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IDENTIFYING CHINESE SUPPLY SHOCKS - EFFECTS OF TRADE ON LABOR MARKETS

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Abstract

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JEL Classification: F10

Keywords: International Trade, employment, Instrumental Variable

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Identifying Chinese Supply Shocks – Effects of Trade on Labor Markets*

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August 9, 2018

Abstract

In a highly influential study, Autor et al. (2013a) analyze the effect of Chinese exports on the U.S. labor market. To identify causality, Chinese exports to the United States are instrumented with Chinese exports to other advanced economies, an identification strategy that relies on the absence of common demand shocks to all advanced economies. Our paper questions this identification assumption. We document that in the period between 1991 and 2007, sector-level exports from China grew parallel to those from other emerging market economies. This positive correlation is stronger for countries with a comparative advantage close to China's. We argue that these patterns are inconsistent with the view that China-specific supply shocks dominated China's export growth. Adjusting the identification strategy in ADH, we find that the qualitative results from ADH survive but are smaller in magnitude.

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1 Introduction

The critique of globalization keeps intensifying. In the political arena protectionism is hailed "to defend America's manufacturing base against Chinese unfair trade practices."[1] Academic work, too, shines the spotlight on the costs of globalization. Ground-breaking work by Autor et al. (2013a) documents strong effects of Chinese exports on manufacturing employment and other variables of the U.S. economy.[2]

A widely accepted narrative states that a China-specific supply shock generated a surge in U.S. imports with severe labor market fallouts. Building on this premise, Autor et al. (2013a) exploit the variation of Chinese import penetration across U.S. commuting zones to assess the effect on trade on manufacturing employment. To establish causality, the authors instrument "growth in U.S. imports from China using Chinese import growth in other high-income markets" a strategy, which "requires that import demand shocks in high-income countries are not the primary cause of China's export surge."

The current paper takes a critical look at this central identifying assumption. We identify China-specific supply shocks based on an intuitive and strikingly simple observation: in a market of many producers, a positive *supply* shock to one of the producers, say *China*, increases *China*'s sales at the expense of its competitors' sales. Conversely, a positive *demand* shock increases sales of all producers alike. In sum, the correlation between changes in sales of *China* and its competitors is negative under idiosyncratic Chinese supply shocks but positive under demand shocks.

Figure 1 plots the sector export growth from China against the sector export growth of emerging market economies (EMEs) with a comparative advantage close to China's.[3] Contrary to the widely accepted narrative, the strong positive correlation in Figure 1 suggests that demand factors were a prevalent factor of Chinese export growth.[4]

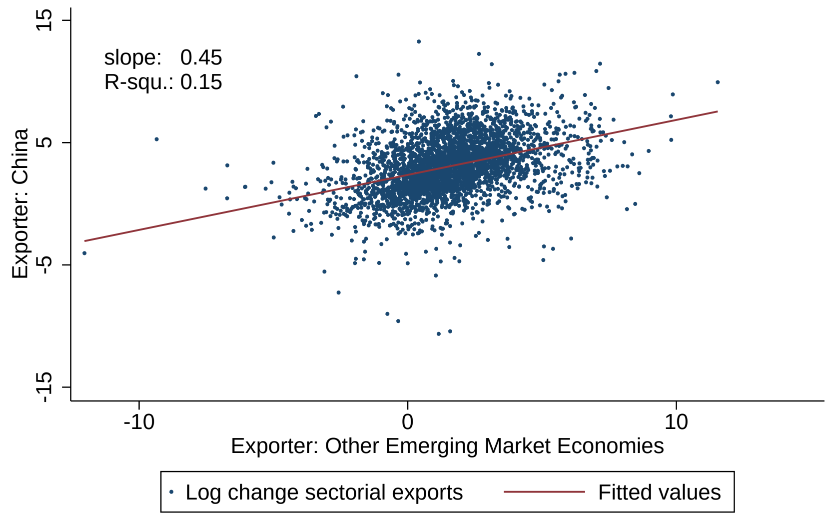
[1] Peter Navarro in "The Four Silver Bullets of Trumpnomics," The National Interest, March 9, 2016.

[2] See also Acemoglu et al. (2012), Autor et al. (2016a), Acemoglu et al. (2016), Pierce and Schott (2016) and Bloom et al. (2016).

[3] The set of other EMEs consists of India, Malaysia, Mexico, Philippines, Poland, Romania, Slovak Republic, Thailand and Turkey. Exports are reported by nine advanced economies for which the sector breakdown is available. The Figure is qualitatively similar when focusing on exports to the United States. See the Appendix for a detailed data description.

[4] Section 2 takes a closer look at the data, showing that the positive correlation in Figure 1 survives various cuts through the data.

Figure 1: **Sector export growth of China and other EMEs,** 1991 - 2007



Note: Log changes of exports between 1991 and 2007 by 6-digit HS class for China and other emerging market economies (India, Malaysia, Mexico, Philippines, Poland, Romania, Slovak Republic, Thailand and Turkey). Exports are defined as trade values in constant 2007 USD reported as imports by the nine advanced economies for which data of 6-digit HS classes are available for 1991 onwards (these are Australia, Denmark, Germany, Finland, New Zealand, Japan, Spain, Switzerland, and, the United States). The estimated coefficient and the R-square of a simple OLS regression are reported in the figure. Data source UN Comtrade.

The pattern of Figure 1 also indicates that the empirical strategy in Autor et al. (2013a) may be problematic. Motivated by this observation, our paper offers two exercises. In the first exercise, we identify the part of Chinese export growth that is accounted for by China-specific supply shocks. We do so in a straight-forward way based on a simple model that can be nested in standard general equilibrium trade models. Applying this model to bilateral trade data, we find that China-specific shocks account for half to four-fifths of China's total export growth in the periods between 1991 and 2007, less in the early and more in the later years. By construction, the rest of Chinese export growth must be accounted for by factors unrelated to China-specific supply, such as demand shocks.

In a second exercise, we adjust the strategy from Autor et al. (2013a) and impute import penetration across U.S. commuting zones that was driven by China-specific sector export shocks only. By eliminating demand shocks and all other effects that are unspecific to Chinese supply, our model-based correction does not require us to pursue an instrumental variable strategy. The corresponding estimates for the full sample from 1991 to 2007 indicate that Chinese import penetration to the United States has reduced U.S. manufacturing employment. Compared to the findings of Autor et al. (2013a), however, the magnitude of this effect drops by more than half. Similar results are obtained in regressions for estimations based on the period 2000 to 2007, i.e., the period following China's accession to the WTO.

We are not particularly surprised by the parallel sector export growth among emerging economies that naturally emerges from the theory of the international product cycle.[5] This theory suggests that products are invented and produced by market leaders in advanced economies (AEs). As time passes, however, standardization of production processes and ongoing invention of new products shift the patterns of comparative advantage so that production gradually transits to EMEs.[6] Overall, production of goods relocates from AEs to EMEs *in a synchronized way* so that product-level trade flows among EMEs increase in parallel. We document a number of bilateral trade patterns that are consistent with the product cycle theory.[7]

More importantly, the mechanics of the international product cycle help interpreting our empirical results. A thorough discussion is indeed needed in view of the fact that classical demand shocks in the United States should induce a *downward bias* on the estimated impact of imports on employment.[8] Controlling for classical demand shocks should therefore *increase* the estimated coefficients of interest.

