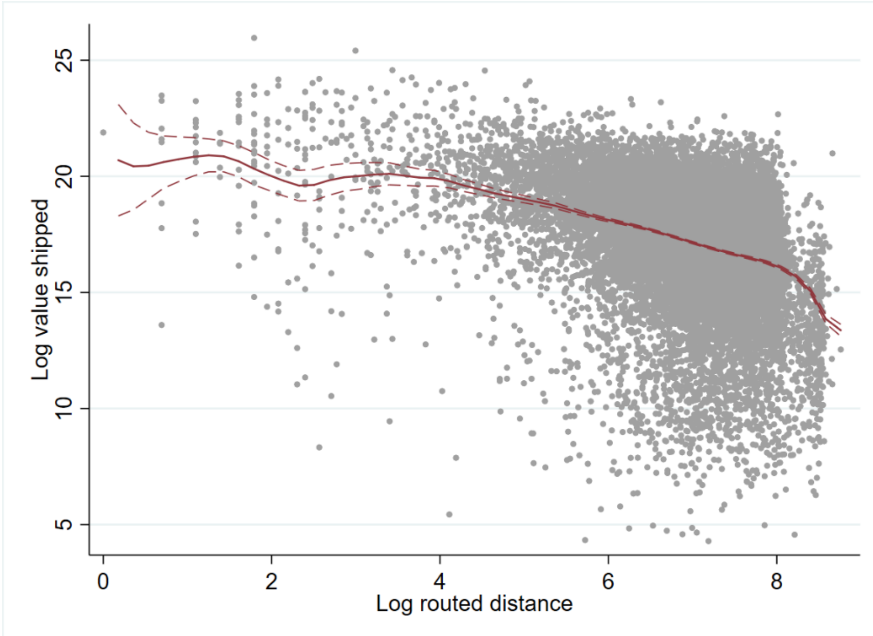
	(1)	(2)	(3)	(4)
Variables	OLS	OLS	OLS	OLS
Log routed distance	-1.019***		-1.020***	
	(0.022)		(0.014)	
Log greater circle distance		-1.006***		-1.022***
		(0.021)		(0.013)
Observations	18,607	18,607	18,607	18,607
Origin FE			yes	Yes
Destination FE			yes	Yes

Table C1. gravity in internal trade flows

Notes: Robust standard errors in parentheses. ***= p<0.01, ** =p<0.05, * =p<0.1

Figure C1 shows a polynomial fit of the value of trade between origin destination pairs as predicted from the log of the reported routed distance. The Figure suggests a log-linear relation with a slope close to the coefficients reported in the Table.

