U.S. Exports, Imports, and Internal Migration : A Balanced View of China Syndrome

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Abstract

This paper revisits previous findings and examines whether the trade exposure of local labor markets to increased import competition has a significant impact on the labor markets. The previous literature showed that higher imports from China cause higher unemployment, reduced wages, the relative reduction in population growth in the U.S. local labor markets, where the import competitive manufacturing industry resides. I repeat the specification of Autor et al. (2013) and Greenland et al. (2019), but I extend the period from 1990-2007 to 1990-2010 and incorporate alternative measures of trade exposure for U.S. commuting zones. The coefficient on manufacturing employment in the working-age population of the Chinese comparative advantage model is -0.305, which is less than half (43%) of the gross Chinese imports model. Although trade exposure reduces manufacturing employment, in models using net Chinese exports per worker or exposure to final goods and intermediate inputs, trade exposure was found to have a statistically significant positive effect on average manufacturing wages. Controlling population trends, the trade exposure coefficient for the decline in population growth using domestic plus international exposure to Chinese exports and the coefficient of the model using change in comparative advantage China-US are reduced to 57% and 28% of that in the model using Chinese imports per worker, respectively. In both IPUMS data and Census data, we find significant reductions in population growth of working-age individuals and of the young.

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1 Introduction

I study the impact of rising in Chinese import competition following the granting of Permanent Normal Trade Relations to China in 2001 on U.S. employment and internal migration. Since China joined the WTO in 2001, exports from China have grown rapidly and employment in the U.S. manufacturing industry has decreased significantly during the same period. China's share of global manufacturing production has grown significantly from 5.5 percent in 2001 to 15.6 percent in 2011 and 23.5 percent in 2019 and the U.S. trade deficit with China surged from $83.8 billion (19.2% of the U.S. trade deficit) in 2000 to $273 billion (43.0% of the U.S. trade deficit) in 2010.

Figure 1: Working-age Population in Manufacturing

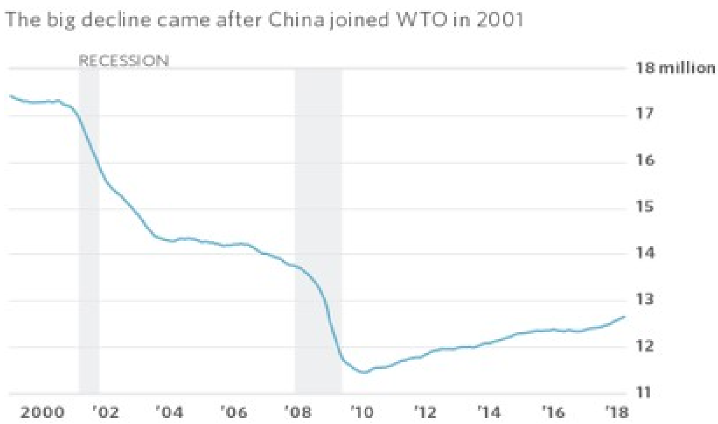
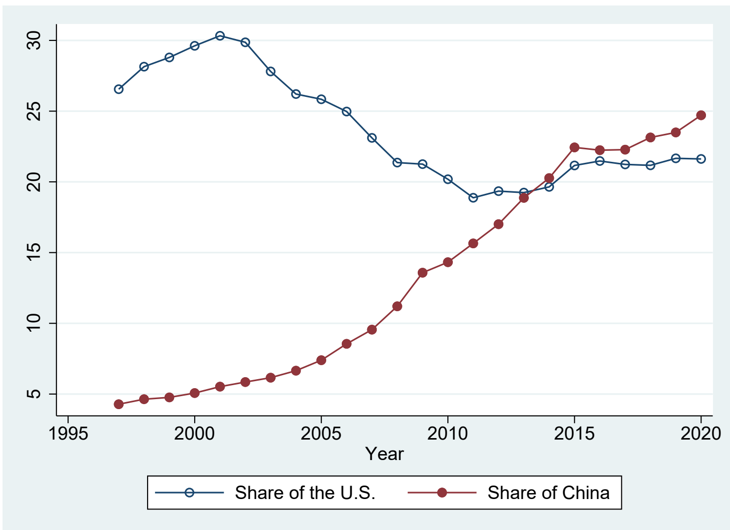


Figure 2: China and U.S.'s Share in Global Production



It is based on the factory shipping price (MSP) of the product and is calculated using Euromonitor data.

The previous literature showed that higher imports from China cause higher unemployment and reduced wages in the U.S. local labor markets, where the import competitive manufacturing industry resides. Autor et al. (2013) document that rising import competition between 1990 and 2007 causes higher unemployment, lower labor force participation, and reduced wages in US local labor markets. In their main specification, import competition explains one-quarter of the contemporaneous aggregate decline in US manufacturing employment. Transfer benefits payments for unemployment, disability, retirement, and healthcare also rise sharply in more trade-exposed labor markets. Acemoglu et al. (2016) estimate that import competition from China, which surged after 2000, was a major force behind both reductions in US manufacturing employment and weak overall US job growth of the 2000s. Their estimates suggest job losses from rising Chinese import competition over 1999-2011 in the range of 2.0-2.4 million. Greenland et al. (2019) found evidence that the regional labor market, which was most exposed to import competition, experienced a relative decline in population growth over the following decade in response to the shock. The authors find that workers seek out markets that are less negatively affected by import competition in the face of large and geographically concentrated costs of trade. Feenstra et al. (2019) find that although import competition reduces jobs, the export expansion also creates a substantial number of jobs. They found that job gains due to U.S. export expansion largely offset job losses due to Chinese import competition, resulting in a net increase of 379 thousand jobs over 1991-2011 at the industrial level, and job gains and losses are roughly balanced at the commuting zone level.

This paper revisits these findings and examines whether the trade exposure of local labor markets to increased import competition has an impact on employment, wages, government transfers, and internal migration. I repeat the specification of Autor et al. (2013), but I extend the period from 1990-2007 to 1990-2010 and focus on alternative measures of trade exposure for U.S. commuting zones.[1] This enables us to explore the robustness by comparing our results to those obtained in Autor et al. (2013). And I repeat the specification of Greenland et al. (2019) but expand to incorporate alternative measures of trade exposure for U.S. commuting zones on population adjustment at the CZ level to view Chinese syndrome from a balanced perspective.

[1] I used alternative measures of trade exposure introduced by Autor et al. (2013). A detailed description of these is given in 2.3 Measuring Trade Exposure.

2 Empirical Methodology

2.1 Impact of Trade Shocks on Employment, Wage, Transfers

First of all, I estimate the relationship between Chinese import exposure and U.S. employment, wage, and transfers. Using the full sample of 722 CZs and weighting each observation by start of period CZ population, I adopt the following empirical specification as in Autor et al. (2013) but I focus more on alternative measures of trade exposure for U.S. commuting zones:

$$\Delta Y_{it} = \gamma_t + \beta_1 \Delta Trade\ Exposure_{uit} + \mathbf{X}_{it}^{'} \beta_2 + e_{ct}, \tag{1}$$

where ΔY_{it} is the decadal change in the outcome (employment share of the working age population, wages, and transfers) in commuting zone i. For the long interval between 1990 and 2010, we stack the 10-year equivalent first differences for the two periods, 1990 to 2000 and 2000 to 2010, and include separate time dummies for each decade in γ_t. The vector $\mathbf{X}_{it}$ contains a set of initial-period controls for CZs' labor force and demographic composition that might independently affect outcome. Standard errors are clustered at the state level to account for spatial correlations across CZs. We expect that $\beta_1 < 0$ as positive net imports (imports - export) reduce employment.