The theory of the international product cycle provides a natural explanation for this puzzling observation. Specifically, in the presence of product

[5]See Krugman (1979) and Flam and Helpman (1987) for early versions of the theory, which goes back to Vernon (1966). The more recent literature on foreign direct investment or outsourcing can be read as a version of the product cycle literature. See, e.g., the literature cited in Antràs (2005).

[6]Other factors like technological progress or population growth in low-income economies may also drive relocation of production from advanced to low-income countries. See Acemoglu et al. (2012).

[7]Interestingly, under the general equilibrium approach of the product cycle theory, it is futile or impossible to disentangle factors related to demand shocks in AE from factors related to supply shocks in EMEs. We take this observation as a sign of absolution for our initial negligence in differentiating between both factors.

[8]Such demand shocks would simultaneously increase U.S. employment and import demand.

cycle forces that gradually tilt the comparative advantage, certain sectors naturally transit towards EMEs. These forces thus simultaneously erode U.S. manufacturing employment and increase import demand. In this case, the estimates in Autor et al. (2013a) should suffer an *upward bias*. Consequently, as soon as we correctly identify Chinese supply shocks, the estimated impact of Chinese exports on U.S. employment should *drop* relative to the estimates in Autor et al. (2013a). This is what they do in our baseline specifications.

Our paper contributes primarily to the literature on the labor market effects of cross-border trade. First and foremost, our paper relates to the ample work by David Autor, David Dorn, Gordon Hanson, and coauthors. In a series of papers, the authors have estimated the effect of Chinese import penetration on key labor market variables (Autor et al. (2013a), Autor et al. (2013b), Autor and Dorn (2013)), technological progress and innovation (Acemoglu et al. (2014) and Autor et al. (2016)), political voting patterns (Autor et al. (2016a), Autor et al. (2016b)) and the marriage market (Dorn and Hanson (2017)). An important and growing literature relies on the identification strategy developed in Autor et al. (2013a). A small and incomplete list of these studies would include Balsvik et al. (2015), Ashournia et al. (2014), Keller and Utar (2016), Dauth et al. (2014), and Malgouyres (2017).[9] Using the correlation of Chinese and other emerging market economies' export growth as an indicator, our paper uncovers a potential problem of the widely used identification strategy from Autor et al. (2013a) and offers a potential alternative.[10]

Other studies, a fraction of which can be mentioned only, use alternative identification strategies to assess the effects of trade on employment.[11] Pierce and Schott (2016) use the elimination of potential tariff increases to

[9]These studies assess the impact of Chinese exports on labor markets in Norway, Denmark, Germany and France, respectively.

[10]Some studies accept the China shock identification strategy but challenge other elements of the Autor et al. (2013a) reduced-form setup. Magyari (2017) finds that, by reducing costs at the firm level, offshoring leads to an increase in total U.S. manufacturing employment in those industries with a U.S. comparative advantage. Feenstra and Sasahara (2017) focus on the value added content of trade and points at the employment gains generated by the increase in U.S. exports. Feenstra et al. (2017), in turn, argue that local house prices are an important omitted variable, which mask employment gains in the (non-manufacturing) construction sector. Using a richer framework, Caliendo et al. (2017) undertake a full general equilibrium analysis. They quantify the effect of additional channels on U.S. employment and find a weaker causal effect of the China trade shock on the manufacturing sector.

[11]McLaren (2017) offers an excellent overview of recent contributions.

identify the causal effect of Chinese imports on U.S. employment at the industry level.[12] Ebenstein et al. (2014) show that the occupational dimension matters more than the industry classification for the impact of globalization on wages. Bloom et al. (2016) document a positive effect of Chinese import competition on firm-specific measures of technical change for firms in twelve European countries between 1996 and 2007. Similar to Pierce and Schott (2016), these authors establish causality relying on the removal of product-specific quotas after China's entry into the World Trade Organization in 2001.[13]

The remainder of our paper is organized as follows. Section 2 lays out a simple model based on which the China-specific export supply-shocks are identified. Section 3 presents our empirical strategy, which is borrowed from Autor et al. (2013a), as well as the empirical results. Section 4 concludes.

2 Identifying China-specific export supply

This section has two objectives. First, it assesses in detail the pattern of Figure 1 and, second, it provides a model-based identification of Chinese export growth that is driven by China-specific supply shocks. The first objective is motivated by the need not to draw premature conclusions from the simple positive correlation in Figure 1. Therefore, we first address potential concerns that this correlation reflects spurious factors and does not warrant conclusions about the relevance of China-specific supply shocks.

In a second step, we isolate China-specific supply shocks from sector shocks that are common to all exporters. Based on a simple model, we identify the part of Chinese export growth that is driven by China-specific sector supply shocks and use this identification to adjust the estimation strategy in Autor et al. (2013a).

Before we proceed, we want to clarify what this section aims to achieve. Motivated by the natural dichotomy of export supply and import demand, our description of Figure 1 has alluded to the presence of demand effects as potential drivers of Chinese exports. However, there are other shocks than these two types of shocks. We will therefore rely on the distinction between

[12]The authors identify a trade-induced shift towards less labor intensive production, thus documenting a link between two primary suspects of employment losses: trade and technological change.

[13]See also Di Giovanni et al. (2014) for the welfare effects of China's integration into the world economy.

China-specific supply shocks on the one hand, and *all* remaining shocks on the other hand. The collection of all other types of shocks includes classical demand shocks, supply shocks that are not specific to China, as well as shocks to import demand related to technological change. We will remain agnostic about the exact nature and composition of this collection of shocks. At the same time, we claim that we can structurally identify China-specific supply shocks.

2.1 A closer look at sector export growth

The starting point of our paper is the conjecture that positive China-specific supply shocks must expand China's exports at the expense of its competitors' exports. Such shocks should induce a *negative* correlation between sector export growth of China and its competitors. While the positive correlation in Figure 1 seems at odds with this prediction, it does not constitute a conclusive proof that Chinese exports were driven by other types of factors. We therefore address concerns related to (i) product-specific effects (e.g., classification and recording practices) and country-specific effects (the composition of our group of EMEs) (ii) effects of within-product-class substitution and (iii) differences across export destinations, in particular between the United States and other advanced economies (OAEs).

2.1.1 Sector and country effects

Our first concern is that the correlation in Figure 1 may be driven by the fact that sales of products fluctuate naturally at the global scale due to reclassification or simply technological progress. For example, as products become smaller and lighter, *Electric motors and generators of an output not exceeding 37.5 W weighting less than 1 kg* (HS 85011020) may be replaced by *Electric motors and generators of an output not exceeding 37.5 W weighting more than 1 kg* (HS 85011010). Further, within the group of other emerging economies, country-specific factors like aggregate growth rates may correlate with comparative advantage, thus inducing the positive correlation of Figure 1. In these cases, fluctuations in sales and exports unrelated to Chinese competition could drive the positive correlation in Figure 1.

Motivated by these concerns, we refine our conjecture above as follows. Under Chinese supply shocks, the correlation of sector export growth from China and from another country should be smaller (more negative), the more intensely both countries compete on international markets.