Figure C1. Shipment value vs. shipping distance for internal U.S. shipments

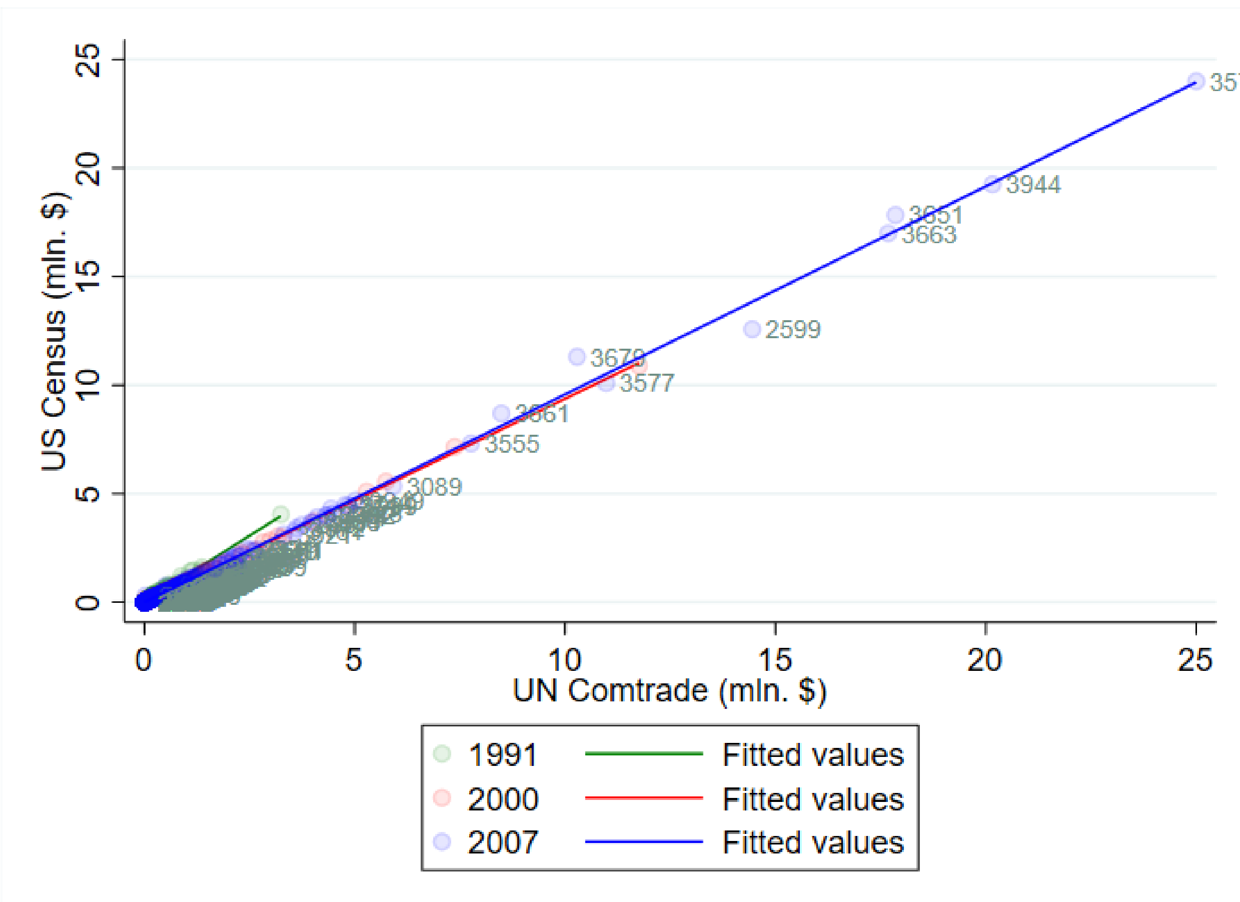


Appendix D US Census vs UN Comtrade data

Our main results are based on import data from the US Census, while related literature frequently uses UN Comtrade. To verify the similarity, we aggregate up our Census data to make them comparable to the UN Comtrade data. We fit the line for each of the three cross-sections of imports from China by SIC code.

In Figure D1, the two data sources show very high overlap. The coefficient of regressing aggregated US Census trade imports by product on UN Comtrade imports by product yields a coefficient of 0.96. The data also show considerable growth in Chinese imports from 1991 to 2000 and to 2007.

Figure D1. similarity of Chinese import data by year across SIC 4 digit industries, of the Comtrade data (horizontal) versus the Census data (vertical)



Appendix E Exports

A commuting zone's exposure to imports from China may be offset by exports to China. As export opportunities present possible job growth that offsets the estimated manufacturing declines, we estimate the impact of net exposure – imports net of exports – on commuting zone manufacturing employment shares.

We construct the imports per worker net of exports based on domestic transport costs by considering the exports by customs district. The change in net imports in product j in port of arrival and shipment d is $\Delta M_{djt} - \Delta X_{djt}$. The commuting-zone specific net import exposure to product j at port d is $s_{id}(\Delta M_{djt} - \Delta X_{djt})$. Aggregating the commuting zone's exposure to net imports in product j gives $\sum_d s_{id}(\Delta M_{djt} - \Delta X_{djt})$, which suggest large exposure if products that are imported from China in nearby ports, but low exposure if those goods are exported to China in nearby ports. The net import penetration measures based on domestic transport costs is then:

$$netIPW_{uit}^{transport} = \sum_j \frac{L_{ijt}}{L_{it}} \frac{\sum_d s_{id}(\Delta M_{djt} - \Delta X_{djt})}{L_{ujt}}.$$

Table E1 shows the results of estimating the baseline shift-share regression using the net import exposure. Per 1,000 dollars of net import exposure, the manufacturing share is estimated to decline by 0.64 (column 1). The estimated impact is slightly larger but not significantly different from the estimate obtained with gross import exposure (-0.54, column 2). The more pronounced impact also shows when not taking into account domestic transport costs, and using industry variation in exposure only: the manufacturing employment share shows a 0.71 decline for \$1,000 in net competing imports (column 3) but a 0.60 decline for \$1,000 in gross competing imports.

