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US exports and employment☆

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ABSTRACT

We study the employment responses to the expansion of US exports and to the import competition, especially from China. We find that although import competition reduces jobs, export expansion also creates a substantial number of jobs. At the industry level, job gains due to US export expansion largely offset job losses due to Chinese import competition, resulting in a net gain of 379 thousand jobs over 1991–2011 in our preferred estimate. At the commuting zone level, job gains and losses are roughly balanced, with a slight net loss of 68 thousand jobs and a substantial range around this preferred estimate depending on the specification.

1. Introduction

Conventional wisdom in economics is that trade liberalization will have two effects on labor market outcomes. On the one hand, firms that face import competition may shrink or even exit and therefore displace workers. On the other hand, firms that gain access to foreign market should enter or expand, therefore generating new jobs. While such effects of job creation and destruction due to international trade are commonly accepted, the recent growing literature on the 'China shock' focuses on the job-reducing effect of surging imports from China or other low-wage countries on the US labor market (Autor et al., 2013; Pierce and Schott, 2016; Acemoglu et al., 2016).[1] Much less explored is the job-creating effect of exports. Autor et al. (2013) begin to explore that issue by including *net* imports from China in their robustness analysis. Instead we shall consider total US exports as compared to imports from China and imports from the rest of the world.

Specifically, this paper provides one of the first accounts of job creation due to the export expansion in the United States, at the industry and the commuting zone levels. The United States is among the leading exporting countries in the world trading system: in 2014, the value of its merchandise exports reached more than 1.6 trillion US dollars, second only after China. Fig. 1 illustrates real merchandise exports and manufacturing exports for the US over 1991 to 2011 (in 2007 US dollars). It shows that either measure

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[1] Notable exceptions include Dauth et al. (2014), who use the German trade and labor data to show that the rise of the East (Eastern Europe and China) caused substantial job losses in regions exposed to import competition, while it also led to strong employment gains in regions that are more export oriented. Their results are driven almost entirely by the rise in Eastern Europe, however, and not by China. Costa et al. (2016) consider explicitly the employment effects on Brazil of both imports from China and exports to China. They find that local labor markets more affected by Chinese import competition experienced slower growth in manufacturing wages. However, local labor markets experiencing larger growth in Chinese demand have gained through faster wage growth and shifts in the local economy towards formal jobs. See also Liang (2018) who studies both U.S. imports and exports.

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0022-1996/

of US exports more than doubled over these two decades, from 600 billion or less in 1991 to more than 1.2 trillion dollars in 2011. No doubt such an expansion in export value generated increased demand for labor. However, the US export expansion was not evenly distributed across industries. Fig. 2 lists the top industries that have experienced the largest increase in export value during 1991 - 2007. Among 392 revised SIC manufacturing sectors, semiconductors experienced the largest increase in export value during 1991-1999, while motor vehicles and petroleum refining have been the champion of export expansion in the period 1999-2007.[2] These top categories reflect America's comparative advantage and grew much faster than many other categories, some of which even saw reductions in exports, therefore creating large variation for our estimation.

Empirically, it is not easy to obtain unbiased estimates of the effects of export expansion due to endogeneity. While increased access to foreign markets drives up demand for labor employment, domestic supply shocks such as new technology or TFP growth will also promote exports, and quite possibly reduce employment, causing difficulty in identification. Uncontrolled (often unobserved) domestic demand shocks, too, can be expected to affect export value and labor employment simultaneously. Lack of plausible instruments probably explains the limited empirical evidence on the employment effects of both exports and imports.

To deal with endogeneity, we adopt two instruments. First, we follow the spirit of Autor et al. (2013), henceforth ADH to look at the export expansion of eight other high-income countries.[3] This is based on the assumption that these high-income countries face similar demand shocks for their sales into foreign countries as does the United States in its exports to those countries. The second instrument that we adopt in this paper relies on a more careful modeling of US exports to each foreign market, based on a CES framework. The export equation that we obtain includes a term that captures the exports of other countries to each foreign market (similar to our first instrument), and in addition, it includes the tariffs faced by the United States and all other countries selling in that market. Thus, we construct a second instrument as the predicted US exports based on foreign demand (except from the US), tariffs that the US faces, and the tariffs that other competing countries face in each foreign market. We likewise use two instruments on the import side: the first is the ADH instrument based on the eight other countries imports (from China or the rest of the world), and the second is predicted US imports incorporating its own change in tariffs, especially the establishment of Permanent Normal Trade Relations with China after its accession to the WTO in 2001, as analyzed by Pierce and Schott (2016) and Handley and Limao (2017).

On the import side, we find that both the ADH instrument and tariffs used in our second instrument, reflecting China's PNTR status within the US, perform very well in the first-stage regressions. That is, both these instruments contribute to the identification of US imports from China. Interestingly, however, adding the tariff information does not have a substantial further effect on the employment losses due to US imports from China. This finding suggests that the ADH instrument based on China's exports to other countries already incorporates the effects of its WTO accession, in addition to other policy changes in China such as reform of state-owned enterprises, etc. All these changes create a quasi-natural experiment that ADH exploit to measure the 'China shock'. In contrast, the analogous instrument on the export side to that used by

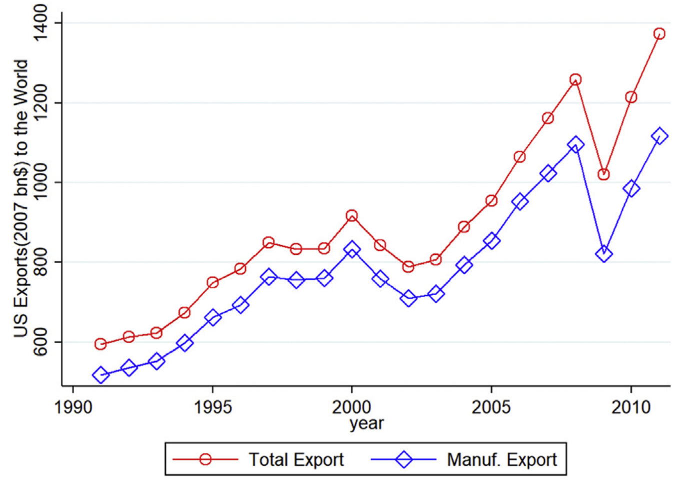

Fig. 1. US export: 1991-2011. Note: Red line shows the aggregate export of the United States, while the blue line shows the manufacturing exports. All values are in billion US $, deflated to 2007 US dollars using the PCE price index. Data source: UN-Comtrade.

ADH, which is the export expansion of eight other high-income countries, does not strongly identify US exports to China, and neither does China's own tariff cuts. US exports to the rest of the world are better identified when using the eight other countries exports to the rest of the world and those tariff changes, but still, there is not the large-scale policy reform at work that we rely on to identify Chinese imports.

With this qualification in mind, our empirical results show important job gains due to US export expansion. Based on the industry level estimation, our preferred results show that US export expansion to the world *net of* import penetration from China and the rest of the world actually led to a net gain of 497,000 jobs in the first decade of 1991-1999, while it led to a net loss of 117,000 jobs for the second period 1999–2011. Over the entire 1991-2011 period, therefore, job gains largely offset job losses, with a net gain of 379,000 jobs. While these results put the job losses created by Chinese imports into a useful perspective, a second qualification is that the job gains and losses can occur in different geographic locations, so incorporating exports does not eliminate the localized job losses and gains that occur in different regions.

To investigate these localized job gains and losses, we also explore the variations across US commuting zones in their exposure to imports and exports. . We find consistently a large job creating effect of export expansion (but with the same qualification just noted, that these gains can occur in different commuting zones than the job losses). In the first period, our preferred specification shows that job gains from export expansion largely offset the job losses from import penetration, resulting in a net gain of 379,000 jobs (just like we find for the entire period in the industry estimates). In the second period, export expansion continues to create large gains around 1200,000 jobs, however, due to the large job losses from import penetration, this leads to a net loss of 447,000 jobs. Over the entire 1991-2011 period, this leads to a slight net loss of 68,000 jobs. Other specifications using alternative instruments or the estimation method of Borusyak et al., 2018 lead to estimates that vary substantially around that preferred specification.

The rest of the paper is structured as follows: Section 2 introduces our empirical strategy, the specifications we use and the two types of instruments we construct. Section 3 presents the estimation results at the industry level and the quantitative employment implications. Section 4 introduces the analysis at the local commuting zone level. Section 5 concludes.

[2] As a comparison, Figure A.1 in the online Appendix presents the top import SIC categories that have experienced the largest increase in volume from China.

[3] ADH (2013) instrument the US import penetration from China using eight other high-income countries' import penetration from China. These countries are: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