To test this hypothesis, we measure the degree of competition on international markets in two ways: first, through the similarity of comparative advantage and second, through the similarity of per capita income. The first is a metric of countries' revealed comparative advantage. Specifically, for a country c we define $prox_c^{CN}$ as the correlation of China's and country c's sector export shares (country export over global exports, logged) in the years between 1991 and 1995.[14]

The second metric relies on the relative GDP per capita, which we take as a measure economic development. Specifically, we define $prox_c^{CN}$ as the absolute difference of the log per capita GDP of country c and China in the initial year 1991. We adopt this alternative measure for the intensity of competition, motivated by the ample evidence that product differentiation depends significantly on the source country's capital endowments or income per capita (e.g., Schott (2003) and Schott (2004) Hallak and Schott (2011)).

In either case, $prox_c^{CN}$ is normalized to vary between zero (minimal proximity) and one (maximal proximity).

For our formal test, we denote export growth (log differences of real values) of country c in sector j with ΔE_j^c. We test whether the conditional correlation between ΔE_j^c and ΔE_j^{CN} increases with $prox_c^{CH}$ (demand shocks) or decreases with $prox_c^{CH}$ (Chinese supply shock). We do so by determining the sign of the coefficient β in the following regression

$$\Delta E_j^c = \beta \cdot \Delta E_j^{CN} * prox_c^{CN} + controls_{cj} + \varepsilon_{cj},$$

where the *controls* include the base variables ΔE_j^c and $prox_c^{CN}$ and a set of dummy variables and the error term ε_{cj} is assumed to be normally distributed. We notice that, by identifying the coefficient of interest β through country-product variation, our specification allows us to control for product- and country-specific effects.

Table 1 reports the estimation results. Columns I - III correspond to the specifications where $prox_c^{CH}$ stands for the initial correlation of the log export shares. Column I refers to a specification where ΔE_j^{CN} and $prox_c^{CN}$ are the only control variables. The estimate of the coefficient of interest β is positive and statistically significant: the higher a country's initial economic proximity to China, the higher is the correlation between both countries'

[14] We take five-year averages to address the concern that measurement errors may affect primarily initial periods (right after the introduction of the HS classification (data source UN Comtrade. We also explore alternative definitions, where *prox* is defined as the initial correlation through the year 1991 only or through the years from 1992 to 1996 and obtain very similar results.

Table 1: Conditional correlations and proximity of comparative advantage

Dep. variable: $\Delta ln(E_j^c)$ = log change in exports, 1991 to 2007						
	I	II	III	IV	V	VI
Def. proximity:	Correlation initial export shares			Similarity initial GDP p.c.		
$\Delta ln(E_j^{CN})$	-0.453***			0.125***		
	(0.023)			(0.005)		
$prox_c$	-1.480***	-0.381		0.820***	0.924***	
	(0.183)	(1.765)		(0.050)	(0.349)	
$\Delta ln(E_{CN}^j) * prox_c$	1.253***	1.076***	1.178***	0.305***	0.263***	0.240***
	(0.044)	(0.197)	(0.190)	(0.013)	(0.053)	(0.049)
HS fe	no	yes	yes	no	yes	yes
Country fe	no	no	yes	no	no	yes
Observations	108,416	108,416	108,416	108,416	108,416	108,416
R-squared	0.06	0.21	0.28	0.08	0.22	0.28

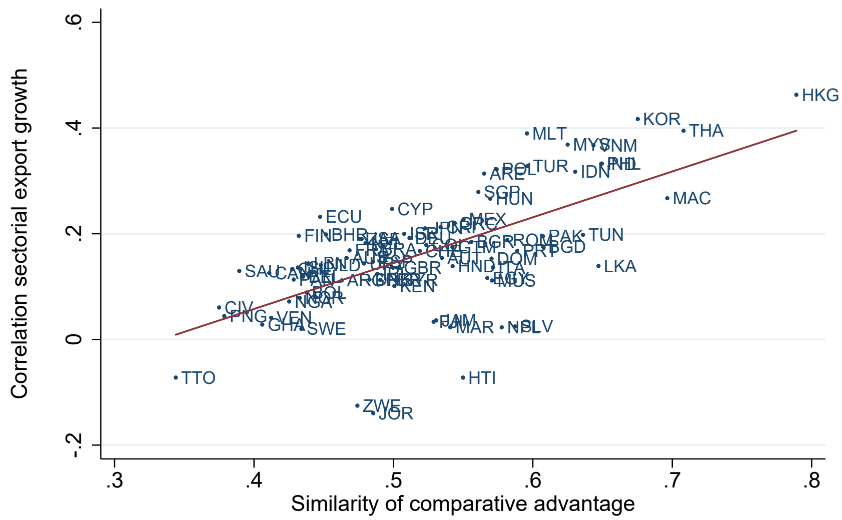
Notes: Exports are those reported as imports by nine advanced economies for which disaggregated data of 6-digit HS classes are available for 1991 onwards. Robust standard errors, clustered at exporter level, in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

sector export growth. The point estimate ($\hat{\beta} = 1.253$) implies that for a hypothetical country with perfect proximity we have $prox_c = 1$, i.e., sector export growth moves at the rate of $1.253 - 0.453 = 0.8$ or almost one-to-one with Chinese export growth.[15] Column II of Table 1 refers to a specification that includes fixed effects for each product class, thus controlling for overall export growth in that class. The estimated coefficient of interest does not change substantially in this specification. While an assessment of the level of the conditional correlation is no longer possible, the point estimate of β in Column II constitutes a striking result. It indicates that Chinese sector export growth co-varies more strongly with its competitors, conditional on sector expansions and contractions on the global market. Finally, Column III adds country fixed effects, controlling for differentials in country growth. Again, the coefficient of interest remains stable and statistically significant. Importantly, the estimations reported in Columns II and III show that the positive correlation in Figure 1 is not driven by general fluctuations in global market shares.

[15] Illustrating our regression results, Figure 2 provides a scatter plot of the raw correlations of sector export growth between each country and China and the similarity of initial comparative advantage. This graphical analysis does not solve the concern about differential sector export growth, which motivates this section's analysis of conditional correlations.

Columns IV to VI of Table 1 refer to specifications where $prox_c$ is defined as the similarity of per capita income in the initial year 1991. Again, the estimation results document that the stronger a country's initial economic proximity to China, the higher (more positive) is the correlation between both countries' sector export growth.

Figure 2: Synchronized export growth and similarity of comparative advantage, 1991 to 2007



Note: The vertical axis shows the correlation of sector export growth between China and the indicated country. The reference period is 1991 to 2007, sector export growth is defined as log changes of 6-digit HS class. Exports are defined as trade values in constant 2007 USD reported as imports by the nine advanced economies as specified in the note to Figure 1. The horizontal axis shows a measure of similarity of comparative advantage, defined as the correlation of log sector exports in the years 1991 to 1995. Figure C2 in the Appendix plots the parallel data, but for export growth defined through the period 2000 to 2007. Data source UN Comtrade

The results reported in Table 1 show that the general message in Figure 1 survives when controlling for sector-specific effects: whenever China's sector exports grew above national trend and above the global sector trend, so did sector exports of its direct competitors (and vice versa). These findings corroborate our earlier interpretation that China-specific supply shocks did not dominate Chinese export growth between 1991 and 2007.[16]

2.1.2 Quality substitution

Another potential concern is that the correlation in Figure 1 is driven by quality substitution. For example, under the pressure of Chinese demand, other EMEs may have upgraded quality of their exports, an effect that has been documented in Brandt et al. (2017) (see also Khandelwal et al. (2013)). In that case, the positive correlation in Figure 1 may reflect a pure price effect stemming from other EMEs starting to export different but more costly products within the same product category.