	(1)	(2)	(3)	(4)
Dependent variable	Change in manufacturing employment share			
net IPW (transport&industry)	-0.64***			
	(0.13)			
IPW (transport&industry)		-0.54***		
		(0.12)		
net IPW (industry only)			-0.71***	
			(0.08)	
IPW (industry only)				-0.60***
				(0.06)
Observations	1,444	1,444	1,444	1,444
controls	yes	yes	yes	yes
year FE	yes	yes	yes	yes
region FE	yes	yes	yes	yes
State clustered s.e.	0.17***	0.15***	0.13***	0.10.***
Kleibergen Paap Fstat	16.19	14.88	36.33	47.64

Table E1. Impacts of competing imports net of competing exports on commuting zone manufacturing employment shares.

Notes. IPW refers to imports per worker. Net IPW refers to the imports per worker net of the exports in the corresponding industry. IPW (transport&industry) and net IPW (transport&industry) are the import penetration measures based on unit elastic decay in domestic transport costs. IPW (industry only) is the import penetration measure based on Comtrade data as in Autor et al. (2013). Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1

Appendix F Where does import competition reduce jobs?

The predicted impacts of import competition for a commuting zone can change for two reasons, when domestic transport costs are accounted for. First, the estimated coefficient $\hat{\beta}$ differs. Second, the average import value per worker differs. The model based on domestic transport frictions in the import penetration measure (Eq. 5) will predict large labor market effects, if the labor market's employment specialization has large overlap with imported products that enter the country through nearby trade infrastructure. The two measures for imports per worker are on a comparable magnitude but need to be equal in the aggregate: if imports are generally far away from the labor markets they compete with, the competitive impact is lower on average.

$$\hat{\beta} IPW_{uit}^{gen} = \hat{\beta} \sum_j \frac{L_{ijt}}{L_{it}} \frac{\sum_d s_{id} \Delta M_{djt}}{L_{ujt}} \tag{18}$$

In aggregate terms, the measured changes in import competition are very similar between the two measures. When multiplying each model's predicted manufacturing job share change with the number of workers at the start of sample, the original import competition measure produces an estimate of 177 million manufacturing jobs lost (95% CI 142 to 213 million jobs). The competition measure that accounts for domestic transport costs produces an estimate of 174 million jobs lost (95% CI 139 to 210 million jobs).

Figure F1 shows the predicted employment share changes when using the transport-based import penetration measure. It is the product of the coefficient estimate and the import penetration change after the year 2000. The largest manufacturing job losses are predicted the Rust Belt, Midwest and the South, and on the West coast.

Figure F1. Predicted employment share changes when using the transport-based import penetration measure