I explore the robustness by comparing our results to those obtained in Autor et al. (2013), who use IPUMS data and estimated the two periods from 1990 to 2000 and from 2000 to 2007. Here, I compared the results of estimating the two 10-year long intervals from 1990 to 2000 and from 2000 to 2010 with the results of the 1990-2007 stacked first differences in Autor et al. (2013). I also estimated the impact of alternative trade exposure for U.S. commuting zones in addition to import exposure, taking into account the control variables such as initial-period controls for CZs' labor force and demographic composition (percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women), routine occupations, and outsourcability.

2.2 Trade Shocks and Internal Migration

I examine changes between 1990 and 2000 and between 2000 and 2010 in the log counts of the following population groups: ages 16 to 64, 16 to 34, 35 to 49, and 50 to 64 years old; individuals without a college degree; and individuals with a college degree. The specification controls for time and Census division fixed effects, the share of employment accounted for by manufacturing, the share of the population with a college degree, the foreign-born share of the population, the female labor force share, the routine task share, and the offshorability index. I fit models of the following empirical specification as in Greenland et al. (2019) but expand to incorporate alternative measures of trade exposure for U.S. commuting zones not just import exposure:

$$\Delta L_{it} = \gamma_t + \kappa_r + \beta_1 \Delta Trade\ Exposure_{uit} + \mathbf{X}_{it}^{'}\beta_2 + e_{ct} \tag{2}$$

While Greenland et al. (2019) use the change in import exposure IPW_{uit} which is instrumented by the variable IPW_{oit}, I consider alternative measures of trade exposure for U.S. commuting zones in order to incorporate exposure to U.S. exports to China (net imports) and indirect competition as used in Autor et al (2013). I study how using alternative trade exposures will change the results of Greenland et al. (2019). And I explore the robustness by comparing our results using Census population data to those obtained in Autor et al. (2013), who use IPUMS data. This is because IPUMS data includes information on labor market outcomes for nationally representative samples of individuals, but IPUMS data are samples of the population, not the entire population. In addition to employing Census count data and extending the analysis to 2010, an important distinction between our paper and Autor et al. (2013) is the fact that we examine labor market and population adjustments using alternative trade exposures while controlling for population trends. These enable us to gauge the robustness of previous literature and view Chinese syndrome from a balanced perspective.

2.3 Measuring Trade Exposure

2.3.1 Import Exposure

The change in imports per worker at the CZ level is measured as

$$\Delta IPW_{uit} = \sum_j \frac{L_{ijt}}{L_{it}} \frac{\Delta M_{ucjt}}{L_{ujt}}, \tag{3}$$

where the u subscript refers to the United States, and the c subscript refers to China, so M_{ucjt} is U.S. imports from China in industry j at time t. Changes in imports per worker in CZ i at time t, ΔIPW_{uit}, are calculated as the weighted average of changes in imports per worker at the national level across all industries j, $\frac{\Delta M_{ucjt}}{L_{ujt}}$, where each industry's weight is equal to its labor share in CZ i, $\frac{L_{ijt}}{L_{it}}$. L_{it} is the start of period employment (year t) in region i and ΔM_{ucjt} is the observed change in U.S. imports from China in industry j between the start and end of the period.

Instrumental variables: It is possible that trade exposure was correlated with economic conditions that would also affect employment and migration. For example, if industrial compositionâand therefore import exposureâwas correlated with recent changes in amenities. As a result, OLS estimates would be biased. In order to isolate the trade shock driven by supply-side shifts, we consider instruments for trade variables.

A concern for our subsequent estimation is that realized U.S. imports from China in equation (3) is subject to endogeneity and may be correlated with industry labor demand shocks. We should use instrumental variables that are not correlated with US shocks, since those shocks on the demand or supply side lead to endogenous changes in employment, imports and exports. To identify the causal effect of rising Chinese trade exposure stemming from Chinese productivity gains and falling trade barriers on U.S. manufacturing employment and other local labor market outcomes, we employ an instrumental variables strategy.

ADH-style Instruments for trade variables: The instruments for changes in import competition follows the approach of ADH (2013), for which they use the imports of eight other high-income countries with China, ΔM_{ocjt}. The subscript o refers to other. The eight other countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Using other advanced nation's imports or exports to instrument for the US imports or exports is intended to reflect China's rising comparative advantage (e.g., productivity shock) and falling trade costs in these sectors that are common to high-income importing countries. Admittedly, this IV will also reflect demand conditions in those eight countries, but provided that those demand conditions are not correlated with US shocks, that should not present a problem for the IV. In addition to using imports in countries other than the United States, Autor et al. (2013) lag industry-specific labor shares by ten years to mitigate concerns that labor markets anticipated rising trade. This yields the following instrument:

$$\Delta IPW_{oit} = \sum_j \frac{L_{ijt-10}}{L_{it-10}} \frac{\Delta M_{ocjt}}{L_{ujt-10}}, \tag{4}$$

2.3.2 Net Chinese Imports per Worker

An important feature missing in many previous analyses is U.S. exports to China. If the authors did not consider what the United States exported to China, the estimate would be overestimated and the China Syndrome would not be properly identified. Because U.S. imports from China are larger than U.S. exports to China, the measure of net imports exposure remain positive, but trade exposure is lower than import exposure. We construct net imports from China by subtracting U.S.

exports from U.S. imports by industry, which following equation (3) yields:

$$\Delta NIPW_{uit} = \sum_j \frac{E_{ijt}}{E_{it}} \frac{\Delta M_{ucjt}}{E_{ujt}} - \sum_j \frac{E_{ijt}}{E_{it}} \frac{\Delta X_{cujt}}{E_{ujt}},$$

We instrument for the net import measure using two variables: the potential import exposure index used in prior Tables (equation 4) and an analogously constructed potential export exposure measure, built using observed exports to China by industry from the eight comparison countries previously used for the potential import exposure measure.