We address these concerns by investigating the corresponding correlation between the weight of exports (measured in kilogram). Specifically, if Chinese competition did indeed induce substitution towards higher quality in other emerging economies, the correlation in Figure 1 should turn negative when measuring exports by weight. Figures C5 and C6 in the Appendix document that this is not the case: for the two periods (1991 to 2007 and 2000 to 2007), the correlation between the weight of Chinese and other EMEs exports remains positive.

2.1.3 Sector export growth by destination markets

Our assessment so far casts doubt on the assumption that "import demand shocks in high-income countries are not the primary cause of China's export surge" as expressed by Autor et al. (2013a). However, by aggregating data of all importers (the United States and eight OAEs) we have neglected the central question whether U.S. demand shocks are correlated with demand shocks of the OAEs. This question is central because the instrumentation strategy in Autor et al. (2013a) is spotless when import demand shocks of both destinations are uncorrelated.[17] Conversely, the strategy leads to bi-

[16] We also point out that this section's results are consistent with the product cycle theory laid out in the introduction. In particular, the physical production of products may transit from AEs to EMEs due to technological progress and shifting comparative advantage, systematically inducing a correlation of export shares along the dimension of countries' economic development.

[17] Autor et al. (2013a) on page 2138 observe that "[a] concern for our 2SLS estimates is that in some sectors, import demand shocks may be correlated across countries. This would run counter to our instrumental variables strategy, which seeks to isolate supply shocks affecting US producers, and would likely bias our results toward zero." Autor et al. (2013a) address this concern by dropping specific industries (computer, construction, or textiles) from the sample and show that their coefficient of interest, the effect of import competition remains robust. We show that the positive correlation of Figure 1 is not

ased estimations if demand shocks between the United States and OAEs are correlated, since a correlation between the instrument and the dependent variable other than through the postulated Chinese supply shock would emerge. We address the question whether or not demand shocks are correlated as follows. First, we run a principle component analysis of the two variables Chinese sector export growth to the United States and other EME's sector export growth to the United States. We label the part of Chinese export growth to the United States explained by the common factor as the *common component* of Chinese export growth to the United States. U.S. demand shocks are picked up by this common component. Second, we replicate these steps for export growth to OAEs, extracting the *common component* of Chinese export growth to OAEs. Demand shocks of OAEs are picked up by this common component.[18] In a third step, we correlate the common components of Chinese export growth to the United States and those to OAEs. Figure 3 plots the results, showing a strong positive correlation between both variables. The figure suggests that demand-induced Chinese export growth to the United States and demand-induced Chinese export growth to OAEs have a strong positive correlation.

Overall, our findings confirm our earlier conjecture based on Figure 1 that the identification strategy in Autor et al. (2013a) is problematic. In particular, instrumenting growth of Chinese exports to the United States by contemporaneous Chinese export growth to eight OAEs, the authors assume that the parallel rise of Chinese imports to the United States and to other high-income countries was driven by a Chinese supply shock. Having expressed our reservations regarding this central identification assumption, we will next aim to disentangle the Chinese supply shock from other shocks in the following section. In a subsequent step, we then adapt the identification strategy of Autor et al. (2013a).

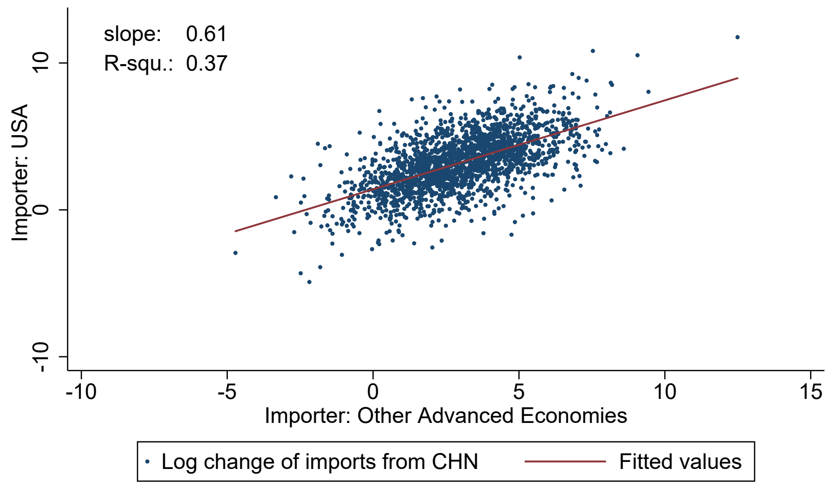
2.1.4 Discussion

Before proceeding, we want to clarify two issues, one regarding the magnitude of U.S. imports from other EMEs and the second regarding the conclusions for aggregate Chinese exports one may draw from Figure 1.

dependent on individual sectors.

[18] We acknowledge that these common components capture not only demand factors but also supply factors that are common to all EMEs. In either case, however, the underlying shocks are distinctly different from the China-specific supply shocks postulated in Autor et al. (2013a). Therefore, whenever both common components are correlated, they will invalidate the identifying assumption in Autor et al. (2013a).

Figure 3: China's Sector Export Growth – Common Component with other EMEs (1991 to 2007)



Note: Common component of Chinese export growth and export growth of Other advanced Economies (OAEs) by destination market. The common component is defined separately for each destination market based on a principle component decomposition with a single common factor of the two series Chinese and OAEs export growth.

Regarding the first issue, we point out that over the relevant period 1991 to 2007 U.S. import growth from other EMEs fell short of corresponding imports from Chinese by an order of magnitude (a point highlighted by Autor et al. (2013a)). Therefore, we stress that the focus on the exports of other EMEs in our analysis is not motivated by their absolute weight in the U.S. import basket, but rather by their importance as an indicator of the true nature of the drivers of Chinese exports to the United States.[19]

The second issue we want to clarify concerns the information content of Figure 1 for the importance of China-specific supply shocks for aggregate Chinese exports. Indeed, this information content is limited. At the risk of stating the obvious, we point out that, by plotting log differences in Figure 1,

[19]A this point, we also stress that the concern that the effects of Chinese exports pick up the impact of exports from other EMEs is unsubstantiated. Not only was the increase in export from other EMEs smaller than China's by an order of magnitude, Autor et al. (2013a) also show that their results are robust towards inclusion of import penetration by other EMEs.

the correlation may be driven by many small, marginal sectors that barely contributed to aggregate export growth.[20] We do not view this fact as a drawback of our strategy, however. Quite contrary, since the estimation strategy of Autor et al. (2013a) crucially relies on the sector variation in Chinese export growth, we argue that a correct identification of supply-induced export growth at the sector level is essential.

With these observations, we now turn to our identification strategy for China-specific shocks.

2.2 Identifying Chinese supply shocks

This section presents a simple framework to separate China-specific sector supply shocks from sector-level demand shocks and common supply shocks. Based on this identification, it defines U.S. import penetration due to Chinese-specific sector supply shocks.