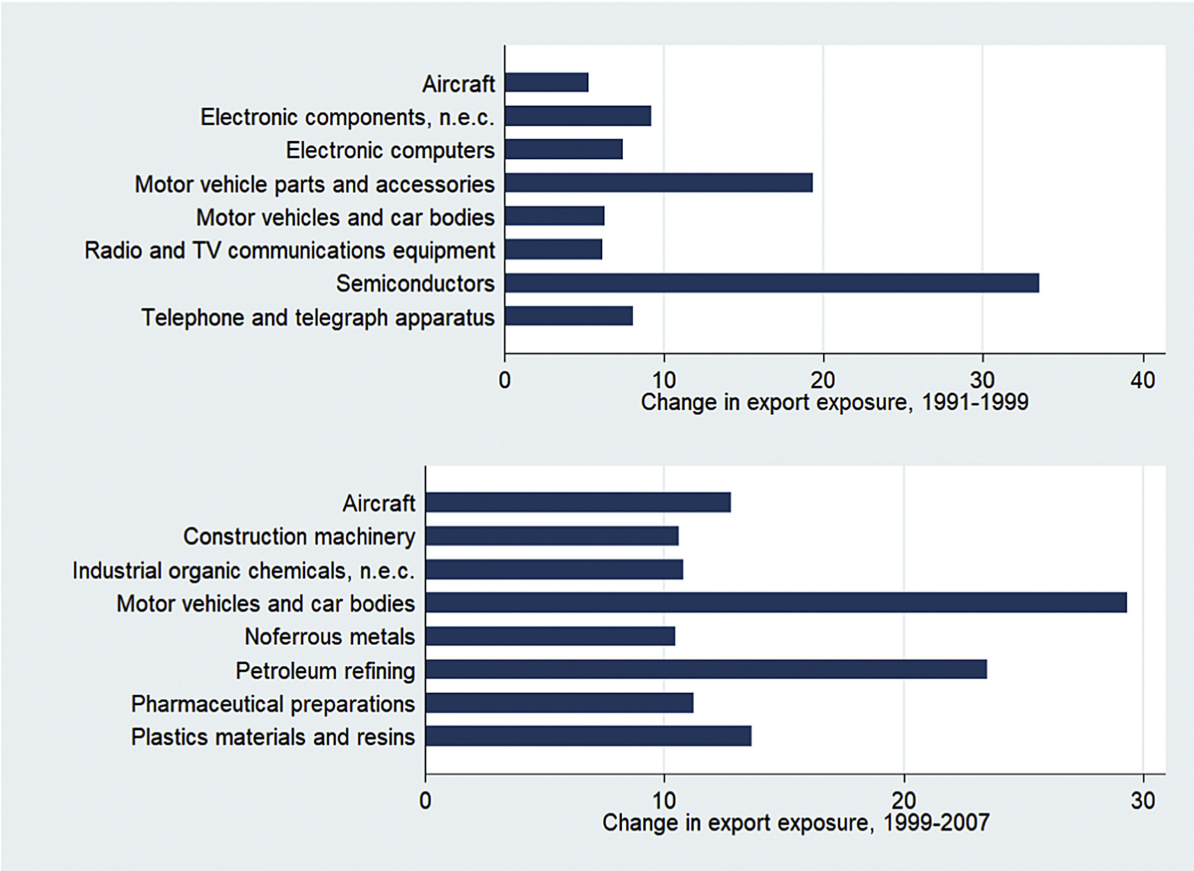

Fig. 2. Changes in US industry real exports: 1991–2007. Note: This figure shows the top 8 SIC products in US exports, in terms of changes in real export value for two subperiods 1991-1999 and 1999-2007. All values are in billion US$, deflated to 2007 US dollars using the PCE price index. Data source: UN-Comtrade.

2. Empirical strategy

2.1. Specification

To identify the effect of import and export exposure on manufacturing employment, we adopt the following empirical specification as in Acemoglu et al. (2016), but expand to incorporate trade beyond US imports from China:

$$\Delta \ \ln(L_{st}) = \alpha_t + \beta_1 \Delta IP_{st}^{us,c} + \beta_2 \Delta IP_{st}^{us,row} + \beta_3 \Delta EP_{st}^{us,c} + \beta_4 \Delta EP_{st}^{us,row} + Z_{s0}\Gamma + \varepsilon_{st}, \tag{1}$$

where $\Delta \ ln \ (L_{st})$ is the annual log change in employment in industry s over time period t, and $\Delta IP_{st}^{us,k}$ and $\Delta EP_{st}^{us,k}$ measure the annual change in US import and export exposure, respectively, for China ($k = c$) and the rest of the world ($k = row$). Z_{s0} is a row vector of industry-specific controls such as the number of production workers and nonproduction workers at the start of period, and other controls that we will discuss in detail in later sections, with the column vector of coefficients Γ. We expect that $\beta_1, \beta_2 < 0$ as imports reduce employment, and $\beta_3, \beta_4 > 0$ as exports increase employment.

Following Acemoglu et al. (2016), we fit this equation for stacked first differences covering two subperiods 1991–1999 and 1999–2011 (which we call 'decades'), while for robustness we sometimes shorten the latter subperiod to 1999–2007 prior to the global financial crisis. All variables in changes are annualized and the regression also includes a dummy for each period α_t and is estimated using the initial year (1991) industrial employment share as weights. For US employment changes we use the County Business Patterns (CBP) for the years 1991, 1999, 2007, and 2011. We use the same data coverage as Acemoglu et al. (2016) and follow their steps to merge the data into 392 manufacturing industries. For additional industry level information within the manufacturing sector, such as wages for example, we use the NBER-CES Manufacturing Industry Database for the same years 1991, 1999, 2007.[4]

Measuring Import Exposure: The change in the industry level import penetration from China is measured as

$$\Delta IP_{st}^{us,c} \equiv \frac{\Delta M_{st}^{us,c}}{Y_{st_0} + M_{st_0} - X_{st_0}}, \tag{2}$$

where s denotes 392 manufacturing industries in the SIC classification, and $\Delta M_{st}^{us,c}$ denotes the change in *US imports from China* in industry s for the time period t (t is either 1991–1999, or 1999–2011, and in some cases 1999–2007). To normalize, $\Delta M_{st}^{us,c}$ is divided by the initial domestic absorption in the US, which consists of industry real shipments, Y_{st_0}, plus industry real net imports, $M_{st_0} - X_{st_0}$, both at initial year $t_0 = 1991$ and deflated by the Personal Consumption Expenditures (PCE) price index. This variable therefore measures the actual increase in import exposure by each US manufacturing industry s.

We extend the method above to capture import penetration in the United States from the rest of the world (ROW), by defining:

$$\Delta IP_{st}^{us,row} \equiv \frac{\Delta M_{st}^{us,row}}{Y_{st_0} + M_{st_0} - X_{st_0}}, \tag{3}$$

as US imports from the rest of the world (not including China) measured relative to initial industry absorption. We can naturally sum the

[4] The NBER-CES database ends at the year 2009.

above variables to obtain total import penetration into the United States as $\Delta IP_{st}^{us} = \Delta IP_{st}^{us,c} + \Delta IP_{st}^{us,row}$.

Measuring Export Exposure: To capture the industrial exposure to export expansion, we use analogous measures to the above variables, where we construct the change in exports relative to initial industry shipments:

$$\Delta EP_{st}^{us,j} \equiv \frac{\Delta X_{st}^{us,j}}{Y_{st_0}}, \tag{4}$$

where $\Delta X_{st}^{us,j}$ in the numerator measures the change in U.S. exports to country j. For example, $\Delta EP_{st}^{us,c}$ measures changes in export exposure of industry s between t-1 and t, defined as changes in US sector exports to China, divided by the initial sectoral shipments Y_{st_0}. Thus, $EP_{st}^{us,j}$ is a measure of export intensity, capturing the share of export value relative to total industrial output. Alternatively, when $j = row$ then we are interested in measuring the total US export expansion to the rest of the world, and if j is absent then we are measuring US export exposure to the entire world, $\Delta EP_{st}^{us} = \Delta EP_{st}^{us,c} + \Delta EP_{st}^{us,row}$.

2.2. Instrumental variables

Eq. (1) is subject to endogeneity of the trade exposure measures. Suppose there is a positive domestic demand shock that increases imports and decreases exports, while raising employment. Then the OLS coefficients on imports would be biased up, while the OLS estimates on exports would be biased down. On the other hand, a US supply shock that is labor saving will reduce employment, raise output and likely reduce imports, but raise exports, which will also bias up the OLS coefficient for import exposure while biasing down the coefficient for export expansion. To address this endogeneity concern, we should use instrumental variables that are not correlated with US shocks.

2.2.1. ADH-style IVs

Our first set of instruments follows the approach of ADH (2013) and Acemoglu et al. (2016). We will use the imports of eight other high-income countries from China (and from the rest of the world), which is intended to reflect China's rising comparative advantage (and likewise from the rest of the world) and falling trade costs in these sectors that are common to high-income importing countries.

$$\Delta IP_{st}^{oth,c} \equiv \frac{\Delta M_{st}^{oth,c}}{Y_{st_0} + M_{st_0} - X_{st_0}}, \tag{5}$$

where $\Delta M_{st}^{oth,c}$ measures the change in *other countries' imports from China* in industry s during the period t by these eight other nations, which is then normalized by the initial US sectoral absorption. The validity of this instrument relies on the assumption that high-income countries are similarly exposed to import competition that is driven by the supply shock in China, while the industry import demand shocks are uncorrelated between these eight countries and the United States.

For import penetration from the ROW, we form the instrument

$$\Delta IP_{st}^{oth,row} \equiv \frac{\Delta M_{st}^{oth,row}}{Y_{st_0} + M_{st_0} - X_{st_0}}, \tag{6}$$

where the numerator is the eight other countries' imports from the rest of the world (not including China or the US) in sector s and year t, again measured relative to initial sectoral absorption in the US. And for US global imports, we have the associated instrument as $\Delta IP_{st}^{oth} = \Delta IP_{st}^{oth,c} + \Delta IP_{st}^{oth,row}$.

On the export side, we aim to identify the impact on US employment from foreign demand shocks: those shocks would lead to a rise in exports and employment that is not contaminated by other shocks in the US market. Our first instrumental variable for export exposure uses the export expansion of eight other high-income economies to China (for $k = c$), and to the rest of the world (for $k = row$) except the United States:

$$\Delta EP_{st}^{oth,k} \equiv \frac{\Delta X_{st}^{oth,k}}{Y_{st_0}}, \quad k = c, row. \tag{7}$$

And for US global exports, we have the associated instrument as $\Delta EP_{st}^{oth} = \Delta EP_{st}^{oth,c} + \Delta EP_{st}^{oth,row}$.

Using other advanced nations' exports to instrument for the US exports closely follows the idea of ADH (2013) and is intended to reflect common foreign demand shocks that drive exports of both the US and the eight other high-income countries. The identification relies on the exogenous component of United States export growth that stems from the world's rising demand for goods in these sectors. This could be due to income growth of emerging economies since the 1980s, when many countries experienced fast growth and moved from low income to middle-income countries, notably China and India. Income growth from emerging economies drives demand for high-quality consumption goods from high-income countries (Costa et al., 2016). Furthermore, emerging economies (China and other newly industrialized economies) are increasingly involved in global supply chains due to the disintegration of the production process (Feenstra, 1998). Increasing production capacity drives up their demand for capital goods, which are largely supplied by high-income countries (Eaton and Kortum, 2001).