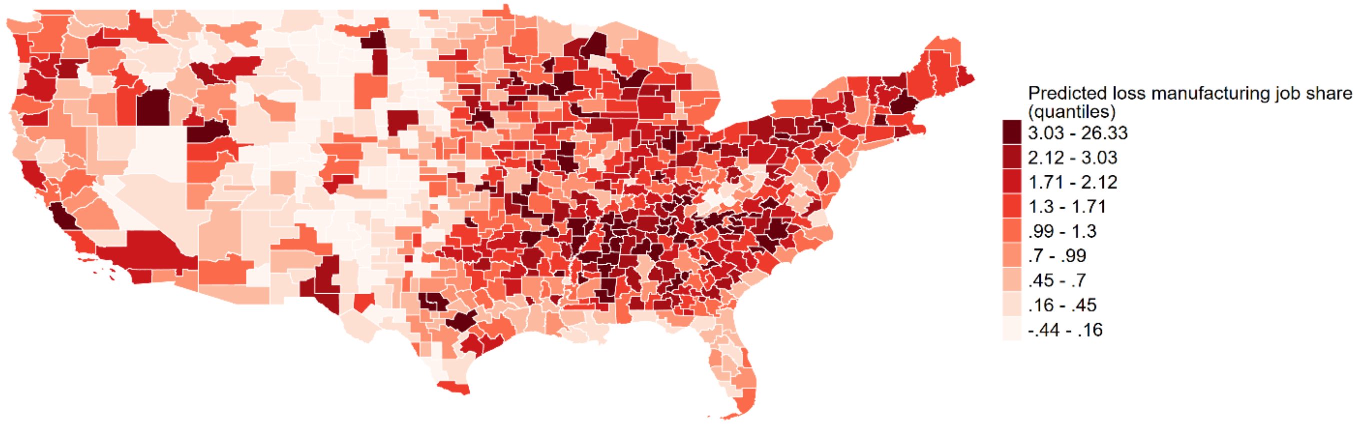
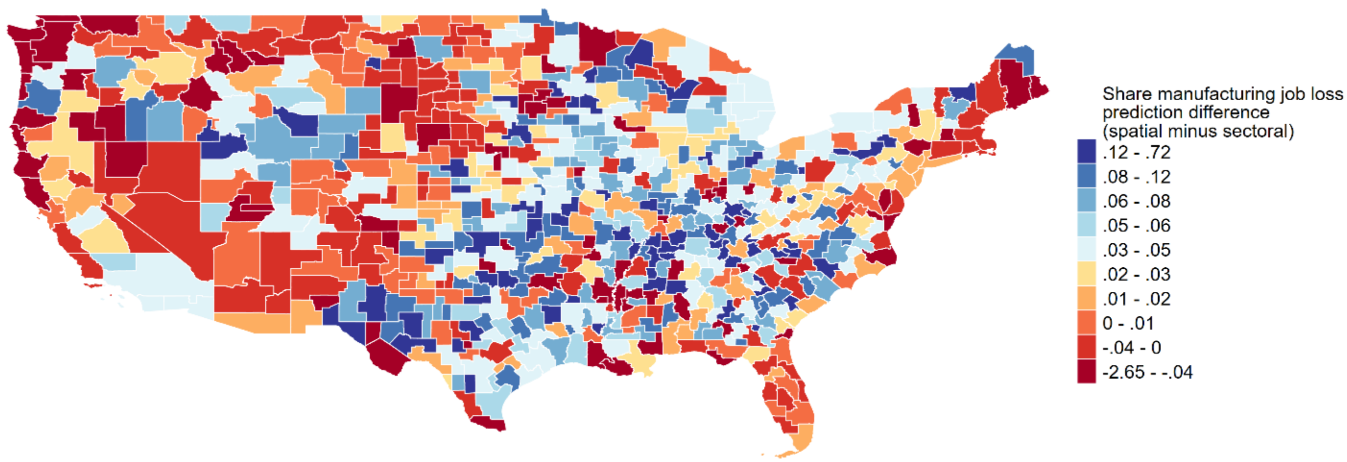


Figure F2 plots the difference in the measured manufacturing employment share change between the transport-based measure and the original measure. In both measures, the mean predicted decline in the manufacturing employment share is around 1.5 percentage point. Across commuting zones, the average difference in the prediction is around 0.1 percentage point, or roughly 7 percent of the overall measured manufacturing decline. The differences show a distinct spatial pattern: the transport-based model identifies far more manufacturing job losses on the coastal areas (up to 2.5 percentage points more than the original measure), while smaller losses (up to 0.7 percentage point) are identified for inland labor market areas, such as those located in the Midwest, New Mexico, and Wyoming.

Figure F2. Difference in the predicted manufacturing employment share change between the transport cost based import competition measure and the original measure



The difference in predicted manufacturing decline between the models derives from the interaction of the transport costs to major ports of entry on the one hand, and the import-competing employment specialization on the other hand. Some commuting zones in Portland and Washington, for instance, are close to major ports but their employment is not concentrated in products that are imported through those ports. Similarly, the original model suggests around 200,000 jobs more manufacturing decline around Los Angeles than the transport-based model does. The reason is that while Los Angeles is a major port, the Chinese goods that it imports compete relatively little with its local workforce. In level terms, the largest loss of manufacturing jobs predicted by the transport based model in excess of what the original model predicts is in Seattle (1.76 mln. in the transport based model vs. 1.66 mln. in the original model).

Appendix G Simultaneous spatial explanations in the controls

An area's exposure to Chinese imports plausibly correlates with other explanations for labor market change. U.S. local labor market that produced similar products to China had comparatively low-skilled workers and a susceptibility to technical change, for instance. The coefficients in Table 1 are estimated conditional on region fixed effects and potentially correlated explanations of labor market change over time to control for confounding explanations.