2.3.3 Factor content of net Chinese imports per worker

As a final specification, we use the factor content of U.S. net imports from China to replace imports per worker. An earlier literature, based on Heckscher-Ohlin trade theory, models trade as affecting labor markets through the import of factor services embodied in goods (Deardorff and Staiger, 1988; Borjas, Freeman, and Katz, 1997). The validity of the factor content approach was the subject of debate in the trade and wages literature of the 1990s (Krugman, 2000; Leamer, 2000; and Feenstra, 2010). See Burstein and Vogel (2011) for recent work. We reestimate our core regressions using the factor content of trade to measure import exposure in CZs. Because our data at the CZ level do not permit measurement of factor content by labor type, we treat labor as a composite factor. In panel F of Table 10, we report results in which we replace the change in imports per worker with the change in the net import of effective labor services,

$$\Delta Factor\ content\ of\ NIPW_{uit} = \sum_j \frac{E_{ijt}}{E_{it}} \frac{\tilde{E}_{uj0}}{V_{uj0}} \frac{\Delta M_{ucjt}}{E_{ujt}} - \sum_j \frac{E_{ijt}}{E_{it}} \frac{\tilde{E}_{uj0}}{V_{uj0}} \frac{\Delta X_{cujt}}{E_{ujt}}.$$

This measure of the labor content of U.S. net imports from China calculates CZ exposure to trade by imputing labor services embodied in net imports using net imports times employment per dollar of gross shipments in U.S. industries at the national level ($\tilde{E}_{uj0}/V_{uj0}$), where we measure $\tilde{E}_{uj0}$ on the direct plus indirect employment of labor used to manufacture goods in an industry. 46 That is, $\tilde{E}_{uj0}$ is the component for industry j of the vector $\mathbf{E}(\mathbf{I}-\mathbf{C})^{-\mathbf{1}}$, where $\mathbf{E}$ is the vector of direct employment in each industry, $\mathbf{C}$ is the industry input-output matrix, and I is the identity matrix (where we use values from 1992 for each element). The implicit assumption is that the labor intensities of U.S. goods that are replaced by Chinese imports and of goods the U.S. exports to China are the same as average U.S. industry labor intensity. In reality, we expect imports from (exports to) China to be relatively labor (capital) intensive. We instrument for the labor content of net imports from China in a manner analogous to our strategy for net imports per worker in panel D.

2.3.4 Domestic plus international exposure to Chinese exports

We modify the definition of import exposure to include competition in other foreign markets. China's growth not only displaces U.S. producers in the U.S. market but may also affect U.S. sales in the foreign markets that U.S. industries serve. We measure global U.S. industry exposure to import competition from China using initial U.S. exports to each market divided by the market's imputed spending on industry output (calculated under the assumptions that preferences are Cobb-Douglas and that foreign industry expenditure shares equal those in the U.S.). Following equations (1) and (3), the total exposure of U.S. region i to imports from China is,

$$\Delta Domestic + International\ Exposure_{uit} = \sum_j \frac{E_{ijt}}{E_{it}} \frac{\Delta M_{ucjt} + \sum_{o \neq c} \frac{X_{oujt}}{X_{ojt}} \Delta M_{ocjt}}{E_{ujt}}.$$

This expression differs from equation (3) due to the second summation term, which captures growth in third markets' imports from China (M_{ocjt}) weighted by the initial share of spending in these markets on U.S. produced goods (X_{oujt}/X_{ojt}). The large share of spending most countries devote to domestic goods means that the imputed share of expenditures directed towards U.S. products is small.

2.3.5 Exposure to final goods and intermediate inputs

A second issue with measuring trade exposure is that imports from China include both final goods purchased by U.S. consumers and intermediate inputs purchased by U.S. firms. If trade with China increases the variety of inputs to which U.S. producers have access, it may raise their productivity (e.g., Goldberg, Khandelwal, Pavcnik, and Topalova, 2010), increasing their demand for labor and partially offsetting the impact of import competition in final goods. Panel C of Table 10 reports results in which we measure industry import exposure using total China imports per worker less China imports of intermediate inputs per worker, in which we calculate industry imported inputs by combining U.S. trade data with the 1992 U.S. input-output Table (assuming that industry patterns of input usage are the same for imports as for U.S. domestic goods). We construct the instrument

2.3.6 Change in comparative advantage China (gravity residual)

An alternative to studying net import effects that circumvents the conceptual and measurement issues discussed above is to apply the gravity residual described in the Theory Appendix. The virtue of the gravity measure is that it captures changes in the productivity or transport costs of

Chinese producers relative to U.S. producers. These relative changes are the force that gives rise to both Chinese imports and U.S. exports. To interpret the scale of the gravity measure, note that a one unit increase in the gravity measure corresponds to a $1,000 per worker increase in a region's Chinese import exposure stemming from a rise in China's productivity or fall in China's trade costs. This scaling is comparable to the import exposure variable in our baseline specification with two slight differences: first, because the gravity residual corresponds to a logarithmic measure of productivity, it is appropriate to exponentiate this coefficient for comparison; second, since changes in Chinese relative productivity or trade costs will affect net rather than gross imports, the gravity estimates are most comparable to the net import exposure models in Panel D.

3 Estimation Results

3.1 The Impact of Trade Shocks on Manufacturing Employment

3.1.1 Panel A. Baseline results: Gross Chinese imports per worker (2SLS)

Table 1 presents the first difference model for the period 1990-2010 with controls such as a set of demographic and labor force measures that tests the robustness. In column (2), we add a control for the share of manufacturing in a CZ's start-of-period employment to address the concern that the import exposure could partially capture the overall trend decline in U.S. manufacturing rather than the component resulting from differences across manufacturing industries. The column 2 estimate implies that a CZ with a one % point higher initial manufacturing share experiences 0.041 percentage points decrease in a differential manufacturing employment share over the subsequent decade. This specification has a smaller effect of import exposure on manufacturing employment than does the corresponding estimate in column 1 by 20.9%, but the relationship remains statistically significant. Column 3 augments the regression model with geographic dummies for the nine Census divisions, which absorb region-specific trends in the manufacturing employment share. These dummies decrease the estimated effect of import exposure on manufacturing employment by 11.9%. Column 4 additionally controls for the start-of-period share of a CZ's population that has a college education, the share of foreign-born population, and the share of employment among working age women. Adding these controls does not affect the main results.

Column 5 adds two variables, share of employment in routine occupations and outsourcability index, which are based on occupational task data. The estimates in column 5, the population share

Table 1: Import Competition and Changes in Manufacturing Employment in CZs: 1990-2010,

Panel A. Baseline results: Gross Chinese imports per worker (2SLS)

	1. 1990-2010 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/worker	-0.857***	-0.678***	-0.597***	-0.570***	-0.665***	-0.712***
	(0.073)	(0.100)	(0.106)	(0.094)	(0.122)	(0.124)
Percentage of employment in manufacturing$_{-1}$		-0.041*	-0.058***	-0.063***	-0.057***	-0.037***
		(0.021)	(0.020)	(0.015)	(0.016)	(0.011)
Percentage of college-educated population$_{-1}$				-0.004		0.019
				(0.018)		(0.016)
Percentage of foreign-born population$_{-1}$				-0.004		0.035***
				(0.009)		(0.012)
Percentage of employment among women$_{-1}$				-0.054**		-0.002
				(0.026)		(0.023)
Percentage of employment in routine occupations$_{-1}$					-0.259***	-0.274***
					(0.073)	(0.075)
Average offshorability index of occupations$_{-1}$					0.443	0.052
					(0.326)	(0.309)
Census division dummies	No	No	Yes	Yes	Yes	Yes
	2. 2SLS first stage estimate					
(Δ imports from China to OTH)/worker	0.668***	0.557***	0.538***	0.515***	0.505***	0.497***
	(0.099)	(0.084)	(0.087)	(0.082)	(0.079)	(0.079)
Prob > First Stage F	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.395	0.426	0.440	0.451	0.455	0.456
* *1990-2007 Autor et al. (2013)*	-0.746***	-0.610***	-0.538***	-0.508***	-0.562***	-0.596***
(Δ imports from China to US)/worker	(0.068)	(0.094)	(0.091)	(0.081)	(0.096)	(0.099)