Admittedly, our identification on the export side does not benefit from a quasi-natural experiment such as the economic reforms in China that ADH use to identify the China import shock. Rather, we are relying on the idea of foreign demand shocks that are correlated between US exports and those of other high-income countries selling to the same foreign markets.[5] It is possible, however, that export expansion may also reflect supply-side shocks in the United States. That potential correlation with supply-side shocks will be apparent in our derivation of the export equation, in the next subsection. In terms of estimation, a US supply shock that is labor saving will reduce US employment but raise exports, resulting in an under-estimated OLS coefficient of exports on employment. On the other hand, a US supply shock that expands product variety tends to *increase* both exports and employment, therefore resulting in an over-estimated OLS coefficient of exports on employment. So in the following subsection we will propose a method of correcting for such supply shocks in the export equation, by using fixed effects to absorb them.

2.2.2. Gravity-based IVs

We develop a specification of US imports and exports based on a constant-elasticity, monopolistic competition framework. That trade equation will provide a method to test and control for US supply shocks, and from which we obtain a second set of IVs for imports and for exports.

Prior to China's accession to the WTO in 2001, China faced uncertainty in the US tariff that was applied. Subject to an annual vote in the US Congress, China could receive the most-favored-nation tariff (MFN) of the WTO (or what is known as "permanent normal trade relations", PNTR, with the US), but this outcome was not guaranteed. If the US Congress would have not approved normal trade relations, then China would have faced the so-called "column 2" tariff from the US tariff schedule as is applied to other Communist countries. Once China joined the WTO, the risk of facing the column 2 tariff disappeared. Pierce and Schott (2016) show that the difference between the column 2 and the MFN tariffs – or the tariff "gap" – is a predictor of the growth in China's exports across industries, and therefore, reduced employment in the United States. Whether or not this source

[5] In the online Appendix, Table A.1, column (3), we present evidence that these foreign demand shocks are not substantially correlated with US domestic demand shocks, so this instrument satisfies that exclusion restriction.

of Chinese export growth is *additional to* the growth in China that is reflected in its exports to other countries, as captured by the ADH instrumental variable, remains to be seen, however. Because the ADH instrument is a reduced form variable representing all the policy changes in China, we will need to assess the extent to which that instrument incorporates China's WTO accession and PNTR with the United States.

On the export side, Caliendo et al. (2017) show that from 1990 until 2011 both MFN tariffs and the preferential tariffs have fallen by nearly 9 percent, most of which was driven by substantial trade liberalization in emerging and developing economies. Notable examples include China's accession into the WTO in 2001, which lowered its own average import tariff from above 15 percent to below 9 percent within just a few years; and the North American Free Trade Agreement (NAFTA), which integrated production chains and the flow of consumer goods across the continent of North America. Romalis (2007) finds a substantial increase in the trade volume and output among the United State, Canada and Mexico, particularly in the products that were previously highly protected.

Inspired by these observations, our second instrument for the US import and export exposure, denoted by $\Delta IP_{st}^{pre,k}$ and $\Delta EP_{st}^{pre,k}$, is constructed as the *predicted* US imports from China or exports to China (for $k = c$) or the rest of the world (for $k = row$). This prediction will be made based in part on demand-shift variables that are identical to the ADH instruments $\Delta IP_{st}^{oth,k}$ and $\Delta EP_{st}^{oth,k}$, and in addition, to reductions in US import tariffs and in tariffs faced by the US exporters and their competitors selling in foreign countries. We derive this new set of instruments first for US exports, while deriving a similar set of instruments for US imports in the online Appendix.[6]

Predicting US Exports: To predict US exports, we start from a simple symmetric CES equation as in Romalis (2007),

$$\frac{X_{svt}^{us,j}}{X_{svt}^{i,j}} = \left(\frac{w_{st}^{us} d^{us,j} \tau_{st}^{us,j}}{w_{st}^{i} d^{i,j} \tau_{st}^{i,j}}\right)^{1-\sigma}, \tag{8}$$

where: $X_{svt}^{us,j}$ is the US exports to country j of variety v in industry s; X_{svt}^{ij} is the exports from country i to j; w_{st}^{us} and w_{st}^{i} are the relative marginal costs of producing varieties of industry s in the United States and country i; $\tau_{st}^{us,j}$ and τ_{st}^{ij} are *ad valorem* import tariffs imposed by importer j on exports from the US or from country i; and $d^{us,j}$ and $d^{i,j}$ are the bilateral distance or other trade costs from the United States or exporting country i to importing country j. Finally, σ denotes the elasticity of substitution.

Suppose that there are N_{st}^{i} identical product varieties in industry s produced and exported by country i. We can re-arrange the above equation by multiplying both sides by N_{st}^{i} and summing over a set of countries $i \neq us$:

$$X_{svt}^{us,j} \sum_{i \neq us} N_{st}^{i} \left(w_{st}^{i} d^{i,j}\right)^{1-\sigma} = \left(w_{st}^{us} d^{us,j} \tau_{st}^{us,j}\right)^{1-\sigma} \sum_{i \neq us} N_{st}^{i} X_{svt}^{i,j} \left(\tau_{st}^{i,j}\right)^{\sigma-1}. \tag{9}$$

We are free to specify the set of countries $i \neq us$ in these summations, and for convenience we will choose to sum over the same eight high-income countries used by ADH (2013).

Multiply this equation by N_{st}^{us}, and denote the total sectoral exports from the United States and country i to country j as $X_{st}^{us,j} \equiv N_{st}^{us} X_{svt}^{us,j}$ and $X_{st}^{i,j} \equiv N_{st}^{i} X_{svt}^{i,j}$, respectively. After a few rearrangements, we can get:

$$X_{st}^{us,j} = \left[\frac{N_{st}^{us}\left(w_{st}^{us} d^{us,j} \tau_{st}^{us,j}\right)^{1-\sigma}}{\sum_{i \neq us} N_{st}^{i}\left(w_{st}^{i} d^{i,j}\right)^{1-\sigma}}\right] \left(\sum_{k \neq us} X_{st}^{k,j}\right) \sum_{i \neq us} \frac{X_{st}^{i,j}}{\sum_{k \neq us} X_{st}^{k,j}} \left(\tau_{st}^{i,j}\right)^{\sigma-1}, \tag{10}$$

where we multiply and divide by $\sum_{k \neq us} X_{st}^{k,j}$ for convenience.

Taking logs of the above equation, we obtain:

$$\ln X_{st}^{us,j} = \alpha_{st}^{us} + \delta^{us,j} + \ln\left(\tau_{st}^{us,j}\right)^{1-\sigma} + \ln\left[\sum_{i \neq us} \frac{X_{st}^{i,j}}{\sum_{k \neq us} X_{st}^{k,j}} \left(\tau_{st}^{i,j}\right)^{\sigma-1}\right] + \ln\left(\sum_{k \neq us} X_{st}^{k,j}\right) + \varepsilon_{st}^{j},$$

where $\alpha_{st}^{us} = \ln\left(N_{st}^{us}(w_{st}^{us})^{1-\sigma}\right)$ and $\delta^{us,j} = (1-\sigma)\ln\left(d^{us,j}\right)$. The former variable is a fixed-effect that reflects a US supply shock (i.e. US export variety and the marginal costs of production) and can be proxied by a set of sector and year fixed effects or their interactions.[7] The latter fixed-effect $\delta^{us,j}$ reflects distance to the destination market and all other sector- and time-invariant trade costs. The term $\varepsilon_{st}^{j} = -\ln\left(\sum_{i \neq us} N_{st}^{i}(w_{st}^{i} d^{i,j})^{1-\sigma}\right)$ is an unobserved error, reflecting the supply shocks in all other source countries.

Empirically, we can therefore use the following specification:

$$\ln X_{st}^{us,j} = \alpha_{st}^{us} + \delta^{us,j} + \beta_1 \ln\left(\tau_{st}^{us,j}\right) + \beta_2 \ln\left(T_{st}^{j}\right) + \ln\left(\sum_{k \neq us} X_{st}^{k,j}\right) + \varepsilon_{st}^{j}, \tag{11}$$

where $\beta_1 = (1-\sigma) < 0$ and $\beta_2 = (\sigma - 1) > 0$. So from the demand side, the US exports of good s to country j are determined by three items aside from the fixed effects: the first is the import tariffs imposed by j on US exporters ($\tau_{st}^{us,j}$); and the second is a measure of country j's average import tariffs on all non-US imports of good s, $T_{st}^{j} \equiv \left[\sum_{i \neq us} \frac{X_{st}^{ij}}{\sum_{k \neq us} X_{st}^{k,j}} \left(\tau_{st}^{i,j}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$. This term captures the substitution between US export products and their competitors, with higher levels of T_{st}^{j} raising demand for US exports.[8]

The final term in the export equation is the total imports by j from other exporters ($\sum_{k \neq us} X_{st}^{k,j}$). As mentioned, we choose to sum over the same eight high-income countries used by ADH, which we are free to specify in this derivation. This means that this final term, after taking a long difference and dividing by initial industry shipments, is *identical* to our first instrument $\Delta EP_{st}^{oth,k}$, which we refer to more briefly as the OTH instrument for the eight *other* high-income countries used by ADH. Our second instrument for US exports, $\Delta EP_{st}^{pre,k}$, is constructed as the predicted US exports as specified by Eq. (11), again after taking a long difference and dividing by initial industry shipments, so this instrument incorporates OTH as well as tariffs. It follows that the *difference* between this second instrument and the OTH instrument comes entirely from the tariff terms appearing in (11) and from the fixed effects. Crucially, we *do not* include the fixed effects α_{st}^{us} when constructing the prediction $\Delta EP_{st}^{pre,k}$, so that it is not contaminated by US supply shocks.

Gravity-based Instruments: To construct our instruments, there are several steps. First, we estimate Eq. (11) at the 6-digit HS level across importing countries j. The data and estimation results are provided in

[6] To take into account the uncertainty that China faced in its US tariff prior to its accession to the WTO, on the import side we include an additional variable to capture the industry-level export growth from China to the US due to the removal of trade policy uncertainty. See the Appendix for details.