2.2.1 A simple theoretical framework

To identify Chinese sector supply shocks, we are guided by a simple framework of constant demand elasticities. Going back to Dixit and Stiglitz (1977), this approach is consistent with a large number of quantitative trade models. Specifically, we consider demand for a single product with price p defined by

$$q = ap^{-\sigma}, \tag{1}$$

where aggregate supply q is the sum of supply from two destination regions, $q = q_{CN} + q_{OE}$. The quantity q_{CN} is the one exported from China and q_{OE} is the one exported from other EMEs.[21] The value of supply from country c equals $e_c = pq_c$ with $c = CN, OE$. The parameter a is a demand-shifter.[22]

We consider China-specific sector supply shocks as well as aggregate demand or supply shocks. Specifically, we consider three different shocks: a

[20] The next section will provide an assessment of the importance of China-specific supply shocks for aggregate Chinese exports.

[21] Motivated by the findings in Schott (2003) and Schott (2004), we thus assume that goods within the same narrow HS class are similar if they are produced in countries of similar technologies and factor endowments. By excluding other countries' exports of the same goods from aggregate supply, we also assume that goods differ if they are produced in countries with dissimilar technologies and factor endowments.

[22] In a richer setting, this demand shifter captures not only shocks to aggregate demand, but also supply of varieties by other non-EME countries and changes in relative demand for goods from specific regions. See Appendix A.

shock to the parameter a, a supply shock to all exporting countries, represented by the factor χ, and an additional China-specific shock represented by the factor χ^{CN}.[23] We write

$$q_{c,1} = \begin{cases} \chi q_{c,0} & \text{if} \quad c = OE \\ \chi^{CN} \chi q_{c,0} & \text{if} \quad c = CN. \end{cases} \tag{2}$$

Denoting the export value of country c at time t with $E_{c,t} = p_t q_{c,t}$, we thus compute the first-order approximation

$$d\ln(E_c) = d\ln(p) + d\ln(q_c), \tag{3}$$

which constitutes a decomposition of the change in export value into a price change (which may result from any kind of supply or demand shocks) and a supply shock to country c.

Our aim is to isolate the growth of Chinese export values induced by χ^{CN}, the China-specific supply shock. To that aim, we first observe that price changes affect sales of all suppliers in the same way. Taking differences and using (2) yields

$$d\ln(E_{CN}) - d\ln(E_{OE}) \quad = \quad \ln(\chi^{CN}). \tag{4}$$

To isolate the change in the value of Chinese exports $p_t q_{CN,t}$ driven by χ^{CN}, we compute

$$\frac{d\ln(E_{CN})}{d\chi^{CN}} = \left[\frac{p'(q)}{p(q)} q_{CN} + 1\right] \frac{dq_{CN}}{d\chi^{CN}},$$

replacing differentials with differences and dividing by $E_{CN,0} = p_0 q_{CN,0}$ yields

$$\frac{E_{CN,1} - E_{CN,0}}{E_{CN,0}} = \left[1 - \frac{1}{\sigma} \frac{E_{CN}}{E_{EE} + E_{CN}}\right] \left[\chi^{CN} - 1\right],$$

where we have used (1) to replace $p'(q)/p(q) = -1/(\sigma_j q)$ and $q_{CN}/q = E_{CN}/(E_{EE} + E_{CN})$.

Combining this equation with (4) and introducing product indices, we obtain the following expression for the Chinese export growth of product j, induced by a China-specific sector shock

$$\widehat{\Delta E}_{CN,j} = E_{CN,j,0} \left[1 - \frac{1}{\sigma_j} \frac{E_{CN,j,0}}{E_{EE,j,0} + E_{CN,j,0}}\right] \left[\frac{E_{CN,1}}{E_{CN,0}} - \frac{E_{OE,1}}{E_{OE,0}}\right]. \tag{5}$$

[23]Chinese productivity gains resulting from trade liberalization are captured by the reduced form factor χ^{CN} specified in equation (2).

We stress that we have not restricted the parameters a and χ to be constant. Thus, our identification of Chinese export growth due to China-specific supply shocks allows for simultaneous demand shocks (to the parameter a) as well as common supply shocks (to the parameter χ).

We also note that variables are readily observable with the exception of the demand elasticities σ_j. To identify the China-specific supply-induced component of Chinese export growth, we therefore take the values for σ_j as estimated by Broda and Weinstein (2004).[24]

Applying this procedure separately to exports to the United States and exports to OAEs, we identify the supply-driven Chinese export growth to the United States and supply-driven Chinese export growth to OAEs. The summary statistics of the resulting aggregates expressed in USD 2007 billion are presented in Table 2. The last column reports that the shares of Chinese export growth explained by China-specific shocks vary between 45.2% (for exports to U.S. between 1991 and 2000) and 79.2% (for exports to the U.S. between 2000 and 2007). Overall, the results document that a substantial part of Chinese exports is explained by factors common to all supplying countries.

Table 2: Summary statistics – Chinese exports, total and supply-induced

	Imports from China	Explained by Chinese Supply	Increase explained by Chinese Supply (%)
	(1)	(2)	(3)
United States			
1991	26.0	-	-
2000	120.7	68.8	45.2%
2007	330.0	286.4	79.2%
Other advanced countries			
1991	28.0	-	-
2000	93.7	62.8	53.0%
2007	264.6	184.9	53.4%

Notes: Numbers in billion 2007 US$. In column (1) raw Comtrade data is reported that is not cleaned using the procedure of Feenstra et al. (2005).

Complementing the summary statistics, the right panel of Figure C4 in the Appendix plots the correlation of supply-driven Chinese export growth to the United States versus supply-driven Chinese export growth to OAEs. For comparison, the left panel of the figure plots the correlation of Chinese

[24] We point out that export growth is defined for the generalized HS classes. The elasticities from Broda and Weinstein (2004) are defined as weighted averages, when generalized HS classes comprises more than one class of the classes according to the HS revision 1. Weights are proportional to overall imports to all nine AEs. Finally, in order to avoid pathological outliers, we restrict the elasticities to be larger or equal to 1. This restriction affects about one percent of all generalized HS classes.

export growth to both destinations as recorded in the data. This strong positive correlation on the left hand side is the basis of the instrumentation strategy in Autor et al. (2013a). In the panel on the right hand side, the R^2 is considerably lower. The data exhibit a positive correlation as well, but the reduced R^2 suggests that part of the positive correlation in the left panel is generated by shocks that are common to all exported and thus are unspecific to China.[25]

2.3 Chinese supply shocks and the U.S. labor market

Autor et al. (2013a) aim to identify the labor market effect of supply-driven Chinese exports to the United States, defining the *import penetration per worker* for each commuting zone as

$$\Delta IPW_i^{CN,US} = \sum_j l_{ij} \frac{\Delta E_j^{CN,US}}{L_j}, \tag{6}$$

where j identifying goods, i commuting zones, l_{ij} is the weight of sector j in the local labor force, L_j is total U.S. labor in sector j and $\Delta E_j^{CN,US}$ is the increase in sector exports from China to the United States, measured in constant 2007 USD.

Parallel to (6), we also define $\Delta IPW_i^{CN,OAE}$ based on Chinese export growth to OAEs, while using with U.S. industry labor L_j and U.S. labor shares l_{ij}:

$$\Delta IPW_i^{CN,OAE} = \sum_j l_{ij} \frac{\Delta E_j^{CN,OAE}}{L_j}. \tag{7}$$

For our estimations below we adapt this strategy as follows. Parallel to (6), we define the import penetration per worker based on the increase in exports that are driven by Chinese-specific supply-shocks as defined in (5).

$$\widehat{\Delta IPW}_i^{CN,US} = \sum_j l_{ij} \frac{\widehat{\Delta E}_j^{CN,US}}{L_j}, \tag{8}$$

[25] We also perform a check that relates to our original observation that supply-driven Chinese export shocks can be expected to reduce exports of other EMEs. If this hypothesis is correct, a negative correlation between supply-driven Chinese exports and other EME exports should emerge. This negative correlation, which remains concealed in the raw export data (see Figure 1), surfaces when plotting supply-driven Chinese exports against the observed export growth of other EMEs.

where $\widehat{\Delta E}_j^{CN,OAE}$ is the supply-induced increase in sector exports from China to OAEs from (5).