Notes: All specifications are same as in Autor et al. (2013). N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2010 period (IPUMS). First stage estimates in Panel A.2 include the control variables that are indicated in the corresponding columns of Panel A.1. Routine occupations are defined such that they account for 1/3 of U.S. employment in 1980. The outsourcability index variable is standardized to mean of 0 and standard deviation of 10 in 1980. Models are weighted by start of period commuting zone share of national population. Robust standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

in manufacturing falls by about 0.259% points for each additional % point of initial employment in routine occupations. This is because if CZs, which has a a large start-of-period employment share in routine occupations, is replaced by manufacturing jobs due to automation, a negative relationship is expected between the routine share variable and the change in manufacturing share. Routine-intensive occupations are a set of jobs whose primary activities follow a set of precisely prescribed rules and procedures that make them easily codifiable. This category includes white collar positions whose main job tasks involve routine information processing and blue collar production occupations that mainly involve repetitive motion and monitoring tasks. The offshorability index used in column 5 measures the average degree to which the occupations in a commuting zone require neither proximity to a specific workplace nor face-to-face contact with U.S. based workers. If offshoring of occupations were a major driver for the decline in manufacturing within CZs, a negative relationship between the offshorability index and the change of the manufacturing employment share can be expected, but the estimate in columns 5 and 6 do not find a negative or statistically significant coefficient for occupational offshorability. The fully augmented model in column 6 shows a robust negative impact of increasing import exposure on manufacturing employment. The decline in manufacturing is greater in local labor markets, where initial manufacturing employment share are larger and employment is concentrated in routine-task intensive occupations. It is smaller when the initial foreign born population is larger. Looking at the model estimates from columns 1 to 6, the overall impact of Import exposure on manufacturing employment in 1990-2010 increased compared to 1990-2007 Autor et al. (2013).

3.1.2 Alternative Trade Exposure (Panel B $\sim$ Panel F)

Panel B to Panel F show the results of estimating the impact of the manufacturing industry on alternative trade exposures while considering control variables. The results show similar patterns of statistical significance to the baseline regressions in panel A. However, in terms of quantitative terms, considering net imports or indirect import competition significantly reduces estimates of the impact on trade exposure on change in manufacturing employment compared to when considering only import exposure. Panel B of Appendix Table 1 presents the results of the impact of net Chinese imports per worker on manufacturing employment. In column 6, which adds all control variables, an increase of $1,000 per worker in Chinese net import exposure reduces the ratio of employment to population in the manufacturing industry by 0.466% points. This point estimate is about 35% smaller than that in Panel A that uses gross income exposure than net income exposure. What is notable is that the estimate of the impact of the share of manufacturing in a CZ's start-of-period employment on the ratio of employment to population in the manufacturing has risen.

In Appendix Table 2, the results of Panel C represent the impact of factor content of net imports from China on changes in manufacturing employment in CZs. The results of the fully aggregated model in column 6 show that the net import of labor services of one U.S. worker displaces 0.801 workers in manufacturing, after adjusting for differences in the scale of the net-labor-services import measure (denominated in labor services per worker in a CZ) and the manufacturing-employment-per-population outcome (manufacturing workers per working-age population in a CZ).[2]

In Appendix Table 3, Panel D shows results in which we measure industry trade exposure using total China imports per worker less China imports of intermediate inputs per worker. Here, I used the result of Autor et al. (2013). They calculate industry imported inputs by combining U.S. trade data with the 1992 U.S. input-output Table (assuming that industry patterns of input usage are the same for imports as for U.S. domestic goods). In column 6, the coefficient on trade exposure is -0.542, 23.9 % smaller than in panel A.

Appendix Table 4 (Panel E) presents regression results in which we replace the import exposure measure (IPW_{oit}) with domestic plus international import exposure to Chinese trade. The coefficients are smaller in absolute value. In column 6, the coefficient of impact of a \$1,000 increase in import competition from China on the manufacturing employment to population share is -0.443. This is a 38% drop in the impact of Chinese trade exposure on manufacturing employment in CZ compared to -0.712 (Panel A) as we allow the U.S. exposure to China through the third markets.

Appendix Table 5 (Panel F) uses the gravity-based approach to measure the exposure of CZs to Chinese trade. Column 6 finds that a \$1,000 per worker increase in net import exposure to Chinese trade resulting from rising relative Chinese productivity or falling transport costs reduces local U.S. manufacturing employment by 0.305 percentage point.

[2]The factor content of net imports is normalized by CZ employment, whereas manufacturing employment in the dependent variable is normalized by working-age CZ population. To place both on the same level, we multiply the point estimate for factor contents by the inverse ratio of CZ employment to CZ population, which is equal to 0.70 at the mid-point of the sample (Autor et al. (2013)). Hence, we calculate that the import of the labor services of one U.S. worker displaces $-0.561 * (1/0.70) = -0.801$ manufacturing workers.

3.2 Trade Exposure and Local Labor Market

3.2.1 Impact of Exposure to Net Imports or Indirect Import Competition on Employment, Wages, Transfers, and Household Income in CZs

In Table 1, we analyze effects of trade exposure shocks on employment (manufacturing and non-manufacturing), wages (manufacturing and nonmanufacturing), government transfers, and Household Income in CZs. All specifications include controls from Autor et al. (2013), which is the fully augmented model. Columns 1 and 2 of Table 2 presents a corresponding set of models for employment using as a dependent variable the share of manufacturing and non-manufacturing employment in the working-age population ages 16 through 64 in the CZ. The regressions of column 1 in Table 2 correspond to that main results of the preceding Tables 1 and Appendix Tables 1∼5 (our earlier models for the manufacturing employment share). The impact of trade exposure on employment in the manufacturing industry is all statistically significant, while their impact on the non-manufacturing industry is not significant. The sum of the first two coefficients in panel A indicates that a $1,000 per worker increase in a CZ's trade exposure reduces its employment to population rate by 0.85 percentage points. About 84% of that decline is due to the decline in manufacturing employment, with the remainder due to loss in non-manufacturing employment. In column 1 of Table 2, when we used gross Chinese imports per worker as a trade exposure as in panel A, the coefficient on manufacturing employment in the working-age population is -0.712, and the coefficient of panel F (Chinese comparative advantage) is -0.305, which is less than half (43%) of panel A of Table 2.

In the estimation approach to wage effects, the dependent variable is the average log weekly earning in a CZ, because it measures the net effect of changes in hours worked and wages paid per hour. In Table 2, columns 3 and 4 present wage effects separately for workers employed in manufacturing and non-manufacturing. Although trade exposure reduces manufacturing employment, it appears to have no significant effects on mean manufacturing wages in CZs. Rather, in Panel B (net Chinese exports per worker) and Panel D (exposure to final goods and intermediate inputs), trade exposure was found to have a statistically significant positive effect on average manufacturing wages. The first explanation for this pattern is that the most productive workers maintain their jobs in the manufacturing industry, and thus increase rather than decrease in manufacturing wages, and the second explanation is that manufacturing plants respond to import competition by accelerating technological and organizational innovation that can increase productivity and wages

(Autor et al. (2013) and Bloom et al. (2009)). By contrast, the results in column 4 observe the effect of negative wage effects from income on US workers in the non-manufacturing industry. Non-manufacturing wages fall by 0.59 log points for a $1,000 increase in Chinese import exposure per worker in panel A. This result suggests that a negative shock to local manufacturing reduces the demand for local non-traded services while increasing the available supply of workers, resulting in downward pressure on wages in the non-manufacturing sector.