	(1)	(2)	(3)	(4)
Dep. Variable	Change in manufacturing employment share			
IPW (industry only)	-0.65***		-0.64***	
	(0.09)		(0.04)	
IPW (transport & industry)		-0.96***		-0.89**
		(0.34)		(0.50)
Share manuf.	-0.02	0.08		
	(0.02)	(0.05)		
Share college	0.01	0.06**		
	(0.02)	(0.03)		
Share foreign born	0.01	0.09***		
	(0.01)	(0.03)		
Share female empl.	-0.01	-0.07		
	(0.03)	(0.05)		
Share routine	-0.19***	-0.39***		
	(0.05)	(0.13)		
Share outsource	-0.07	0.86		
	(0.24)	(0.73)		
State clustered se for IPW	0.10***	0.27***	0.06***	0.33***
Observations	1,444	1,444	1,444	1,444
controls	yes	yes	no	no
year FE	yes	yes	yes	yes
region FE	no	no	yes	yes
Kleibergen Paap Fstat	49.03	13.42	139.6	4.945

Table G1. Simultaneous spatial explanations in the controls

Notes. IPW refers to imports per worker. IPW (transport&industry) is the import penetration measure based on unit elastic decay in domestic transport costs. IPW (industry only) is the import penetration measure based on Comtrade data as in Autor et al. (2013). Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1

The measure of import competition based on domestic transport costs plausibly correlates differently with the controls than other measures do. Consequently, the overlap in explanations between the controls and the import competition measure may change. The transport-cost based import measure is often higher near trade infrastructure, which may correlate with confounding explanations, such as the presence of routine or offshorable jobs. Including fixed effects might similarly cause large changes: comparing employment outcomes within but not between Census regions could magnify the spatial nature of the transport costs based import competition measure.

To understand the role of the regional fixed effects and controls in either measure of import competition, Table G1 shows the results obtained by omitting either the set of regional fixed effects or the controls from the regression. When accounting for domestic transport costs, the estimated coefficient shows considerable sensitivity. It changes from -0.54 to -0.96 and -0.89 when omitting regional fixed effects or controls, respectively. The original import penetration measure (not accounting for domestic transport) shows only minor changes (-0.60 to -0.65 when omitting regional fixed effects resp. -0.64 when omitting controls). The difference in coefficient sensitivity suggests that the transport-cost based import penetration correlates more with region-specific explanations than the original import penetration measure. Similarly, when considering the coefficients of the controls, the role of college-educated workers, foreign-born workers, and routine jobs play a larger role conditional on a transport-based import competition measure, than they do conditional on the original import competition measure.

Appendix H Regressions based on quantiles of isolation from international trade

A corollary of our argument is that industrial employment overlap with imports leads to more job losses, if the labor market is closer to the infrastructure of international trade. That prediction can be tested in a standard import competition regression, by testing the stability of the coefficient across subsamples of labor markets ordered by their proximity to trade infrastructure.

We follow the standard instrumental variable regression of Autor et al. (2013), but permit subsample heterogeneity in the coefficient for imports per worker:

$$\Delta L_{it}^{m} = \sum\nolimits_{q} \beta_q \, D_q \Delta IPW_{uit} + \sum\nolimits_{q} \delta_q \, D_q + \gamma X_{it} + \alpha_t + \varepsilon_{it}. \tag{19}$$

Here, D_q is a dummy for the quintile split of the sample, identifying a separate coefficient for a group of CZs. Here, the focus is on ordering the CZs into groups that are plausibly ordered in their exposure to rising imports from China due to proximity to ports or trade infrastructure, or other causes of economic openness other than their sector employment structure.

To quantify a commuting zone's level of shelter or isolation from imports, D_q, we use four different measures of proximity to import infrastructure. First, we calculate each commuting zone's road distance over the principal road network to the nearest of the 10 largest U.S. ports by value of imports. Second, from the Commodity Flow Survey, we consider all shipments of a commuting zone that are destined to be exported and calculate their average shipping distance inside the US. This reflects that from some commuting zones, the internal shipment distance to hub of international trade is longer than others. Third, use the "trade closedness", calculated as the complement to one of trade openness. We calculate the share of value of every commuting zone's shipment destined to a foreign country in total shipments of the commuting zone (which also includes internal shipments and shipments to other areas of the US). Hence, closedness is calculated as $closedness_c = 1 - export_c / shipments_c$. We use trade flows of manufactured products (with first digit 3) to calculate openness. Fourth, we estimate the trade frictions from a gravity model for shipments. We use a standard CES model of trade, with σ as the elasticity of substitution, τ_{ij} as the iceberg trade costs between locations i and j, and $\varphi_{ij} = {\tau_{ij}}^{1-\sigma}$ as the freeness of trade. We aggregate the value of trade by origin-destination pair and consider destinations outside the US as a single destination. We estimate a doubly constrained gravity model, such that:

$$logtrade_{ij} = A_i + A_j + a_{ij}.$$

We estimate this equation by OLS as there are no observations for the bilateral trade flows are equal to zero. After identifying A_i and A_j from estimates on the full sample, we impute a_{ij} for all observations where the destination j is foreign. Following a standard interpretation of this gravity model, $a_{ij} = log\varphi_{ij}$, which we use as a measure of trade freeness.

The advantage of estimating trade costs from the gravity model is that variation comes exclusively from bilateral frictions. By construction, the estimated trade costs are orthogonal to the fixed effects A_i. This measure of a commuting zone's intercontinental trade frictions allows controlling for the multilateral resistance terms of domestic origins and destinations, and so controls for the commuting zone's own general propensity to trade and that of rivalling origins and destinations, when identifying the estimate of trade costs with respect to other countries.

Appendix I Industry-location-specific impacts

Our prior analyses employ aggregated exposure measures across industries by commuting zone. With the aggregation, the regression coefficient measures the net local employment effects of net local exposure. However, one could alternatively ask whether local industry employment declines, if a nearby port imports products that compete with the industry.

An analysis at the industry-location level differs from the location level analysis for important reasons. The main drawback of the location-industry analysis is that it produces a likely violation of the stable unit treatment value assumption (SUTVA). If workers laid off by one industry find employment in another industry in the same location, the analysis of location-industry employment will likely overstate the import competition impact away from zero – even more so if location-specific fixed effects are included in the analysis. The main advantage of the location-industry level of analysis is that it measures industry exposure directly (Acemoglu et al. 2016), so that it uses different source of variation to measure import competition.

Analyzing the industry-level local employment variation has two distinct advantages over an analysis at the commuting zone level. First, the industry-location analysis encompasses earlier identification at both commuting zone-averaged imports per worker (Autor et al., 2013) and national industry-averaged imports per worker (Acemoglu et al., 2016). The industry-location employment regression allows for industry-time and commuting-zone time fixed effects to control for either. Hence, the analysis produces a new source of variation for identification based on the interaction of location and industry, which is robust to location-specific or industry-specific confounders. Second, as the commuting zone averages can be controlled for, the coefficient only measures import competition effects if an industry loses more employment closer to the entry location of its competing imports – conditional on overall industry decline and the location specific shocks in employment losses. Hence, the expected coefficient is only nonzero, if the impacts of import competition structurally vary with domestic transport costs.

We use the industry-level regression equation, adapted for locations i (from Acemoglu et al., 2016):

$$\Delta Empl_{ijt} = \Delta M_{ijt} + \alpha_{it} + \alpha_{jt} + u_{ijt} \tag{20}$$

where $\Delta Empl_{ijt}$ is the change in employment in area i in industry j and $\Delta M_{ijt} = \sum_d s_{id} M_{djt}$ is the imports in product aggregated across all ports of entry, weighted by the domestic transport costs in s_{id}. We use the commuting zone employment at the SIC classification in 2007 (Acemoglu et al. 2016) for the final year of industry-location employment data. We instrument the import measure, as before, with the projected imports based on the interaction between port specialization in products and the flows of those products to other advanced economies, $\widetilde{\Delta M_{djt}}$. In eq. (20), CZ-specific controls are redundant, in that any time varying CZ specific shock is now controlled for, as are sector-time specific shocks.

The estimates in Table I1 suggest 0.027 job losses for every 1,000 dollars of competing imports, or a job lost per $37,000 in competing imports. This job loss estimate is probably overstated as a consequence of SUTVA violations. Consistent with that interpretation, the coefficient with a less specific fixed effects structure (Column 2) or without fixed effects (Column 3) reduce the coefficient estimate – now consistent with around 1 job lost per $93,000 in competing imports. Columns 4 and 5 repeat the estimates without instrumenting for imports. They show coefficient estimates closer to zero than the IV regressions, and one job lost per $100,000 resp. $233,000 in competing imports.