[7] A reduction in w_{st}^{us} reflects an improvement in productivity (a supply shock) that may increase exports and decrease labor employment simultaneously. An increase in N_{st}^{us} reflects an expansion in US product variety that may increase both exports and labor employment simultaneously. We especially want to control for the latter product variety effect, since it would overstate the OLS coefficient of US exports on employment.

[8] Note that the difference between the tariffs on US imports and the multilateral tariff term comes from the deviation from MFN tariffs (i.e. preferential tariffs due to free trade agreements, for example).

Table 1
Summary statistics.

	1991–1999			1999–2007		1999–2011	
	N	Mean	S.D.	Mean	S.D.	Mean	S.D.
100× annual log Δ in manufacturing employment	392	−0.30	3.49	−3.62	4.15	−4.32	3.85
100× annual log Δ in non-manufacturing employment	87	2.46	2.38	1.54	1.59	0.57	1.56
100× annual Δ in CHN import exposure	392	0.27	0.75	0.84	1.61	0.66	1.33
PRE instrument for imports ($\Delta IP^{pre,\ c}$)	392	0.16	0.39	0.69	1.26	0.65	1.19
OTH instrument for imports ($\Delta IP^{oth,\ c}$)	392	0.19	0.46	0.67	1.19	0.66	1.18
TAR instrument for imports ($\Delta IP^{tar,\ c}$)	392	−0.03	0.14	0.02	0.17	−0.01	0.22
100× annual Δ in ROW import exposure	392	1.33	2.23	0.593	2.74	0.34	2.12
PRE instrument for imports ($\Delta IP^{pre,\ row}$)	392	0.35	2.63	1.53	2.76	1.07	2.31
OTH instrument for imports ($\Delta IP^{oth,\ row}$)	392	0.345	2.66	1.77	3.26	1.30	2.56
TAR instrument for imports ($\Delta IP^{tar,\ row}$)	392	0.01	0.52	−0.24	0.80	−0.23	0.59
100× annual Δ in CHN export exposure	392	0.05	0.09	0.11	0.26	0.12	0.23
PRE instrument for exports ($\Delta EP^{pre,\ c}$)	392	0.05	0.13	0.22	0.49	0.27	0.60
OTH instrument for exports ($\Delta EP^{oth,\ c}$)	392	0.08	0.17	0.36	0.79	0.44	0.97
TAR instrument for exports ($\Delta EP^{tar,\ c}$)	392	−0.03	0.06	−0.14	0.30	−0.17	0.38
100× annual Δ in ROW export exposure	392	0.87	1.49	0.51	2.37	0.36	2.49
PRE instrument for exports ($\Delta EP^{pre,\ row}$)	392	0.28	0.84	1.19	2.12	0.92	2.14
OTH instrument for exports ($\Delta EP^{oth,\ row}$)	392	0.42	1.66	2.49	4.04	1.89	3.95
TAR instrument for exports ($\Delta EP^{tar,\ row}$)	392	−0.15	0.91	−1.30	1.98	−0.97	1.86

Note: For each manufacturing industry, the change in US import (or export) exposure is computed by dividing 100 × the annualized increase in the value of US imports (exports) over the indicated periods by 1991 US market value (1991 US industry output) in that industry. All observations are weighted by 1991 industry employment.

the online Appendix (Table A.1 columns (1)-(3) for exports and columns (4)-(5) for imports). Note that for all regressions we constrain the coefficient for the term reflecting the exports or imports of the eight other countries, $\ln(\sum_{k\neq us}X_{st}^{j,k})$, to be unity. This ensures that this term captures exactly the OTH instrument as used by ADH on the import side.

We then predict US exports to country j for each HS6 products $g, \hat{X}_{gt}^{us,j}$. After that, we aggregate the predicted exports across export destinations to get the US industry exports, denoted as $\hat{X}_{gt}^{us}$. To facilitate the comparison with the effect of import exposure and employment changes, we construct our export exposure and the instrumental variables at the revised SIC (standard industrial classification) level that has been adopted by ADH (2013) and Acemoglu et al. (2016). The US export data at 6-digit HS product level could be readily converted to the revised SIC product level by adopting the crosswalk (with weights) in Acemoglu et al. (2016), ending up with export values for 392 revised 4-digit SIC codes, covering each year from 1991 to 2011, which we denote accordingly as $\hat{X}_{st}^{us,k} = \sum_{g\in s}\omega_{gs}\hat{X}_{gt}^{us,k}$, where $k = c,row$, and s denotes the SIC sector, while ω_{gs} is the weights used in matching HS product g to SIC industry s.

We apply similar steps to predict US imports from China or the rest of the world (for $k = row$). Put these together, we have the second sets of instruments as:

$$\Delta EP_{st}^{pre,k} \equiv \frac{\Delta\hat{X}_{st}^{us,k}}{Y_{s,t_0}}, \quad \text{and} \quad \Delta IP_{st}^{pre,k} \equiv \frac{\Delta\hat{M}_{st}^{us,k}}{Y_{st_0}+M_{st_0}-X_{st_0}}, \tag{12}$$

which is at the revised SIC industry level and $k = c,row$. For US global exports and imports, we construct the associated instruments as $\Delta EP_{st}^{pre} = \Delta EP_{st}^{pre,c} + \Delta EP_{st}^{pre,row}$, and $\Delta IP_{st}^{pre} = \Delta IP_{st}^{pre,c} + \Delta IP_{st}^{pre,row}$.

Based on Eq. (11), our second instrument for US exports, $\Delta EP_{st}^{pre,k}$, is composed of two components. The first component is the OTH instrument, which reflects exports by the eight other advanced economies to their foreign markets. The second component reflects the tariff terms (i.e. the tariffs faced by the US exporters and the tariffs faced by the eight other exporting countries), which we often refer to as TAR. The contribution of the tariffs can be obtained by taking the difference between the PRE and OTH instruments:

$$\Delta EP_{st}^{tar,k} \equiv \Delta EP_{st}^{pre,k} - \Delta EP_{st}^{oth,k}. \tag{13}$$

and likewise on the import side:

$$\Delta IP_{st}^{tar,k} \equiv \Delta IP_{st}^{pre,k} - \Delta IP_{st}^{oth,k}, \tag{14}$$

where we use $k = c$ for China and $k = row$ for the rest of the world. We will use the OTH term and TAR terms simultaneously as the instruments for the endogenous trade shocks.

Table 1 summarizes the main variables of interest, including the actual changes in US imports from China and the rest of world, US global exports, along with the mean changes in the various instruments we shall use.[9] On the import side, we see that the PRE instrument rises at nearly the same rate as the OTH instrument for China, but somewhat more slowly than the OTH instrument for the ROW in the second period (1999–2007 or 1999–2011). On the export side, the PRE instrument rises at nearly the same rate as the OTH instrument for China in the first period, but somewhat more slowly in the second period, while for the ROW the PRE instrument rises more slowly than the OTH instrument in both periods. In other words, tariff reductions in the eight other high-income countries and the ROW – especially in the second period – apparently lead to more growth of trade between them than between the ROW and the United States, so that the growth of the OTH instruments for imports and exports exceed the growth of the PRE instruments. Of course, it is not (only) the mean values of these IVs that determine their usefulness in explaining actual trade and employment changes, but also their correlations across industries with those changes.

2.3. First stage results

Table 2 reports the first stage results of regressing endogenous import and export exposure on our constructed instruments. For the sake of brevity, we will only report results using the full sets of instruments, and report the Sanderson-Windmeijer (S-W) multivariate F-statistics at the bottom of each column.

Column (1) shows the first stage results for US exports to China ($\Delta EP^{us,c}$). For this particular variable only, it can be seen that none of the constructed instruments have explanatory power. The F-stat is only 6.12, indicating weak identification. The explanation for this finding, as already noted, is that our identification on the export side is not based on a quasi-natural experiment such as the economic

[9] All these mean changes are computed by weighting the industry changes by 1991 industry employment.

Table 2
Initial first stage results, OTH & TAR IVs, 1991–2011.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta EP^{us,c}$	$\Delta IP^{us,c}$	$\Delta EP^{us,row}$	$\Delta IP^{us,row}$	ΔEP^{us}	ΔIP^{us}
$\Delta EP^{oth,c}$	−0.04	0.03	0.49	0.76	0.46	0.80
	(0.09)	(0.21)	(0.87)	(0.75)	(0.87)	(0.91)
$\Delta EP^{tar,c}$	−0.37	0.39	1.78	2.46	1.41	2.89
	(0.25)	(0.59)	(2.59)	(2.27)	(2.53)	(2.77)
$\Delta IP^{oth,c}$	−0.02	0.99***	−0.14	−0.10	−0.16	0.90***
	(0.01)	(0.14)	(0.11)	(0.12)	(0.11)	(0.20)
$\Delta IP^{tar,c}$	0.02	1.06***	−0.05	−0.61	-0.04	0.45
	(0.03)	(0.19)	(0.43)	(0.77)	(0.44)	(0.84)
$\Delta EP^{oth,row}$	−0.02	0.09*	0.57**	−0.03	0.55**	0.06
	(0.02)	(0.05)	(0.23)	(0.16)	(0.22)	(0.16)
$\Delta EP^{tar,row}$	−0.06*	0.21**	0.81**	−0.08	0.75**	0.14
	(0.03)	(0.10)	(0.37)	(0.26)	(0.35)	(0.27)
$\Delta IP^{oth,row}$	0.01***	0.01	0.12***	0.60***	0.13***	0.61***
	(0.00)	(0.01)	(0.03)	(0.08)	(0.04)	(0.07)
$\Delta IP^{tar,row}$	−0.02	0.01	−0.41*	0.11	−0.43**	0.13
	(0.02)	(0.04)	(0.21)	(0.28)	(0.21)	(0.28)
S-W F-stat	6.12	40.23	18.45	28.40	13.97	29.93

Note: Robust standard errors in parentheses, clustered on three digit SIC industries.*p < 0:10, **p < 0:05, ***p < 0:01. The sample includes 784 observations: 392 SIC manufacturing sectors during two periods (1991-1999 & 1999-2007). All regressions are weighted by start-of-period employment share of the sector and include decadal dummies. All regressions include controls for sectoral dummies, trend, and industry initial conditions.

reform in China that is used by ADH to identify the China import shock. US *exports* to China are not well-explained by any of our instruments. In contrast, column (2) shows strong and significant contributions from both the OTH and TAR instruments, $\Delta IP^{oth,c}$ and $\Delta IP^{tar,c}$, in explaining US *imports* from China. Note that we expect the coefficients for both terms to have a value of unity, since the tariff term has incorporated the estimated elasticities into the formula.[10] That is exactly we obtain in column (2), and the first stage F-stat is 40.23, well above the Stock-Yogo critical value.