Table 2: Impact of Exposure to Net Imports or Indirect Import Competition on Employment, Wages, Government Transfer, and Household Income in CZs, 1990-2010 (IPUMS)

	Employment/pop		Average Log wages		Transfers, HH wage inc	
	(1)	(2)	(3)	(4)	(5) log	(6) Avg log
	Mfg	Nonmfg	Mfg	Nonmfg	transfers	HH wage inc
Panel A. Baseline results: Gross Chinese imports per worker (2SLS)						
(Δ imports from China to US)/worker	-0.712***	-0.140	0.802	-0.590*	1.389***	-2.149***
	(0.124)	(0.147)	(0.535)	(0.332)	(0.506)	(0.578)
* *1990-2007 Autor et al. (2013)*	-0.60***	-0.18	-0.15	-0.76***	-1.01***	-2.14***
Panel B. Net Chinese imports per worker (2SLS)						
(Δ net imports of US from China)	-0.466***	-0.0100	1.041**	-0.186	0.927**	-1.015*
/worker	(0.118)	(0.156)	(0.502)	(0.300)	(0.461)	(0.518)
* *1990-2007 Autor et al. (2013)*	-0.45***	-0.09	0.46	-0.47*	0.73**	-1.39**
Panel C. Factor content of net Chinese imports per worker (2SLS)						
(Δ factor content of net imports	-0.561***	-0.0697	0.684	-0.630**	0.662*	-1.504***
from China) /worker	(0.0940)	(0.116)	(0.476)	(0.249)	(0.372)	(0.424)
* *1990-2007 Autor et al. (2013)*	-0.57***	-0.12	0.59	-0.66**	0.81**	-1.70***
Panel D. Exposure to final goods and intermediate inputs (2SLS)						
(Δ imports from China to US net	-0.542***	0.0445	1.301**	-0.176	1.194**	-1.067
of intermediate inputs)/worker	(0.139)	(0.182)	(0.543)	(0.357)	(0.507)	(0.693)
* *1990-2007 Autor et al. (2013)*	-0.49***	-0.01	0.71	-0.41	0.84**	-1.23
Panel E. Domestic plus international exposure to Chinese exports (2SLS)						
(Δ domestic+ international exposure	-0.443***	-0.0838	0.232	-0.445**	0.711**	-1.449***
to Chinese imports)/worker	(0.0620)	(0.0839)	(0.289)	(0.185)	(0.298)	(0.315)
* *1990-2007 Autor et al. (2013)*	-0.51***	-0.12	0.16	-0.60***	0.87***	-1.77***
Panel F. Change in China-US productivity differential (OLS gravity residual)						
Δ comparative advantage China	-0.305***	-0.0483	0.0135	-0.279*	0.517***	-0.822***
(gravity residual)	(0.0461)	(0.0629)	(0.254)	(0.146)	(0.165)	(0.219)
* *1990-2007 Autor et al. (2013)*	-0.29***	-0.03	-0.04	-0.26*	0.53***	-0.78***

N = 1,444 (722 CZs in two panels). Dependent variable is change in log CZ population. All specifications include controls from Autor et al. (2013). Population counts for rows 1, 2, 4, and 5 come from IPUMS USA. Population counts for rows 3 and 6 come from the Census Bureau intercensal estimates, which also include 15-year-olds. All specifications weighted by start-of-period CZ population shares. Standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

The results of the impact of trade exposure on transfer payments and household income are analogous to those of Autor et al. (2013). Transfer payments per capita is measured using the BEA Regional Economic Accounts and the Social Security Administration's Annual Statistical Supplement. In Table 2, column 5 reports the estimated effect of changes in trade exposure on log change in individual transfers per capita for total transfers. We can conjecture that the decline in employment and wages in CZs facing an growing trade exposure is likely to lead to an increase in residents' demand for public transfer payments. The effect of import exposure on transfer payments to CZs is sizable. We estimate that a $1,000 increase in gross Chinese import exposure leads to a rise in transfer payments of 1.389 log points per capita. Trade exposure shocks may also lead to a decrease in household income. Column 6 of Table 2 shows that the combination of reduced employment and increased transfer payments negatively affects the household income level in local labor markets exposed to rising import competition. The models in column 6 find that a $1,000 increase in a CZ's import exposure leads to a fall in CZ average household wage income per working age adult of 2.149 log points. The effect of import competition on household incomes is statistically significant. As with the estimation results for employment, models using exposure to net imports or indirect import competition show that the impact of alternative trade exposures on transfer payments and household income is reduced by around half of Autor et al. (2013). In addition, comparing the estimates in columns 5 and 6 of Table 3, it was found that the increasing transfer income offsets most of the decline in household wage and salary income.

3.3 Trade Shocks and Internal Migration

3.3.1 Alternative Measures of Trade Exposure and Internal Migration (IPUMS)

In this section, I examine changes between 1990 and 2000 and between 2000 and 2010 in the log counts of the following population groups: ages 16 to 64, 16 to 34, 35 to 49, and 50 to 64 years old; individuals without a college degree; and individuals with a college degree. I repeat the specification of Greenland et al. (2019), but expand to incorporate alternative measures of trade exposure for U.S. commuting zones on population adjustment at the CZ level:

$$\Delta L_{it} = \gamma_t + \kappa_r + \beta_1 \Delta Trade\ Exposure_{uit} + \mathbf{X}_{it}^{\prime} \beta_2 + e_{ct}$$

The specification controls for time and Census division fixed effects, the share of employment accounted for by manufacturing, the share of the population with a college degree, the foreign-born share of the population, the female labor force share, the routine task share, and the offshorability index. While Greenland et al. (2019) use the change in import exposure IPW_{uit}, I consider alternative measures of trade exposure for U.S. commuting zones in order to incorporate exposure to U.S. exports to China (net imports) and indirect competition as used in Autor et al (2013). First, Table 3 reproduces the results of 1990-2007 of Autor et al. (2013) by extending the period to 1990-2010. As in Autor et al. (2013), we do not find evidence of population adjustment in response to increasing import competition in most models.