Model	(1)	(2)	(3)	(4)	(5)
Dep. variable: change in manufacturing jobs					
Competing imports ($1000) spatial decay	-0.03**	-0.01***	-0.01***	-0.01***	-0.00***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Obs.	567,492	567,492	567,492	567,492	567,492
Fixed Effects:					
CZ-year FE	yes			yes	
Industry-year FE	yes			yes	
CZ FE		yes			
Industry FE		yes			
Year FE		yes			
Kleibergen Paap Fstat	456.2	1,852	2,551		
Estimation method	IV	IV	IV	OLS	OLS

Table I1. Industry-specific impacts

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix J Results on labor force impacts

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variables: labor force	All workers	College ed	Non-College ed	16-34	35-49	50-64
Panel a						
IPW (transport & industry)	0.33	0.15	0.56	0.44	0.39	0.55
	(0.62)	(0.56)	(0.76)	(0.80)	(0.49)	(0.74)
State clustered se	0.63	0.71	0.72	0.91	0.65	0.74
Kleibergen Paap Fstat	14.88	14.88	14.88	14.88	14.88	14.88
Panel b						
IPW (industry only)	-0.05	-0.03	-0.05	-0.14	0.37	-0.14
	(0.45)	(0.43)	(0.49)	(0.56)	(0.39)	(0.47)
State clustered se	0.75	0.69	0.82	1.19	0.56	0.65
Kleibergen Paap Fstat	47.64	47.64	47.64	47.64	47.64	47.64
Observations	1,444	1,444	1,444	1,444	1,444	1,444
controls	yes	yes	yes	yes	yes	Yes
year FE	yes	yes	yes	yes	yes	Yes
region FE	yes	yes	yes	yes	yes	Yes

Table J1. Labor force impacts

*Notes: Regression across 722 commuting zones over two time period. Standard errors clustered at the state level in parentheses. Regressions are weighted to start-of-period CZ population. Controls include percentage of employment in manufacturing; Percentage of college-educated population; Percentage of foreign-born population; Percentage of employment among women; Percentage of employment in routine occupations: Average offshorability index of occupations. The outcomes are labor force changes for the groups denoted where College ed reflects workers with a college education and the last three columns refer to age groups. *** p<0.01, ** p<0.05, * p<0.1*

Appendix K Results on elections, mortality and fertility

	(1)	(2)	(3)	(4)
Election years around 2000	1988-2012		1992-2008	
IPW (transport and industry)	-1.61***		-1.29***	
	(0.41)		(0.34)	
IPW (industry only)		-0.22		-0.16
		(0.13)		(0.12)
State clustered se	0.68**	0.38	0.75*	0.39
Kleibergen Paap Fstat	14.88	47.64	14.88	47.64
Observations	1,444	1,444	1,444	1,444
controls	yes	yes	yes	yes
year FE	yes	yes	yes	yes
region FE	yes	yes	yes	yes

Table K1. Impacts of competing imports on the vote share for the Republican presidential candidate.

Notes. The outcome variable is the percentage of votes for the republican candidate, calculated as the percentage of Republican votes in the sum of Republican and Democrat votes across all counties in the commuting zone. IPW refers to imports per worker. IPW (transport&industry) and net IPW (transport&industry) are the import penetration measures based on unit elastic decay in domestic transport costs. IPW (industry only) is the import penetration measure based on Comtrade data as in Autor et al. (2013). Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)
Cause	poisoning	suicide	assault	accident	Other causes
Panel a					
IPW (spatial and sectoral)	25.43***	-4.47**	9.93	-18.54***	252.55**
	(5.61)	(1.80)	(8.03)	(5.04)	(104.30)
State clustered se	(10.99)**	(2.55)*	(13.88)	(6.56)***	(213.60)
Kleibergen Paap Fstat	14.88	14.88	14.88	14.88	14.88
Panel b					
IPW (Dorn)	14.10***	-0.32	-1.30	-13.78***	84.64**
	(2.79)	(1.27)	(5.57)	(4.39)	(43.10)
State clustered se	(5.71)**	(2.48)	(7.05)	(4.14)***	(77.11)
Kleibergen Paap Fstat	47.64	47.64	47.64	47.64	47.64
Observations	1,444	1,444	1,444	1,444	1,444
R-squared	0.50	0.70	0.48	0.75	0.66
controls	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes
region FE	yes	yes	yes	yes	yes

Table K2. Impacts of competing imports on the cumulative mortality by cause.