Column (3) examines the first stage results for US exports to the rest of world ($\Delta EP^{us,row}$). In this case, both instruments $\Delta EP^{oth,row}$ and $\Delta EP^{tar,row}$ have significant and positive effects on US exports, and the F-stat is 18.45. Column (4) looks at the first stage results for US imports from the rest of world ($\Delta IP^{us,row}$), which shows that other eight countries' imports from the rest of world ($\Delta IP^{oth,row}$) has significant effect while the coefficient of ($\Delta IP^{tar,row}$) is positive but not significant. The last two columns examine the instruments for US global exports (ΔEP^{us}) and global imports (ΔIP^{us}). Again, our constructed instruments strongly predict the endogenous variables and the first stage F-stats are above the critical value.

To summarize, the first stage results in Table 2 indicate that predicted exports using both the OTH term ($\Delta EP^{oth,row}$) and the tariff term ($\Delta EP^{tar,row}$) are good instruments for US global exports, while the predicted exports to China using either the OTH term ($\Delta EP^{oth,c}$) or the tariff term ($\Delta EP^{tar,c}$) are not good instruments for US exports to China. For US imports from China, both the OTH term ($\Delta IP^{oth,c}$) and the tariff term ($\Delta IP^{tar,c}$) are highly significant, but for US imports from the rest of the world only the OTH term ($\Delta IP^{oth,row}$) is significant.

3. Estimation results

3.1. Benchmark

Based on the first stage results presented in last section, Table 3 experiments with our benchmark regression as specified in Eq. (1), with different sets of endogenous trade shock variables and corresponding instruments. We focus on stacked first differences over the two subperiods 1991-1999 and 1999-2011, while reporting the estimation results over 1991-2007 in the online Appendix.[11] To control other economic fluctuations that are correlated with trade shocks, we follow Acemoglu et al. (2016) and include three groups of controls. The first is a set of dummies for 10 one-digit broad manufacturing categories, which allows for differential trends across these one-digit sectors. Second, we consider sectoral controls drawn from the NBER-CES database, including the share of production workers in sectoral employment, the log of the industrial average wage, the ratio of capital to value added (all measured in 1991), and computer and high tech equipment investment and pretrend variables in 1990 as a share of total 1990 investment. Finally, we also include secular trends to control for the decline in the US manufacturing sector since the 1950s and the decline in manufacturing employment since the 1980s. Also, we add the change in the industry's share of total US employment and the change in the log of the industry average wage, both measured over 1976-1991, as controls for pretrend. We include all three sets of controls simultaneously and weight the regressions by start-of-period industry employment.

Column (1) presents the OLS estimation results of employment changes, with both import and export shocks, from China and the rest of world (ROW). Consistent with the findings of ADH and Acemoglu et al. (2016), import exposure from China exerts a negative impact on US employment. In contrast, import from ROW ($\Delta IP^{us,row}_{st}$) has a positive and significant impact. That surprising positive coefficient is probably due to the general equilibrium effect of international trade: when imports from China increase, imports from other countries may actually decrease even while employment is falling, so that the OLS estimates are biased upwards. Exports to China have a large and significant impact on US employment in these OLS estimates, while exports to the ROW have only an insignificant impact.

To correct the bias due to endogeneity, we apply both components of the predicted US imports and exports – i.e., the OTH term and the tariff term – as instruments for each endogenous variable. The 2SLS result in column (2) shows that the impact of imports from China remains significant and negative, and becomes larger in magnitude, while impact of exports to China remains positive and also becomes larger in magnitude, indicating the OLS results understate the effects of both exports and imports with China. The impacts of trading with the rest of world (i.e., the coefficients for $\Delta EP^{us,row}_{st}$ and $\Delta IP^{us,row}_{st}$) are both insignificant, however. As indicated by the first stage F value, column (2) has weak instruments, which primarily comes from the poor fit for US exports to China, as shown in column (1) of Table 2.

Thus, we modify the specification in column (3) to constrain the coefficients on US exports to China and to the ROW to be equal, therefore using US exports to the world (ΔEP^{us}_{st}) which is the sum of US exports to China and ROW. This change increases both the AIC and BIC statistics slightly, and it improves the strength of instruments substantially so that the first stage F value is now 16.39, well above the Stock-Yogo critical value of 11.39.[12] Furthermore, the Hansen J test has a p-value of 0.52, indicating good exogeneity of the instruments. In addition, the magnitude of the employment coefficient on global exports, 0.49 in column (3), is quite reasonable as compared to the magnitude of the employment coefficient on Chinese imports of 0.81.[13] Column (3) is therefore our preferred specification. We have used the equality of the

[10] That is, $\Delta IP^{tar,c}_{st}$ reflects $\hat{\beta}_1 \Delta\ \ln(\tau^{c,us}_{st}) + \hat{\beta}_2 \Delta\ \ln(T^c_{st}) + \hat{\beta}_3 GAP^c_{st}$, as indicated in Equations (A.6) and (A.9).

[11] In particular, we report in the online Appendix a full set of estimation results, including the first stage, with different sets of IVs (using only OTH or both OTH and TAR instruments) and over longer (1991-2011) or shorter periods (1991-2007).

[12] In the online Appendix Table A.2 that reports estimates over the period 1991-2007, however, the AIC and BIC values are slightly lower in column (3) than in column (2).

[13] Notice that without constraining the coefficients on Chinese and rest-of-world exports, the former has a high coefficient of 2.15, which more than doubles in size to 4.92 in column (6) if rest-of-world exports are dropped. This indicates a strong positive correlation between US exports to China and the rest of the world, so that it is difficult to disentangle their separate impacts. The same problem does not arise on the import side, where the employment coefficient of US imports from China is strongly identified whether US imports from the rest of the world are included or not.

Table 3
Benchmark industrial estimation of US employment, OTH & TAR IV, 1991–2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log change in industry employment, 1991-2011, IVs: OTH & TAR						
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Δ Global Imports				-0.30^{***}	-0.18^{**}		
				(0.08)	(0.08)		
Δ CHN Imports	-0.50^{***}	-0.80^{***}	-0.81^{***}			-0.78^{***}	-0.79^{***}
	(0.10)	(0.18)	(0.18)			(0.22)	(0.21)
Δ Non-CHN Imports	0.30^{***}	0.11	0.11				
	(0.10)	(0.18)	(0.18)				
Δ Global Exports			0.49^{*}	1.05^{***}	0.82^{***}		
			(0.26)	(0.22)	(0.22)		
Δ CHN Exports	1.37^{***}	2.15^{**}				4.92^{***}	2.51^{**}
	(0.50)	(1.00)				(1.14)	(1.25)
Δ Non-CHN Exports	0.07	0.38					
	(0.11)	(0.25)					
# of IV		8	8	8	4	8	4
Hansen J p-value		0.472	0.52	0.018	0.31	0.134	0.292
Min S-W F		6.12	16.39	13.97	9.38	12.64	7.92
S-Y critical value (10%)		11.39	11.39	11.39	10.27	11.39	10.27
AIC	3912.3	3949.5	3965.5	4140.0	4058.2	3977.8	3962.5
BIC	4014.9	4052.1	4063.4	4233.3	4151.5	4071.1	4055.7
Predicted Job Change (1,000) 1991-1999							
Import	344	−98	−111	−701	−420	−300	−302
Export	177	578	607	1208	966	304	159
Net	510	479	497	629	605	14	−138
Predicted Job Change (1,000) 1999-2011							
Import	−135	−521	−533	−554	−317	-610	−615
Export	288	600	411	732	613	748	410
Net	139	91	−117	367	384	177	−183
Predicted Job Change (1,000) 1991-2011							
Total Import	208	−619	−644	−1255	−737	−910	−917
Total Export	465	1178	1018	1941	1579	1052	568
Total Net	649	570	379	996	989	191	−322

Note: Robust standard errors in parentheses, clustered on three digit SIC industries.*p < 0:10, **p < 0:05, ***p < 0:01. The sample includes 784 observations: 392 SIC manufacturing sectors during two periods (1991-1999 & 1999-2011). All regressions are weighted by start-of-period employment share of the sector and include decadal dummies. All regressions include controls for sectoral dummies, trend, and industry initial conditions.

employment coefficients on US exports to China and to the rest of the world to assist in the identification of these effects.

In column (4), we experiment with further constraining the coefficients on US imports from China and from ROW to be equal, therefore using US imports from the world (ΔIP_{st}^{us}). In that case, the AIC and BIC statistics are considerably higher and the Hansen J-test strongly rejects the exogeneity of the instruments. In column (5), we also impose the same constraints on the instruments, thus using $\Delta EP_{st}^{oth,world}$ and $\Delta EP_{st}^{tar,world}$ to instrument for US global exports (ΔEP_{st}^{us}) , while using $\Delta IP_{st}^{oth,world}$ and $\Delta IP_{st}^{tar,world}$ to instrument for US global imports (ΔIP_{st}^{us}). In this case the Hansen J-stat passes the exogeneity test, but the instrument is weak as indicated by the S-W F-stat. In summary, we still prefer the export-constrained specification in column (3) over the other columns.