3.3.2 Alternative Measures of Trade Exposure and Internal Migration, Controlling Population Trends (IPUMS)

Table 4 takes into account preexisting trends in CZ populations, which is a 10-year lagged change in the log population for the relevant group excluded in Autor et al. (2013). The lag variable measures CZ log population change between 1980 and 1990 (associated with 1990-2000 outcome variable observations) and between 1990 and 2000 (associated with 2000-2007 outcome variable observations). As a result of our consideration of trends in the CZ population, the point estimates of trade exposure in panel A (gross Chinese imports per worker), panel E (domestic plus international exposure to Chinese exports), panel F (Change in comparative advantage China-US) are statistically significant and consistently negative. It was found that the negative effects of migration from import competition for those without a college education and young people aged 16-34 are statistically significant. That is, an increase in import competition would have reduced population growth among 16-34 year-olds and individuals without a college degree. Our results suggest that much of the population adjustment to rising import competition occurred at a considerable lag. It should be noted that the trade exposure coefficient of panel E (domestic plus international exposure to Chinese exports) and the coefficient of panel F (change in comparative advantage China-US) are reduced to 57% and 28% of that in panel A (gross Chinese imports per worker), respectively.

Table 3: Alternative Measures of Trade Exposure and Internal Migration (IPUMS)

1990-2010 Changes in Log CZ Population	(1) 16-64	(2) College	(3) No College	(4) 16-34	(5) 35-49	(6) 50-64
Panel A. Baseline results: Gross Chinese imports per worker (2SLS)						
(Δ imports from China to US)/worker	-0.0554	0.187	-0.310	-0.693	0.738	0.130
ΔIPW_{uit}	(0.767)	(0.664)	(0.863)	(0.935)	(0.664)	(0.898)
Panel B. Exposure to final goods and intermediate inputs (2SLS)						
(Δ imports from China to US net	0.165	0.476	-0.164	-0.166	0.802	0.116
of intermediate inputs)/worker	(0.696)	(0.582)	(0.799)	(0.888)	(0.621)	(0.768)
Panel C. Change in China-US productivity differential (OLS gravity residual)						
Δ comparative advantage China	0.0669	0.210	-0.0736	-0.226	0.450**	0.0876
(gravity residual)	(0.189)	(0.167)	(0.233)	(0.253)	(0.209)	(0.240)
Panel D. Factor content of net Chinese imports per worker (2SLS)						
(Δ factor content of net imports	0.259	0.639*	-0.0800	-0.137	0.838**	0.402
from China) /worker	(0.448)	(0.340)	(0.554)	(0.619)	(0.409)	(0.479)
Panel E. Net Chinese imports per worker (2SLS)						
(Δ net imports of US from China)	0.164	0.436	-0.108	-0.194	0.852	0.117
of /worker	(0.578)	(0.475)	(0.688)	(0.742)	(0.526)	(0.627)
Panel F. Domestic plus international exposure to Chinese exports (2SLS)						
(Δ domestic+ international exposure to	0.0546	0.148	-0.0424	-0.380	0.516	0.210
Chinese imports)/worker	(0.468)	(0.420)	(0.516)	(0.538)	(0.417)	(0.568)
* *1990-2007 Autor et al. (2013)*	-0.050	-0.026	-0.048	-0.138	0.367	-0.138
ΔIPW_{uit}	(0.746)	(0.685)	(0.823)	(1.190)	(0.560)	(0.651)

N = 1,444 (722 CZs in two panels). Dependent variable is change in log CZ population. All specifications include controls from Autor et al. (2013). All specifications weighted by start-of-period CZ population shares. Standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

Table 4: Alternative Measures of Trade Exposure and Internal Migration, Controlling Population Trends (IPUMS)

1990-2010	(1)	(2)	(3)	(4)	(5)	(6)
Changes in Log CZ Population	16-64	College	No College	16-34	35-49	50-64
Panel A. Greenland et al. (2019): Gross Chinese imports per worker (2SLS)						
(Δ imports from China to US)/worker	-0.806*	-0.558	-1.041**	-1.491**	-0.0599	-0.475
ΔIPW_{uit}	(0.426)	(0.551)	(0.453)	(0.731)	(0.443)	(0.611)
Panel B. Net Chinese imports per worker (2SLS)						
(Δ net imports of US from China)	-0.545	-0.241	-0.845*	-0.944	0.134	-0.517
/worker	(0.424)	(0.526)	(0.467)	(0.774)	(0.438)	(0.545)
Panel C. Factor content of net Chinese imports per worker (2SLS)						
(Δ factor content of net imports	-0.347	0.0794	-0.504	-0.680	0.424	-0.284
from China) /worker	(0.316)	(0.346)	(0.390)	(0.578)	(0.345)	(0.421)
Panel D. Exposure to final goods and intermediate inputs (2SLS)						
(Δ imports from China to US net	-0.382	-0.107	-0.631	-0.704	0.312	-0.508
of intermediate inputs)/worker	(0.372)	(0.455)	(0.418)	(0.674)	(0.383)	(0.459)
Panel E. Domestic plus international exposure to Chinese exports (2SLS)						
(Δ domestic+ international exposure to	-0.461*	-0.345	-0.605**	-0.945**	-0.0459	-0.144
Chinese imports)/worker	(0.251)	(0.331)	(0.257)	(0.406)	(0.264)	(0.378)
Panel F. Change in China-US productivity differential (OLS gravity residual)						
Δ comparative advantage China	-0.226**	-0.0654	-0.347**	-0.527**	0.112	-0.156
(gravity residual)	(0.112)	(0.133)	(0.137)	(0.221)	(0.170)	(0.164)
* *1990-2007 Autor et al. (2013)*	-0.709	-0.592	-0.710	-1.039	-0.194	-0.530
with $\Delta ln(population_{t-10})$ ΔIPW_{uit}	(0.485)	(0.582)	(0.483)	(1.037)	(0.329)	(0.527)

N = 1,444 (722 CZs in two panels). Dependent variable is change in log CZ population. All specifications include controls from Autor et al. (2013). All specifications weighted by start-of-period CZ population shares. Standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

3.3.3 Alternative Measures of Trade Exposure and Internal Migration, Controlling Population Trends (Census data)

I compared the results of estimating using IPUMS data and Census population data. Autor et al. (2013) use IPUMS data, which include information on labor market outcomes for nationally representative samples of individuals. However, IPUMS data are samples of the population, not the entire population. I repeat the previous specification, using data from the complete Census rather than IPUMS.[3] In addition, we explore changes in the age groups of 15−64 and 15−34, which are more subdivided than those aged 16 to 64 and 16 to 34. These enable us to gauge the robustness of our results in 3.3.2 alternative measures of trade exposure and internal migration, controlling population trends using IPUMS.

As can be seen from Table 5, the point estimate using census data is similar to that obtained using IPUMS data. We find that the point estimates of trade exposure in panel A (gross Chinese imports per worker) and panel F (Change in comparative advantage China-US) are statistically significant. The coefficient for the trade exposure of Panel F (Chinese comparative advantage) is reduced to about half of Panel A, which uses gross Chinese imports per worker. Table 5 presents an effect among the younger group that is approximately twice as large as the total working-age population effect. In both IPUMS data and Census count data, we find statistically significant reductions in population growth of working-age individuals and of the young. Interestingly, the use of Census data instead of IPUMS data reduces the absolute value of the negative coefficient for the internal migration for Chinese imports per worker by about 10%, while the negative effect of population growth in the local markets increases by more than 50% in the gravity residual model.

[3] These data are not available by education group, so we are able to explore variation only by age category.