Notes. The outcome variable is the commuting zone's mortality by cause of death. IPW refers to imports per worker. IPW (transport&industry) and net IPW (transport&industry) are the import penetration measures based on unit elastic decay in domestic transport costs. IPW (industry only) is the import penetration measure based on Comtrade data as in Autor et al. (2013). Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)
	poisoning	suicide	assault	accident	Other causes
Panel a					
IPW (spatial and sectoral)	13.53***	-3.81***	1.16	-8.61***	27.77*
	(2.79)	(0.96)	(2.74)	(2.11)	(15.03)
State clustered se	(6.34)**	(1.64)**	(3.35)	(3.44)**	(20.45)
Kleibergen Paap Fstat	14.93	15.40	15.43	15.17	17.08
Panel b					
IPW (Dorn)	7.04***	-2.07**	1.33	-10.41***	42.66***
	(1.07)	(0.89)	(2.46)	(1.99)	(11.23)
State clustered se	(3.17)**	(1.51)	(3.20)	(2.51)***	(19.00)**
Kleibergen Paap Fstat	46.62	47.47	47.57	47.67	47.96
Observations	1,444	1,444	1,444	1,444	1,444
controls	yes	yes	yes	yes	yes
year FE	yes	yes	yes	yes	yes
region FE	yes	yes	yes	yes	yes

Table K3. Impacts of competing imports on the gender gap in cumulative mortality by cause.

*Notes. The outcome variable is difference between the male and the female mortality by cause of death. IPW refers to imports per worker. IPW (transport&industry) and net IPW (transport&industry) are the import penetration measures based on unit elastic decay in domestic transport costs. IPW (industry only) is the import penetration measure based on Comtrade data as in Autor et al. (2013). Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
		Marital status			Fertility				HH type			Children's HH type		
Dep. Variable:	Married	Widowed divorced/ separated	Never married	Birth rate	Perc. women with children	Percent mothers unmarried	Percent children in HH undue poverty line	Living w spouse	Living w partner	No partner	Married couple	Parent plus partner	Single parent	Grand parent
Panel a														
IPW	0.35**	0.02	-0.38**	-0.95***	0.59***	-0.11	0.71***	0.28**	-0.04**	-0.24**	-0.03	-0.06**	0.04	0.05
(transport and industry)	(0.14)	(0.03)	(0.16)	(0.24)	(0.17)	(0.09)	(0.17)	(0.13)	(0.02)	(0.12)	(0.06)	(0.03)	(0.04)	(0.03)
State Clustered se	(0.17)**	(0.05)	(0.18)**	(0.33)***	(0.22)***	(0.13)	(0.34)**	(0.15)*	(0.05)	(0.16)	(0.08)	(0.04)	(0.07)	(0.05)
Kleibergen Paap Fstat	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88	14.88
Panel b														
IPW	-0.17***	-0.06***	0.23***	-0.84***	0.13**	0.12**	0.36***	-0.15***	-0.02	0.16***	-0.13**	-0.03**	0.07*	0.09***
(industry only)	(0.05)	(0.02)	(0.05)	(0.13)	(0.05)	(0.05)	(0.06)	(0.05)	(0.02)	(0.06)	(0.05)	(0.02)	(0.03)	(0.03)
State Clustered se	(0.10)*	(0.04)	(0.12)*	(0.24)***	(0.09)	(0.09)	(0.13)***	(0.08)*	(0.06)	(0.12)	(0.06)**	(0.03)	(0.06)	(0.05)*
Kleibergen Paap Fstat	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64	47.64
Observations	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444
Controls, yr.&region FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table G4. Impacts of competing imports on the fertility and household formation.

Notes. The outcome variable is difference between the male and the female mortality by cause of death. IPW refers to imports per worker. IPW (transport&industry) and net IPW (transport&industry) are the import penetration measures based on unit elastic decay in domestic transport costs. IPW (industry only) is the import penetration measure based on Comtrade data as in Autor et al. (2013). Adao et al. (2019) standard errors are reported in parentheses. State-clustered standard errors are reported in the row below the coefficients with asterisks for significance. *** p<0.01, ** p<0.05, * p<0.1