The final two columns focus on US bilateral trade with China: column (6) uses the full set of instruments, while column (7) only uses instruments for China. Column (7) has lower AIC and BIC, but it also suffers from weak instruments.[14] As indicated by the 2SLS estimation in column (7), a 1 percentage point increase in the import exposure to Chinese imports leads to 0.7 percentage point reduction in industry employment. On the other hand, a 1 percentage point rise in exports to China would increase the industry employment by 2.5 percentage point. As we will show in the next section, although the estimated impact of exports to China is much larger than that of imports from China, the *net* impact of bilateral trade with China is still negative (i.e., net job loss) since the increase in Chinese imports is much larger than the increase in exports to China. It is worth noting that the first stage regressions in Table 2 show that the proposed instruments for US exports to China are not significant, so the results in these final columns should be interpreted with caution.

3.2. Quantifying the employment effects

Relying on the estimation results in Table 3, we can evaluate the economic magnitude of trade shocks on labor employment. The results in our preferred specification column (3) indicate that a 1 percentage point rise in industry import penetration from China reduces domestic industry employment by 0.81 percentage points from 1991-2011. This number is only a bit higher than the point estimate by Acemoglu et al. (2016) for the same period (Table 3, col. (3)). Such job loss is offset, however, by the job created due to expansion in US exports to China and the ROW: a 1 percentage point rise in export expansion to the world increases industrial employment by 0.5 percentage points.

To quantify the employment effect, we rely on Eq. (1), and express the changes in industrial employment brought about by the increase in imports and exports as:

$$\Delta L_t = \sum_s \left[L_{s,t}\left(1 - e^{-\left(\widehat{\Delta IP}_{st} + \widehat{\Delta EP}_{st}\right)}\right)\right], \tag{15}$$

where $\Delta\hat{I}P_{st} \equiv \hat{\beta}_1 \Delta IP_{st}^{us,c} + \hat{\beta}_2 \Delta IP_{st}^{us,row}$ and $\Delta\hat{E}P_{st} \equiv \hat{\beta}_3 \Delta EP_{st}^{us} + \hat{\beta}_4 \Delta EP_{st}^{us,row}$ are the estimated import and exports effects from column (2), while our preferred specification in column (3) assumes $\hat{\beta}_3 = \hat{\beta}_4$, column (4) further assumes $\hat{\beta}_1 = \hat{\beta}_2$, and columns (5) and (6) have $\hat{\beta}_2 = \hat{\beta}_4 = 0$.

[14] In the online Appendix A.2 a similar result occurs over 1991-2007, and in that case column (6) fails exogeneity at the 10% level.

Hypothetically, this equation calculates the difference between the actual and counterfactual manufacturing employment in year t if there were no changes in import and export exposure.[15]

Applying the actual changes in import penetration (ΔIP_{st}) and export expansion (ΔEP_{st}), we calculate the net employment changes due to these trade shocks. Moreover, we can compute separately the effects of imports and exports by using the second-order approximation $e^x - 1 \approx x + x^2/2$. Applying this formula for $x = \Delta \hat{I}P_{st} + \Delta \hat{E}P_{st}$, $x = \Delta \hat{I}P_{st}$ and $x = \Delta \hat{E}P_{st}$, we obtain:

$$\sum_s L_{st}\left(1 - e^{\left(\Delta \hat{I}P_{st} + \Delta \hat{E}P_{st}\right)}\right) \approx \sum_s L_{st}\left[\left(1 - e^{\Delta \hat{I}P_{st}}\right) + \left(1 - e^{\Delta \hat{E}P_{st}}\right) - C_{st}\right], \tag{16}$$

where $C_{st} = \Delta \hat{I}P_{st} \Delta \hat{E}P_{st}$. We interpret the first two terms on the right of this equation as a decomposition of the total employment impact into that due to imports and that due to exports, while the third term C_{st} becomes a weighted cross-moment of the import and export effects when multiplied by L_{st} and summed across sectors. If this cross-moment is negative due to imports reducing employment and exports raising it in most industries, but small, then the combined effect measured by the left-side of this equation will slightly exceed the sum of import and export effects on the right.

At the bottom of each column of Table 3, we present the implied job gain or loss for imports and exports, and for each period separately. Focusing on our preferred specification in column (3), export expansion to the world *net of* import penetration from China *and* from the rest of the world actually led to a net gain of 497,000 jobs in the first decade 1991-1999, since exports created more jobs than the jobs destructed by import competition. For the second decade over 1999-2011, it led to a net loss of 117,000 jobs, mainly due to a surge of imports from China since the coefficient on non-China imports is tiny. Summing these estimates implies over the whole period 1991-2011 a net gain of 379,000 jobs.[16] Thus, the job losses due to US imports from China measured by ADH and Acemoglu et al. (2016) are fully offset by the job gains due to US exports. If we focus on US bilateral exports and imports with China in column (7), exports to China is substantially smaller than imports from China, so both periods see net losses between 138,000 and 183,000 jobs. Over the whole period, trading with China caused about 322,000 job losses.

As robustness checks, we examine the same specifications in Table 3, but using only the ADH style instruments (i.e, the OTH instruments), or shortening the sample period to 1991-2007. We report the regression results and the associated first stage results in the online Appendix, while we summarize in Table 4 the implied employment effects associated with our preferred specification in column (3) in each case. The top panel reports the case of using OTH instruments only, for 1991-2007 (the top left) and 1999-2011 (the top right). The bottom panel then reports the case of using both OTH and TAR instruments. So the bottom right panel corresponds to what we have already discussed in Table 3 using both instruments. In all cases, there are very strong job gains due to exports and smaller job losses due to imports in 1991-1999, so in this period the *net* gain is about 500,000 to 625,000 jobs. For the later periods, 1999-2007 or 1999-2011, we estimate more than 500,000 job losses from imports, which are nearly completely offset by strong job gains due to exports. Moreover, using more restricted instruments (i.e. just OTH) gives *greater* net gains than using both OTH and TAR as IVs. An inspection of the regression results in the Appendix Table A.8, in particular, shows that when using only the OTH instruments then the coefficient on US global exports is higher than in Table 3, while the coefficient on US imports from China is lower. Combined with the higher *growth* of OTH global exports than PRE global exports in Table 1, it is not surprising that using only the OTH instruments leads to *greater* employment gains from exports. By also incorporating tariffs, we are therefore arriving at slightly *lower* employment gains due to exports and on net. This finding suggests that the ADH instrument based on China's exports to other countries already incorporates the effects of China's WTO accession, because including that tariff variable on the import side (reflecting reduced uncertainty in the US) does not contribute to any further job losses.

3.3. Other industry outcomes

Next, we explore the impact of trade exposure on other industry outcomes. We follow the approach in the previous section of reporting results using both OTH and TAR instruments, as shown in Table 5. The top panel of each table uses the County Business Patterns (CBP) data while the bottom panel uses the NBER-CES database. Since the NBER data covers years up to 2009, so in Table 5 we will focus on the period 1991-2007. Each column represents one important aspect of labor market outcomes.

In the top panel using CBP data, increasing import exposure reduces employment while export expansion creates employment (column 1), which can be further decomposed into the response in the number of establishment (column 2) and the average employment per establishment (column 3). From the coefficient estimates, about 60 percent of the negative impact of import shock from China is on the *intensive margin*—the average employment per establishment, while the other 40 percent is on the *extensive margin*—the number of establishments. Similarly, 57 percent of the impact of global export shock is on the *intensive margin* and 43 percent on the *extensive margin*. Import penetration and export expansion have offsetting effects on the total industry wage bill (column 4) while the impacts on the log real wage rate are both positive but insignificant.[17] Impacts of non-China imports are always small and insignificant.

Turning to the bottom panel using NBER-CES data, columns (1)-(2) show that import shock reduces employment of both production workers and non-production workers, with a greater impact on the former. Export expansion, on the other hand, increases the employment of both with roughly equal elasticity. Increasing import exposure from China has no significant effect on real wages of production workers but does reduce wages of nonproduction workers (columns 3 and 4). In contrast, export expansion increases the real wage of production workers but has only an insignificant effect on the wage of nonproduction workers. Finally, column (5) in the bottom panel shows that export expansion increases real industry output while import competition from China decreases it, though both are not significant.

4. Export and import exposure on local labor markets

The industry level results compare changes in relative employment across manufacturing sectors with different exposure to import penetration and export expansion. In this section, we follow ADH (2013) and Acemoglu et al. (2016) and explore the geographic differences in trade shocks, based on 722 commuting zones (CZs) that cover the entire US mainland.

[15] We are assuming that when $\Delta IP_{st} = \Delta EP_{st} = 0$, then the China shock and export opportunities have zero impacts on the *level* of employment, and not just on its difference. In other words, we are assuming that import penetration and export expansion do not create a common employment effect across industries that we are omitting in the diff-in-diff specification.

[16] Looking only at imports, we calculate from column (3) a total job loss of 644,000 jobs over 1991-2011. In comparison, adjusted by the first stage partial R-squared (0.56), Acemoglu et al. (2016) estimate that import penetration from China led to about 463,000 job loss during the period 1991-2011 (see their footnote 30). We are obtaining a higher estimate because we do not adjust by the partial R-squared of the first-stage regressions.

[17] Acemoglu et al. (2016), Table 5, p. S168) also find a positive and insignificant impact of Chinese import competition on the real wage rate.

Table 4
Summary of employment effects.

Specification		1991–2007: 1991–1999	1991–2007: 1999–2007	1991–2007: 1991–2007	1991–2011: 1991–1999	1991–2011: 1999–2011	1991–2011: 1991–2011
OTH	Import	−124	−547	−671	−202	−513	−715
	Export	735	463	1198	740	489	1229
	Net	613	−71	542	550	−3	547
OTH & TAR	Import	−92	−558	−650	−111	−533	−644
	Export	718	453	1171	607	411	1018
	Net	625	−96	529	497	−117	379

Note: This table reports the employment effects of US exports and imports at industry level. The top panel use only OTH instruments, with the left covering 1991-2007 and the right panel covering 1991-2011. The bottom panel use both OTH and TAR instruments. Detailed regressions and the associated first stages for each specification are reported in the appendix Table A.2–A.9.