Table 5: Alternative Measures of Trade Exposure and Internal Migration, Controlling Population Trends (Census data)

1990-2010	(1)	(2)	(3)	(4)
Changes in Log CZ Population	15-64	15-34	35-49	50-64
Panel A. Greenland et al. (2019): Gross Chinese imports per worker (2SLS)				
(Δ imports from China to US)/worker	-0.701*	-1.353**	-0.023	-0.345
ΔIPW_{uit}	(0.390)	(0.646)	(0.399)	(0.506)
Panel B. Net Chinese imports per worker (2SLS)				
(Δ net imports of US from China)	-0.468	-0.861	0.168	-0.490
/worker	(0.403)	(0.701)	(0.405)	(0.466)
Panel C. Factor content of net Chinese imports per worker (2SLS)				
(Δ factor content of net imports	-0.196	-0.487	0.502	-0.199
from China) /worker	(0.298)	(0.504)	(0.321)	(0.384)
Panel D. Exposure to final goods and intermediate inputs (2SLS)				
(Δ imports from China to US net	-0.157	-0.438**	0.183	-0.120
of intermediate inputs)/worker	(0.101)	(0.189)	(0.161)	(0.143)
Panel E. Domestic plus international exposure to Chinese exports (2SLS)				
(Δ domestic+ international exposure to	-0.319	-0.595	0.324	-0.570
Chinese imports)/worker	(0.348)	(0.605)	(0.348)	(0.398)
Panel F. Change in China-US productivity differential (OLS gravity residual)				
Δ comparative advantage China	-0.381*	-0.825**	-0.0161	-0.0284
(gravity residual)	(0.224)	(0.354)	(0.238)	(0.312)
* *1990-2007 Census data with*	-0.602	-1.283**	0.023	-0.175
$\Delta ln(population_{t-10})$ ΔIPW_{uit}	(0.407)	(0.601)	(0.405)	(0.473)

N = 1,444 (722 CZs in two panels). Dependent variable is change in log CZ population. All specifications include controls from Autor et al. (2013). All specifications weighted by start-of-period CZ population shares. Standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

4 Conclusion

Since China joined the WTO in 2001 and was granted Permanent Normal Trade Relations, China's share of global manufacturing production has grown significantly from 5.5 percent in 2001 to 15.6 percent in 2011 and 23.5 percent in 2019. During this period, the U.S. trade deficit with China surged from $83.8 billion (19.2% of the U.S. trade deficit) in 2000 to $273 billion (43.0% of the U.S. trade deficit) in 2010. Between 1999 and 2011, 2.4 million people lost their jobs in Michigan, Ohio, and Pennsylvania, called the Rust Belt, leaving a significant number of U.S. manufacturing jobs significantly reduced. The previous literature showed that higher imports from China cause higher unemployment and reduced wages in the U.S. local labor markets, where the import competitive manufacturing industry resides.

My analysis and extension - which greatly benefited from Autor et al. (2013) and Greenland et al. (2019)'s coding and data - conclude that their findings of the impact on employment, wages, government transfers, and internal migration from trade exposure at the local labor market might be overestimated. While Greenland et al. (2019) use the change in import exposure IPW_{uit} which is instrumented by the variable IPW_{oit}, I consider alternative measures of trade exposure for U.S. commuting zones in order to incorporate exposure to U.S. exports to China (net imports) and indirect competition as used in Autor et al (2013). I study how using alternative trade exposures will change the results of Greenland et al. (2019). And I explore the robustness by comparing our results using Census (entire) population data to those obtained in Autor et al. (2013), who use IPUMS data (samples of the population). In addition to employing Census count data and extending the analysis to 2010, an important distinction between our paper and Autor et al. (2013) is the fact that we examine labor market and population adjustments using alternative trade exposures while controlling for population trends. These enable us to gauge the robustness of previous literature and view Chinese syndrome from a balanced perspective.

First, I repeat the specification of Autor et al. (2013), but I extend the period from 1990-2007 to 1990-2010 and focus on alternative measures of trade exposure for U.S. commuting zones. The impact of trade exposure on employment in the manufacturing industry is all statistically significant, while their impact on the non-manufacturing industry is not significant. A $1,000 per worker increase in a CZ's trade exposure reduces its employment to population rate by 0.85 percentage points. About 84% of that decline is due to the decline in manufacturing employment, with the remainder due to loss in non-manufacturing employment. When we used gross Chinese imports per worker as a trade exposure, the coefficient on manufacturing employment in the working-age population is -0.712, and the coefficient of Chinese comparative advantage model is -0.305, which is less than half (43%) of gross Chinese imports model. Although trade exposure reduces manufacturing employment, it appears to have no significant effects on mean manufacturing wages in CZs. Rather, in models using net Chinese exports per worker or exposure to final goods and intermediate inputs, trade exposure was found to have a statistically significant positive effect on average manufacturing wages. The explanation for this pattern is that highly productive workers maintain jobs in the manufacturing industry, thus increasing manufacturing wages rather than decreasing, and accelerating technological and organizational innovation in manufacturing plants to increase productivity and wages in response to import competition. Also, it was found that the increasing transfer income offsets most of the decline in household wage and salary income. As with the estimation results for employment, models using exposure to net imports or indirect import competition show that the impact of alternative trade exposures on transfer payments and household income is reduced by around half of Autor et al. (2013).

Second, I repeat the specification of Greenland et al. (2019) but expand to incorporate alternative measures of trade exposure for U.S. commuting zones on population adjustment at the CZ level. When we use IPUMS and control population trends, the trade exposure coefficient of the model using domestic plus international exposure to Chinese exports and the coefficient of the model using change in comparative advantage China-US are reduced to 57% and 28% of that in the model using Chinese imports per worker, respectively. With Census data, the coefficient of the model using Chinese comparative advantage as a trade exposure is reduced to about half of that of the model using Chinese imports per worker. In both IPUMS data and Census data, we find significant reductions in population growth of working-age individuals and of the young.

Still, in terms of originality and robustness, this paper has shortages such as the method of constructing alternative trade measures as Instrumental variables. As China and the United States occupy different positions in the global production chain, exports based on customs clearance may not be an accurate measure in terms of value-added. China has a comparative advantage in labor-intensive assembling, which tends to be the last step in the supply chain of importing intermediate goods from Korea and Japan, producing final goods, and exporting them to the United States, while US exports tend to be early in the production chain. This means that U.S. products bound for China can be shipped through third countries. Therefore, the U.S. trade deficit on a value-added basis with the U.S. is significantly reduced than the value of the customs clearance standard, and the impact of trade exposure on the U.S. labor market may be further reduced. For example, before semiconductors are sent to China for assembly and testing, American technology is used by

Korean companies to manufacture chips for mobile phones. And considering that China's share of the U.S. trade deficit decreased to 43.0% in 2010 and 34.3% in 2020, the impact of import competition with China on the U.S. economy is likely to be dispersed to other countries. Further research reflecting value-added trade and the latest data will contribute to this literature so that China Syndrome can be viewed in a balanced perspective.