3 Empirical Strategy and Results

This section specifies our estimation strategy and reports the estimation results of our estimation strategies.

3.1 Empirical Strategy

Following Autor et al. (2013a), we estimate the effect of trade on manufacturing employment departing from the simple empirical model

$$\Delta L_i^m = \alpha + \beta \cdot \Delta IPW_i^{CN,US} + \gamma \cdot controls_i + \varepsilon_i, \tag{9}$$

where ΔL_i^m is the decadal change in the manufacturing employment share of the working-age population in commuting zone i in the United States. The key independent variable $IPW_i^{CN,US}$ is defined in (6). Since we aim to identify the effect of Chinese supply on U.S. labor markets, we replace the original variable $\Delta IPW_i^{CN,US}$ by the variable based on supply-induced increases in Chinese exports to the United States, i.e., $\widehat{\Delta IPW}_i^{CN,US}$ from (8). Specifically, we estimate

$$\Delta L_i^m = \alpha + \beta \cdot \widehat{\Delta IPW}_i^{CN,US} + \gamma \cdot controls_i + \varepsilon_i. \tag{10}$$

We stress that through the construction of the supply-induced shocks (5), this specification solves endogeneity concerns of U.S. demand shocks.[26] Specifically, by definition of (5), export growth based on U.S. import demand or other effects common to all EME exporters are eliminated from the expression $\widehat{\Delta E}_j^{CN,US}$, the need to instrument this adapted regressor vanishes. We therefore refrain from following the instrumentation strategy in Autor et al. (2013a) but present simple OLS instead.

We estimate model (10) with two samples: once for a stacked panel regression for the two periods 1991-2000 and 2000-2007, which Autor et al. (2013a) present as their central specification. We also estimate the model in cross-section with a second sample of changes in the period 2000-2007.

[26] Autor et al. (2013a) in Table 10 Panel E insert residuals from a sector gravity model between China and the United States in $\Delta IPW_i^{CN,US}$ to obtain an OLS estimate that corrects for possible productivity and transport gains. Their strategy however does not address the endogeneity concerns that we raise regarding demand shocks.

3.2 Results

Table 3 reports our estimation results. The six columns correspond to those of Table 3 in Autor et al. (2013a), each column includes a different set of control variables.[27]

The first Panels (i) to (iii) correspond to a panel regression based on changes between 1991 - 2000 and 2000 - 2007. To facilitate comparison to the original estimates, Panel (i) of the table reports the estimates emerging from the strategy in Autor et al. (2013a) with instrumentation but based on our data.[28] The complete estimation results including coefficients of the first stage and the full set of dependent variables are reported in Tables D3 - D8 in the Appendix.

[27]These controls are the same as in Autor et al. (2013a). These controls are the percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, average offshorability index of occupation, and census division dummies.

[28]Tables D1 and D2 document that these estimates differ somewhat from those in Autor et al. (2013a) due to the fact that we employ data publicly available on uncomtrade.com. In particular, our estimates are slightly lower. We do not interpret this difference as a problem of the original study but rather a confirmation that the results are robust to the use of similar yet distinct data sets. Tables D3 to D8 in the Appendix report the estimations for all our specifications including the full set of controls.

Table 3: Baseline estimations

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points)	(1)	(2)	(3)	(4)	(5)	(6)
	(i) Replication ADH: panel 1991 - 2007					
$\Delta IPW_i^{CN,US}$	-0.703***	-0.538***	-0.472***	-0.444***	-0.501***	-0.533***
	(0.066)	(0.105)	(0.101)	(0.091)	(0.100)	(0.102)
	(ii) Supply-induced OLS: panel 1991 - 2007					
$\widehat{\Delta IPW}_i^{CN,US}$	-0.390***	-0.207***	-0.190***	-0.148***	-0.176***	-0.185***
	(0.062)	(0.048)	(0.052)	(0.048)	(0.039)	(0.038)
R^2	0.116	0.249	0.353	0.393	0.435	0.444
	(iii) OLS: 1991-2007					
$\Delta IPW_i^{CN,US}$	-0.333***	-0.152***	-0.134***	-0.102***	-0.121***	-0.130***
	(0.0534)	(0.0421)	(0.0389)	(0.0337)	(0.0265)	(0.0258)
R^2	0.13	0.25	0.35	0.39	0.43	0.44
N	1444	1444	1444	1444	1444	1444
	(iv) Replication ADH: cross-section 2000-2007					
$\Delta IPW_i^{CN,US}$	-0.671***	-0.340***	-0.344***	-0.342**	-0.345***	-0.386***
	(0.068)	(0.116)	(0.129)	(0.133)	(0.114)	(0.120)
	(v) Supply-induced OLS: cross-section 2000-2007					
$\widehat{\Delta IPW}_i^{CN,US}$	-0.420***	-0.143**	-0.172**	-0.151**	-0.135**	-0.154**
	(0.066)	(0.054)	(0.074)	(0.074)	(0.057)	(0.059)
R^2	0.158	0.458	0.553	0.565	0.582	0.608
	(vi) OLS: 2000-2007					
$\Delta IPW_i^{CN,US}$	-0.388***	-0.119**	-0.132**	-0.115*	-0.0980**	-0.115**
	(0.0570)	(0.0475)	(0.0601)	(0.0593)	(0.0462)	(0.0468)
R^2	0.20	0.46	0.55	0.56	0.58	0.60
N	722	722	722	722	722	722

Notes: Panel (i) reports regression results based on our replication of the strategy in Autor et al. (2013a) for the entire period 1991 to 2007. Panels (ii) and (iii) correspond to an OLS estimation with the regression as defined in (8) and in (6), respectively. Panels (iv) - (vi) report the corresponding estimates based on the later period 2000 to 2007. Columns (1) to (6) correspond to those in Table 3 of Autor et al. (2013a). successively including the control variables.
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel (ii) reports the results from our OLS estimations as specified in (10). Compared with the coefficients of the original specification, the point estimates drop by about two-thirds on average for the six specifications and, in particular, in the fully controlled specification of Column (6). The statistical significance is preserved throughout.[29]

To further connect our results to those of Autor et al. (2013a), Panel (iii) of Table 10 also presents the OLS based on the second stage of model (9), i.e., the original second stage of Autor et al. (2013a) in the absence of any instrument and using the uncorrected variable (6). The worry regarding such

[29] In a different exercise, Autor et al. (2013a) also show in Table 10 Panel E that their OLS correction for productivity and efficiency improvements of transport leads to a lower coefficient for the import competition variable of 0.29.

a specification (not shown in the original paper Autor et al. (2013a)) is that shocks to U.S. import demand may increase both, demand for local labor as well as import demand, thus biasing the estimated (negative) impact of Chinese exports on U.S. labor towards zero. Indeed, comparing Panels (i) to (iii), the estimated coefficients of Panel (iii) are the lowest in magnitude throughout all six columns. Comparing Panels (i) and (iii), the narrative based on Autor et al. (2013a) would suggest that the bias induced through shocks to U.S. demand blurred about three quarters of the negative impact of Chinese exports on U.S. manufacturing employment (taking estimates of Column (6), compute $0.130/0.533 = 0.244$). Our estimates in Panel (ii), instead, indicate that the 'true' impact of Chinese imports on manufacturing employment (Panel (iii)) was only mildly higher than the one including demand effects (taking Column (6) again, compute $0.130/0.185 = 0.703$). In that case, the effects of U.S. demand were only moderate.