We begin by first constructing the Bartik measures of CZ level import and export exposure as:

$$\Delta IP_{it}^{CZ} = \sum_s \frac{L_{is,t_0}}{L_{i,t_0}} \Delta IP_{st}, \qquad and \qquad \Delta EP_{it}^{CZ} = \sum_s \frac{L_{is,t_0}}{L_{i,t_0}} \Delta EP_{st}, \tag{17}$$

where i denotes commuting zone, s denotes SIC manufacturing sectors, ΔIP_{st} and ΔEP_{st} are sectoral import and export exposure that we have used in the previous sections. So ΔIP_{it}^{CZ} and ΔEP_{it}^{CZ} denote the increases in import and export exposure respectively, by commuting zone i for time period t (either 1990-2000, or 2000-2007/2011). Note that L_{is,t_0} is the *start of period* employment in manufacturing sector s and commuting zone i, while L_{i,t_0} is the *start of period* total employment for commuting zone i, including both manufacturing and nonmanufacturing employment. The variation in import and export exposure across commuting zones comes entirely from the differences in local industry structure in employment in the initial year. Goldsmith-Pinkham et al. (2018) argue that the industry structure in the initial year is the essential instrument that is being used in a Bartik regression. In contrast, Borusyak et al. (2018) argue that the China shock variable is a valid instrument (under an exclusion restriction) in a transformed version of the CZ regression that is run at the industry level. They further argue (following Adão et al. 2018) that the standard errors of the conventional Bartik regression are under-estimated, which is corrected in this transformed version and which we shall investigate in this section.

As with the industry measure of trade shocks, the CZ level import and export exposures are also likely to be subject to endogeneity. We therefore apply the Bartik formula to the industry level instruments, obtaining commuting zone level instrument for import and export exposure. We then estimate the following specification across 722 commuting zones:

$$\Delta L_{it} = \beta_t + \beta_1 \Delta IP_{it}^{CZ} + \beta_2 \Delta EP_{it}^{CZ} + \gamma X_{it_0}^{CZ} + \gamma_r + e_{it}, \tag{18}$$

where ΔL_{it} is the annual change in employment share of the working age population in commuting zone i over time period t. To be consistent with the industry level specification, we continue to stack the annualized first differences for the two periods, 1991-1999 and 1999-2007 or 1999-2011. In all regressions, we also include a dummy for each period β_t to control for different time trends, a set of census division dummies to control for regional specific trends, as well as the initial share of manufacturing workers (in 1991). All regressions are weighted by the start of period (1991) commuting zone's share of national population, and the standard errors are clustered at the commuting zone level.

The first three columns of Table 6 present results for 1991-2011, starting with local effects of exposure to China imports in column (1). It shows that the impact of CZ level import exposure from China on the local employment share is negative and significant. Next column (2) shows that besides the negative effect of imports from China, regional export expansion has a positive and significant employment effect, while non-China imports has no significant effect. Column (2) uses the predicted terms of exports to the world (both OTH and TAR terms) as the export instruments, while in column (3) we instead use a full set of 4 instruments for US exports. The export exposure is found to have a substantial and significant impact on commuting zone overall employment. Specifically, taking column (3) as benchmark, a 1 percentage point increase in the average import penetration from China reduces the local employment rate by 1.02 percentage points. At the same time, a 1 percentage point increase in the average export expansion raises the local employment rate by 0.98 percentage point.

In the bottom rows, we report the quantitative employment effects associated with each column. First, column (1) confirms the ADH finding that import competition at the regional level leads to large

Table 5
US trade exposure and other labor market outcome, 1991–2007.

	CBP data				
	(1)	(2)	(3)	(4)	(5)
	Emp.	Num estabs.	Emp per estab.	Real wage bill	Real wage
Δ Global Exports	0.59***	0.25	0.34**	0.63***	0.04
	(0.19)	(0.16)	(0.15)	(0.21)	(0.06)
Δ CHN Imports	-0.77***	-0.30***	-0.47***	-0.76***	0.02
	(0.15)	(0.08)	(0.12)	(0.15)	(0.05)
Δ Non-CHN Imports	0.11	0.07	0.04	0.12	0.01
	(0.12)	(0.10)	(0.07)	(0.12)	(0.02)
Observations	784	784	784	784	784
R^2	0.579	0.221	0.467	0.535	0.686
	NBER data				
	(1)	(2)	(3)	(4)	(5)
	Prod. Emp.	Non-Prod. Emp.	Real Prod. Wage	Real Non-Prod. Wage	Real shipments
Δ Global Exports	0.59***	0.56***	0.14**	0.11	0.60
	(0.21)	(0.18)	(0.07)	(0.09)	(0.69)
Δ CHN Imports	-0.79***	-0.66***	0.02	-0.13*	-0.30
	(0.16)	(0.14)	(0.07)	(0.07)	(0.33)
Δ Non-CHN Imports	0.18	0.19*	-0.06	0.02	0.34
	(0.13)	(0.10)	(0.06)	(0.04)	(0.35)
Observations	768	768	768	768	768
R^2	0.607	0.459	0.481	0.453	0.458

Note: Robust standard errors in parentheses, clustered on three digit SIC industries.*p < 0:10, **p < 0:05, ***p < 0:01. The sample from the CBP dataset includes 784 observations: 392 SIC manufacturing industries during two periods (1991–1999 & 1999–2007). The sample from the NBER-CES dataset include 768 observations: 384 SIC manufacturing sectors during two periods. All regressions are weighted by start-of-period employment share of the industry and include decadal dummies and sectoral controls. For all regressions, we use the full set of OTH and TAR IVs.

Table 6
US trade exposure and local employment, 1991–2011.

	Overall employment 1991–2011			Overall employment 1991–2011		
	(1)	(2)	(3)	(4)	(5)	(6)
CHNimport	−1.10**	−1.08**	−1.02**	−0.85**	−0.95**	−0.98**
	(0.50)	(0.45)	(0.44)	(0.35)	(0.37)	(0.38)
ROWimport		−0.27	−0.28		−0.23	−0.52
		(0.25)	(0.26)		(0.37)	(0.38)
USexport		0.83**	0.98***		1.14**	1.43***
		(0.37)	(0.36)		(0.52)	(0.55)
N	1444	1444	1444	784	784	784
# of IV	1	6	8	1	6	8
First Stage SW F stat	66.36	23.05	15.37	9.35	4.66	3.27
Hansen J		0.01	0.02		0.02	0.03
Predicted Job Change (1,000) 1991–1999						
China Import	−481	−473	−444	−372	−415	−428
ROW Import		−588	−614		−498	−1127
Export		1222	1437		1669	2094
Net Change		161	379		755	539
Predicted Job Change (1,000) 1999–2011						
China Import	−1550	−1521	−1430	−1196	−1337	−1379
ROW Import		−206	−216		−175	−395
Export		1019	1199		1392	1746
Net Change		−709	−447		−119	−28
Predicted Job Change (1,000) 1991–2011						
China Import	−2031	−1994	−1874	−1567	−1752	−1807
ROW Import		−795	−830		−673	−1522
Export		2240	2636		3061	3840
Net Change		−548	-68		636	511

Note: Robust standard errors in parentheses, clustered on commuting zones.*$p<0{:}10$, **$p<0{:}05$, ***$p<0{:}01$. Columns (1)-(3) following Acemoglu et al. (2016) and use 722 commuting zones over two stacked subperiods (1991-1999, and 1999-2011). All regressions are weighted by start-of-period population share of the commuting zone and include controls for initial commuting zone manufacturing employment share, US census regions dummies, and a time dummy for the second period. Column (1) uses OTH instrument for China import shock, column (2) uses both OTH and ROW instruments for China imports, ROW imports, and US global exports shocks, column (3) uses the same instruments for import shocks, but use OTH and TAR exports to the rest of world (ROW) and to China as instruments for US global exports. Columns (4)-(6) adopt the approach by Borusyak et al. (2018) to transform the commuting zone level regression to a weighted industry level regression, which corrects the standard errors. Lower panels present the first-stage F statistics for excluded instruments and predicted employment changes due to trade shocks (We follow Acemoglu et al. (2016) and take the discount factor = 0.56).

employment losses, in particular in the second period from 1999 to 2011. In total, from 1991-2011, China import competition is estimated to cause 2 million job losses at the commuting zone level. Secondly, column (2) shows that export expansion largely offsets the job losses due to imports. In the first period, imports from China and imports from ROW each led to around 500,000 job losses, but they are more than offset by the job expansion due to exports. In the second period, the job losses due to faster growth of China imports amounts to about 1.5 million, much higher than that due to imports from ROW, while export expansion generates about 1 million new jobs. Summing both periods together, the net employment change at the commuting zone level is 548,000 job losses. Finally, in column (3) we use a full set of instruments for exports. The coefficient estimate for US exports becomes larger, resulting in a small net employment loss of 68,000 jobs for the whole period.

In a recent paper, Borusyak et al. (2018) argue that the standard errors of the ADH estimates at the commuting zone level may be underestimated, because the variance of the quasi-experimental shocks needs to be accounted for (Adão et al. 2018). They show that one can transform the commuting zone level regression into a weighted industry-level regression, which could correct the standard errors. In columns (4)-(6), we follow Borusyak et al. (2018) and transform all variables by taking their initial-employment-share-weighted average over regions to obtain the industry-level regressions.[18] All coefficient estimates have the expected signs and the effects of China imports and US exports remain significant. Interestingly, the standard errors of the transformed regressions have not increased much.[19] But notice that the first stage S-W F statistics are much lower in columns (4)-(6) and are surely more accurate as compared to columns (1)-(3). For this reason, all the columns will suffer from weak instruments and the results should be interpreted with caution.

Still, if we take the coefficient estimates in columns (4)-(6) and apply them to the commuting zone level trade shocks, we can estimate the employment effects in the same way as in columns (1)-(3) of Table 6, which are reported in the bottom rows on the right. The results are quite close to what we have found using the ADH specification on the left, though the job creation effects of US exports are estimated to be even larger. Taking column (5) for example, in the first period, US exports generate more than 1.6 million jobs, more than offseting the 900 thousand job losses due to imports from China and the ROW, while in the second period the job losses due to fast growth of China imports amounts to about 1.3 million, plus nearly 175 thousand job losses due to imports from ROW, which is slightly more than the job gains of 1.3 million due to US exports. Summing both periods together, the net employment change at commuting zone level is 636, 000 job gains. Column (6) uses the full set of instruments for exports and in this case, both coefficients for US exports and ROW imports increase, while the net effect remain very similar to what we obtain in column (5).