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Appendix

Appendix Table 1: Net Imports from China on Changes in Manufacturing Employment in CZs: 1990-2010 (IPUMS),

Panel B. Net Chinese imports per Worker (2SLS)

	1. 1990-2010 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/worker	-0.753***	-0.522***	-0.410***	-0.383***	-0.416***	-0.466***
	(0.0890)	(0.107)	(0.126)	(0.108)	(0.118)	(0.118)
Percentage of employment in manufacturing$_{-1}$		-0.050**	-0.072***	-0.083***	-0.079***	-0.064***
		(0.019)	(0.020)	(0.016)	(0.015)	(0.010)
Percentage of college-educated population$_{-1}$				-0.016		0.005
				(0.015)		(0.012)
Percentage of foreign-born population$_{-1}$				-0.007		0.031***
				(0.008)		(0.011)
Percentage of employment among women$_{-1}$				-0.051**		-0.001
				(0.023)		(0.022)
Percentage of employment in routine occupations$_{-1}$					-0.199***	-0.212***
					(0.073)	(0.075)
Average offshorability index of occupations$_{-1}$					0.026	-0.231
					(0.356)	(0.344)
Census division dummies	No	No	Yes	Yes	Yes	Yes
Prob > First Stage F	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.424	0.470	0.483	0.487	0.487	0.487

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2010 period (IPUMS). Models are weighted by start of period commuting zone share of national population. Robust standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

Appendix Table 2: Factor Content of Net Imports from China and Changes in Manufacturing Employment in CZs: 1990-2010 (IPUMS),

Panel C. Factor Content of Net Chinese Imports per Worker (2SLS)

	1. 1990-2010 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ factor content of net imports	-0.858***	-0.639***	-0.479***	-0.526***	-0.472***	-0.561***
from China)/worker	(0.103)	(0.108)	(0.101)	(0.094)	(0.081)	(0.094)
Percentage of employment in		-0.041**	-0.065***	-0.072***	-0.074***	-0.058***
manufacturing$_{-1}$		(0.017)	(0.018)	(0.015)	(0.014)	(0.011)
Percentage of college-educated				-0.024		-0.002
population$_{-1}$				(0.015)		(0.012)
Percentage of foreign-born				-0.002		0.035***
population$_{-1}$				(0.008)		(0.011)
Percentage of employment				-0.052**		-0.004
among women$_{-1}$				(0.024)		(0.023)
Percentage of employment in					-0.170**	-0.181**
routine occupations$_{-1}$					(0.079)	(0.082)
Average offshorability index of					-0.148	-0.371
occupations$_{-1}$					(0.402)	(0.382)
Census division dummies	No	No	Yes	Yes	Yes	Yes
Prob > First Stage F	0.000	0.000	0.000	0.000		0.000
Adjusted R^2	0.561	0.581	0.600	0.601	0.600	0.601

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2010 period. Models are weighted by start of period commuting zone share of national population. Robust standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

Appendix Table 3: Total Chinese Import less Intermediate Inputs and Changes in Manufacturing Employment in CZs: 1990-2010 (IPUMS),

Panel D. Exposure to Final Goods and Intermediate Inputs per Worker (2SLS)

	1. 1990-2010 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US net	-0.850***	-0.599***	-0.457***	-0.422***	-0.485***	-0.542***
of intermediate inputs)/worker	(0.098)	(0.121)	(0.142)	(0.119)	(0.140)	(0.139)
Percentage of employment in		-0.048***	-0.070***	-0.083***	-0.076***	-0.061***
manufacturing$_{-1}$		(0.019)	(0.019)	(0.015)	(0.014)	(0.010)
Percentage of college-educated				-0.018		0.005
population$_{-1}$				(0.015)		(0.013)
Percentage of foreign-born				-0.007		0.033***
population$_{-1}$				(0.008)		(0.011)
Percentage of employment				-0.051**		0.002
among women$_{-1}$				(0.023)		(0.021)
Percentage of employment in					-0.206***	-0.221***
routine occupations$_{-1}$					(0.071)	(0.073)
Average offshorability index of					0.033	-0.250
occupations$_{-1}$					(0.346)	(0.338)
Census division dummies	No	No	Yes	Yes	Yes	Yes
Prob > First Stage F	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.448	0.487	0.502	0.506	0.506	0.506

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2010 period. Models are weighted by start of period commuting zone share of national population. Robust standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

Appendix Table 4: Domestic plus International Exposure to Chinese Exports and Changes in Manufacturing Employment in CZs: 1990-2010 (IPUMS),

Panel E. Domestic plus International exposure to Chinese Exports (2SLS)

	1. 1990-2010 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ domestic + international Exposure to Chinese inmports) / worker	-0.529***	-0.406***	-0.385***	-0.353***	-0.428***	-0.443***
	(0.044)	(0.049)	(0.052)	(0.047)	(0.061)	(0.062)
Percentage of employment in manufacturing$_{-1}$		-0.050**	-0.063***	-0.073***	-0.064***	-0.050***
		(0.020)	(0.019)	(0.015)	(0.014)	(0.010)
Percentage of college-educated population$_{-1}$				-0.007		0.015
				(0.016)		(0.013)
Percentage of foreign-born population$_{-1}$				-0.008		0.030**
				(0.009)		(0.012)
Percentage of employment among women$_{-1}$				-0.051**		0.002
				(0.024)		(0.023)
Percentage of employment in routine occupations$_{-1}$					-0.248***	-0.259***
					(0.063)	(0.064)
Average offshorability index of occupations$_{-1}$					0.330	-0.040
					(0.282)	(0.272)
Census division dummies	No	No	Yes	Yes	Yes	Yes
Prob > First Stage F	0.000	0.000		0.000	0.000	0.000
Adjusted R^2	0.599	0.626	0.637	0.641	0.641	0.641

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2010 period. Models are weighted by start of period commuting zone share of national population. Robust standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.

Appendix Table 5: Change in Comparative Advantage China and Changes in Manufacturing Employment in CZs: 1990-2010 (IPUMS),

Panel F. Change in China-US Productivity Differential (OLS Gravity Residual)

	1. 1990-2010 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ Comparative Advantage China	-0.468***	-0.319***	-0.300***	-0.281***	-0.299***	-0.305***
(gravity residual)	(0.075)	(0.054)	(0.048)	(0.044)	(0.047)	(0.046)
Percentage of employment in		-0.072***	-0.084***	-0.098***	-0.094***	-0.085***
$\text{manufacturing}_{-1}$		(0.015)	(0.016)	(0.014)	(0.013)	(0.011)
Percentage of college-educated				-0.018		0.005
population_{-1}				(0.013)		(0.010)
Percentage of foreign-born				-0.012		0.026**
population_{-1}				(0.009)		(0.011)
Percentage of employment				-0.054**		-0.003
among women_{-1}				(0.022)		(0.021)
Percentage of employment in					-0.192***	-0.199***
$\text{routine occupations}_{-1}$					(0.059)	(0.061)
Average offshorability index of					-0.115	-0.357
occupations_{-1}					(0.303)	(0.300)
Census division dummies	No	No	Yes	Yes	Yes	Yes
R^2	0.197	0.293	0.419	0.455	0.497	0.507

Notes: N=1444 (722 commuting zones x 2 time periods). All regression include a constant and a dummy for the 2000-2010 period. Models are weighted by start of period commuting zone share of national population. Robust standard errors clustered at the state and indicated in parentheses. Significant at ***1%, **5%, and *10%.