Panels (iv) and (vi) of Table 3 repeat these estimations but for differences for the estimations based on changes between 2000 to 2007 only, i.e., under a cross-section specification.[30] Again, Panel (iv) reports the results of our replication of the original estimation strategy from Autor et al. (2013a), while Panel (v) reports the OLS regressions with supply-induced Chinese export growth and Panel (vi) plots unadjusted OLS. Compared to the original estimates in Panel (iv), the coefficients in the adjusted OLS regression (Panel (v)) drop substantially in magnitude. The drop is over half on average in the six specifications, while the negative sign of the coefficient of interest is preserved throughout. And again, the magnitude of the OLS estimates with unadjusted Chinese exports (Panel (vi)) lie substantially below both prior estimates in all columns (compute $0.115/0.154 = 0.75$ in Column (6)).

Overall, our new estimates in Panels (ii) and (v) of Table 3 show that the estimated impact of Chinese exports on U.S. manufacturing employment is much weaker in our adjusted OLS specification than originally estimated by Autor et al. (2013a). Our correction of the estimation strategy, which identified China's supply-driven export growth through the structural model in Section 2.2 do indeed seem to matter for the estimated impact of import penetration on the local labor force in the United States. Given that we

[30] While panel regressions are generally preferable, we point out that **?** consider the according regressions as the more meaningful, since the more substantive increase of Chinese import penetration to the United States occurred after China's accession to the WTO in 2001.

correctly identified the China-specific supply shocks, the causal impact of Chinese exports on U.S. manufacturing employment is much lower than previously documented in Autor et al. (2013a).

The estimates in Table 3 constitute the main empirical results of this section and suggest a relatively mild impact of Chinese exports on U.S. manufacturing employment. How do these findings square with theory? The answer is not obvious, since the coefficients in Autor et al. (2013a) should be biased *downward* in the presence of pure demand effects, as correctly pointed out in Autor et al. (2013a). If our strategy successfully eliminates demand effects, we should rather expect an increase in the estimated coefficients.

We offer two answers to this question. First, the supply shocks that drove Chinese exports to the U.S. and which reduced U.S. employment were common to all EMEs. Since our approach relies on the identification of China-specific supply shocks that materialized *in addition* to those of other EMEs, our estimates do not capture the impact of these common, potentially more important, shocks. Second, the increase in Chinese exports might actually result from adverse technology shocks in the United States, which induced a simultaneous reduction in U.S. manufacturing employment and a surge in import demand.[31] Such effects may arise, for example, if standardization of production processes shift comparative advantage in favor of EMEs.

Both effects are closely related, the main difference being that the first originates in EMEs, while the latter originates in the United States. Both effects also tend to generate a negative correlation between Chinese exports to the United States and U.S. manufacturing employment. Therefore, by controlling for both potential effects, our estimated causal impact of the remaining, genuinely China-specific shocks on U.S. employment must be reduced. While our identification strategy does not allow us to distinguish between both common effects described above, we consider each of them to be a possible and relevant explanation for the fact that the estimated coefficient of interest is reduced in our specification.

[31] Discussing this option, Autor et al. (2013a) write that Chinese export growth "may reflect technology shocks common to high-income countries that adversely affect their labor-intensive industries, making them vulnerable to Chinese competition so that "automation drives imports from China rather than the other way round.

4 Conclusion

The seminal paper Autor et al. (2013a) identifies the impact of Chinese exports on U.S. manufacturing employment. Their instrumental variable strategy relies on the assumption that there are no common import demand shocks to the United States and other advanced economies. This identification assumption has been readily accepted by other researchers.[32]

This paper offers two separate contributions. First, it documents strong empirical patterns which suggest that a central assumption of the identification strategy in Autor et al. (2013a) is likely to be violated. Specifically, our evidence suggests that demand shocks in the United States and other advanced economies are correlated.

For the second contribution, we use a simple structural model to identify China-specific supply shocks. We then use the resulting supply-induced Chinese exports to adapt the estimation strategy in Autor et al. (2013a). The estimated impact of Chinese imports on U.S. labor markets is markedly reduced in the baseline specification of Autor et al. (2013a).

Overall, our contribution uncovers a potential endogeneity problem in standard identification strategies that estimate the impact of Chinese exports on the U.S. labor market. The resulting bias could ultimately lead researchers to erroneously attribute employment and wage losses to international trade flows. While the manufacturing worker with a job loss may be indifferent towards the source of misery, the correct identification of the underlying shock is highly relevant for adequate policy responses.

[32]E.g., Ashournia et al. (2014), Balsvik et al. (2015), Dauth et al. (2014) and Malgouyres (2017)).

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Appendix A: Extended Model

In this section, we motivate our choice of the reduced-form model in Section 2.2.1, as the reduced form version derived from a generalized demand function. Specifically, referring to varieties produced in any geographical region (not only EMEs), we assume that U.S. demand for a given sector is derived from a CES aggregator standard of the form

$$X = \left[\sum_{g=1}^{G} \alpha_g \left(\sum_{k \in S_g} x_{gk}^{1-1/\eta_g} \right)^{\frac{\eta_g}{\eta_g - 1} \frac{\sigma - 1}{\sigma}} \right]^{\sigma/(\sigma-1)} \tag{11}$$

with the elasticities $\sigma > 1$ and $\eta_g > \sigma$ and the demand shifters α_g.

Each of the G different sets $\{x_{gk}\}_k$ represents closely substitutable varieties. In our specific context, we will think of varieties x_{gk} as differentiated by their geographical origin. Thus, g indicates sets of countries that produce varieties that are highly substitutable. The findings of Schott (2003) suggest that countries with similar technologies and factor endowments produce closely substitutable goods. We therefore identify the set of emerging market economies with similar technologies and comparative advantage with one group, wlog $g = 1$.