Table 6 focuses on the overall impact of trade shocks, while in Table 7 we explore the differential impact of trade exposure on different types of industries within local labor markets. We follow Acemoglu et al. (2016) and group employment changes into three broad sectors: exposed sector, nonexposed tradable sector, and nonexposed nontradable sector.[20] Empirically, we interact each of the three sectoral dummies with three types of trade shocks (China imports, imports from ROW, and US exports). In all regressions, we have included time dummies, census division dummies, and the initial manufacturing employment share, which are interacted with the sector dummies. Column (1) of Table 7 focuses on CHN imports, which is consistent to what has been reported in Acemoglu et al. In particular, the employment effects of import competition from China are completely on exposed sectors. Columns (2) and (3) then include the shocks of ROW imports and US global exports. It shows consistently that US exports have strongly generated jobs in the nonexposed, nontradable sectors, while interestingly, imports from ROW destroy jobs in this sector but generate jobs in the nonexposed, tradable sector. In the bottom panel we provide a decomposition of the employment effect of import and export shocks (as shown in the bottom panel of Table 6) into the three types of sectors. Job losses due to China imports are completely in the exposed sector, which amount to about 600 thousands jobs in the first period and become more than tripled in the second period. On the other hand, such negative effect of import competition is largely offset by US exports, which create jobs mainly in the nonexposed, nontradable sector. In a recent study, Fort et al. (2018) find that US manufacturing firms have

[18] More specifically, within an industry, we take the weighted average of regional employment changes and trade shocks using the initial regional employment shares as weights (i.e. using the Bartik weights); see Borusyak et al., 2018, Eqs. (1)-(4). In practice, since the ADH commuting zone regressions are weighted by working age population, the industry average also needs to be multiplied by the regional population weights.

[19] We conjecture this result might be because our regressions also include additional controls such as regional dummies, time dummies and start-of-period manufacturing share. Borusyak et al. suggest that in this case one need to further residualize the instruments by regressing regional instruments on the vector of industry employment share in each region. That means in our case estimating 392 coefficients (since there are 392 manufacturing sectors) using a sample of 722 commuting zones, which we did not pursue.

[20] We simply adopt the classification by Acemoglu et al. (2016). Admittedly this approach only separates industries by their exposure to import competition. More specifically, the exposed sector include all manufacturing industries for which predicted import exposure rose by at least 2 percentge points between 1991 and 2011, and all industries for which the predicted upstream import exposure measure increased by at least 4 percentage points. Other industries are regarded as non-exposed, which are then further decomposed into tradables and nontradables.

Table 7
US trade exposure and local employment, 1991–2011.

	Sectoral employment, 1991-2011		
	(1)	(2)	(3)
CHNimport × 1{exposed sector}	−1.41***	−1.42***	−1.35***
	(0.17)	(0.17)	(0.17)
CHNimport × 1{*non*exposed tradable sector}	0.08	0.10	0.10
	(0.08)	(0.09)	(0.08)
CHNimport × 1{*non*exposed nontradable sector}	0.23	0.24	0.24
	(0.38)	(0.36)	(0.35)
ROWimport × 1{exposed sector}		0.11	0.12
		(0.11)	(0.10)
ROWimport × 1{*non*exposed tradable sector}		0.13*	0.12**
		(0.07)	(0.06)
ROWimport × 1{*non*exposed nontradable sector}		−0.50**	−0.53**
		(0.22)	(0.23)
USexport × 1{exposed sector}		-0.10	-0.00
		(0.14)	(0.13)
USexport × 1{*non*exposed tradable sector}		-0.16	-0.15
		(0.10)	(0.10)
USexport × 1{*non*exposed nontradable sector}		1.10***	1.13***
		(0.35)	(0.34)
N	4332	4332	4332
All instruments are interacted with three sectoral dummies Number of IVs	3	18	24
Predicted Job Change (1,000) 1991–1999			
China Import × 1{exposed sector}	−615	−619	−592
China Import × 1{nonexposed tradable sector}	34	42	44
China Import × 1{nonexposed nontradable sector}	100	105	104
ROW Import × 1{exposed sector}		228	266
ROW Import × 1{nonexposed tradable sector}		275	270
ROW Import × 1{nonexposed nontradable sector}		−1091	−1150
US export × 1{exposed sector}		−153	−1
US export × 1{nonexposed tradable sector}		−237	−221
US export × 1{nonexposed nontradable sector}		1611	1659
Predicted Job Change (1,000), 1999–2011			
China Import × 1{exposed sector}	−1981	−1993	−1906
China Import × 1{nonexposed tradable sector}	109	135	140
China Import × 1{nonexposed nontradable sector}	323	337	335
ROW Import × 1{exposed sector}		80	93
ROW Import × 1{nonexposed tradable sector}		96	95
ROW Import × 1{nonexposed nontradable sector}		−383	−404
US export × 1{exposed sector}		−127	−1
US export × 1{nonexposed tradable sector}		−198	−185
US export × 1{nonexposed nontradable sector}		1344	1384
Predicted Job Change (1,000) 1991-2011			
China Import × 1{exposed sector}	−2597	−2612	−2498
China Import × 1{nonexposed tradable sector}	142	176	184
China Import × 1{nonexposed nontradable sector}	423	441	440
ROW Import × 1{exposed sector}		307	359
ROW Import × 1{nonexposed tradable sector}		371	365
ROW Import × 1{nonexposed nontradable sector}		−1473	−1554
US export × 1{exposed sector}		−280	−1
US export × 1{nonexposed tradable sector}		−435	−406
US export × 1{nonexposed nontradable sector}		2955	3043

Note: Robust standard errors in parentheses, clustered on commuting zones.*p < 0:10, **p < 0:05, ***p < 0:01. Sample includes 722 commuting zones over two stacked subperiods (1991-1999, and 1999-2011). All regressions are weighted by start-of-period population share of the commuting zone and include controls for initial commuting zone manufacturing employment share, US census regions dummies, and a time dummy for the second period. Column (1) use OTH instrument for China import shock, column (2) use both OTH and ROW instruments for China imports, ROW imports, and US global export shocks, column (3) use the same instruments for import shocks, but use OTH and TAR exports to the rest of world (ROW) and to China as instruments for US global exports. Lower panels present the first-stage F statistics for excluded instruments and predicted employment changes due to trade shocks (We follow Acemoglu et al. (2016) and take the discount factor = 0.56).

increased their non-manufacturing establishments and employed more non-manufacturing workers. This is consistent with our findings of a strong increase in nonexposed, nontradable sector employment due to export expansion.

5. Conclusions

The work of Autor et al. (2013), Pierce and Schott (2016), and Acemoglu et al. (2016) has alerted us to the impact of the China shock on US employment and unemployment. As exports from China grew rapidly following its WTO accession in 2001, there was a marked fall in US manufacturing employment. What has not received the same degree of attention in the literature is the potential for a rise in employment within industries that produce and benefit from growing US exports. ADH (2013) experimented with using net manufacturing imports from China, but that variable did not give results that were greatly different from what they obtained with gross imports from China.

In this paper, we have re-examined the employment impact of US exports, by expanding the Acemoglu et al. (2016) framework to incorporate trade beyond US imports from China. We consider US imports from China and from the rest of the world, along with US exports to China and to the rest of the world. We construct two types of instruments for all four trade variables, which are endogenous. The first type of instruments follows the approach of ADH (2013) and Acemoglu et al. (2016), for which we use the imports or exports of eight other high-income countries with China (and with the rest of the world). Using other advanced nation's imports or exports to instrument for the US imports or exports is intended to reflect common foreign supply shocks or demand shocks that drive imports or exports of both the US and the eight other high-income countries. The second type of instruments builds on a constant elasticity, monopolistic competition framework, in which we derive a US export or import equation that can test and control for US demand and supply shocks. Compared with the ADH-style instruments, our gravity-based instrument is composed of two components. One is exactly the ADH instrument, which reflects multilateral trade by eight other high-income countries, and the other is the tariff term, reflecting the tariffs faced by US and eight other advanced economies. Our first-stage regressions indicate that the identification of US exports is on weaker econometric grounds as compared with US imports, since our instruments are not from any quasi-natural experiment. In comparison, ADH utilize the economic reforms in China and its accession to the WTO as an exogenous source of the China import shock.

Our results fit the textbook story that job opportunities in exports make up for jobs lost in import-competing industries, or nearly so. At the industry level, the US exports created enough jobs to offset the job losses due to import competition, which led to a net gain of 497,000 jobs in the first decade of 1991-1999; while for the second period 1999-2011, it led to a net loss of 117,000 jobs; over the entire 1991-2011 period, job gains entirely offset job losses, with a net gain of 379,000 jobs. At the commuting zone level, we also find the job creating effect of export expansion. In the first period, job gains from export expansion largely offset the job losses from import penetration, resulting in a net gain of 379,000 jobs (just like the total period in the industry estimates). In the second period, export expansion continues to create large gains around 1200,000 jobs, but due to the large job losses from import penetration, there is still a net loss of 447,000 jobs. Over the entire 1991-2011 period, job gains and losses are roughly balanced with a slight net loss of 68,000 jobs. Nevertheless, we stress that workers laid off in some industries or some local markets may not be in a position to easily shift to another industry or place, so that even achieving rough balance between jobs lost and created can still generate a substantial amount of unemployment, or workers no longer in the labor force. This is one reason to find a smaller net impact of trade on local employment in the commuting zone analysis, and also less robust estimates. We have only begun to implement the recommendations of Borusyak et al. (2018) and Goldsmith-Pinkham et al. (2018) for using of Bartik weights at the regional level, and more work remains to be done.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2019.05.002.

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