Agents purchase the optimal mix of varieties subject to the total expenditure E, solving the program

$$\max_{\{x_{gk}\}_{g,k}} \left[\sum_{g} \alpha_g \left(\sum_{k} x_{gk}^{1-1/\eta_g} \right)^{\frac{\eta_g}{\eta_g - 1} \frac{\sigma - 1}{\sigma}} \right]^{\sigma/(\sigma-1)} \qquad \text{s.t.} \quad \sum_{g,k} p_{gk} x_{gk} \leq E$$

The optimality condition wrt x_{gk} is

$$\alpha_g x_{gk}^{-\frac{1}{\eta_g}} \left(\sum_{k'} x_{gk'}^{\frac{\eta_g - 1}{\eta_g}} \right)^{\frac{\eta_g}{\eta_g - 1} \frac{\sigma - 1}{\sigma} - 1} \left[\sum_{g'} \alpha_{g'} \left(\sum_{k'} x_{g'k'}^{\frac{\eta_g - 1}{\eta_g}} \right)^{\frac{\eta_g}{\eta_g - 1} \frac{\sigma - 1}{\sigma}} \right]^{\frac{\sigma}{\sigma - 1} - 1} = \lambda p_{gk}$$

Simplifying expressions, we will denote the bundle from country group g by

$$x_g = \left(\sum_{k} x_{gk}^{1-1/\eta_g} \right)^{\eta_g/(\eta_g - 1)}$$

and the respective ideal price index by p_g. The optimality conditions then simplify to

$$\alpha_g x_g^{-1/\sigma} \left[\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)} \right]^{\sigma/(\sigma-1)-1} = \lambda p_g \tag{12}$$

so that, when multiplying by x_g and summing over g, we get

$$\sum_g \alpha_g x_g^{1-1/\sigma} \left[\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)} \right]^{\sigma/(\sigma-1)-1} = \lambda \sum_g p_g x_g = \lambda E$$

and thus

$$\lambda = \frac{\left[\sum_g \alpha_g x_g^{(1-1/\sigma)} \right]^{\sigma/(\sigma-1)}}{E}$$

Equation (12) therefore becomes

$$\alpha_g x_g^{-1/\sigma} = \frac{p_g}{E} \sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)} \tag{13}$$

Taking log derivatives wrt p_g yields

$$-\frac{1}{\sigma} \frac{dx_g/dp_g}{x_g} = \frac{1}{p_g} - \frac{d}{dp_g} \ln(E) + \left(1 + \frac{1}{\sigma}\right) \frac{\alpha_g x_g^{(1-1/\sigma)}}{\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)}} \frac{dx_g/dp_g}{x_g}$$

We will further assume that expenditure E is constant so that[33]

$$-\frac{1}{\sigma} \frac{dx_g/dp_g}{x_g} = \frac{1}{p_g} + \left(1 + \frac{1}{\sigma}\right) \frac{\alpha_g x_g^{(1-1/\sigma)}}{\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)}} \frac{dx_g/dp_g}{x_g}$$

Now, defining the price elasticity of demand for group g as

$$\varepsilon_g = -\frac{dx_g/dp_g}{x_g} p_g$$

Multiplying with p_g, we thus get

$$\frac{1}{\sigma} \varepsilon_g = 1 - \left(1 - \frac{1}{\sigma}\right) \frac{\alpha_g x_g^{(1-1/\sigma)}}{\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)}} \varepsilon_g$$

The expenditure share on product group g is $s_g = p_g x_g / \sum_{g'} p_{g'} x_{g'} = \alpha_g x_g^{(1-1/\sigma)} / \sum_{g'} p_{g'} x_{g'}^{(1-1/\sigma)}$ so that we have

$$\varepsilon_g = \frac{1}{\frac{1}{\sigma} + \left(1 - \frac{1}{\sigma}\right) s_g}$$

[33] For the more general case, where E is a function of prices we have see Auer and Schoenle (2016).

Setting this elasticity to a constant $\bar{\varepsilon}_g$, we can approximate the generic demand function for group 1 by

$$x_1 = \Lambda p_1^{-\bar{\varepsilon}_1}$$

with Λ being a function of the parameters $\{\alpha_g\}_{g=1,..G}$, $\{x_g\}_{g=2,..G}$ and $\{p_g\}_{g=2,..G}$.

Finally, we will also assume that varieties of products from the group of emerging market economies ($g = 1$) are perfect substitutes, i.e., $\eta_1 = \infty$. Thus, in the particular case of $g = 1$, the optimality condition is

$$\sum_k x_{1k} = \Lambda p_1^{-\bar{\varepsilon}_1} \tag{14}$$

where $p_{1k} = p_1$ must hold, since price differences among perfectly substitutable goods cannot survive. Renaming $\sum_k x_{1k} = q$ and $\Lambda = a$, we have thus reduced the demand of goods from emerging market economies to the generic demand function (1) postulated in Section 2.2.1. Importantly, all shocks to demand ($\{\alpha_g\}_{g=1,..G}$), other country's supply ($\{x_g\}_{g=2,..G}$) and prices ($\{p_g\}_{g=2,..G}$) affect demand only through the factor Λ, thus showing that the parameter a in the demand function (1) concisely summarizes all relevant shocks, which are not specific to one of the EMEs (see also footnote 22).

Appendix B: Data

Our analysis primarily relies on trade, employment, and output data from 1991 to 2007. All data sources and their compilation are as described in Autor et al. (2013a). A brief summary runs as follows. Bilateral trade flows, measured in values, are from UN Comtrade, recorded according the HS classification system at the 6-digit level. After dropping a residual classification (code 999999), the product classes are deflated by the implicit deflator of U.S. Personal Consumption Expenditures to be expressed in constant 2007 dollars and mapped to industry-specific SIC87 classification. Unlike Autor et al. (2013a), we rely on publicly available trade data instead of mildly processed and cleaned ones, which results in slightly lower aggregates that those reported by Autor et al. (2013a), with differences less than one percent. Based on the resulting trade flows at the industry level, the import penetration per commuting zone are computed, using the codes at the website of David Dorn.

Following Autor et al. (2013a), we use data reported by nine countries that adopted the HS system as of 1991 (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, Switzerland and the United States). In addition to the trade flows used in Autor et al. (2013a), we use imports of these countries from all countries, in particular those, which we define as other EMEs (see next section).

The key dependent variable, i.e., manufacturing employment at the level of the commuting zone as well as all control variables are as reported in Autor et al. (2013a) and readily available at the website of David Dorn.

The source of GDP and GDP per capita in current USD is the World Bank.

B.1 Selection criteria for other emerging market economies

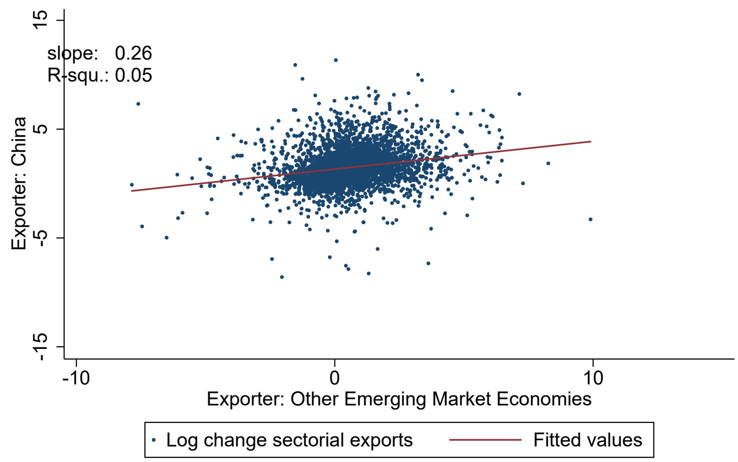
In identify EMEs, we follow Auer et al. (2013), who define a country to be other emerging market economies if a nation's average GDP per capita (averages from 1995 to 2008) is less than 25% of the average GDP per capita (in current U.S. dollars) for Italy, Germany, France, Sweden and the United Kingdom (average GDP for the five countries between 1995 and 2008). There are 137 countries with a per capita GDP of less than 25% of average European GDP per capita. In addition, only countries with a share of manufactured exports (in percent of total merchandizing exports) exceeding 70% are kept. These criteria leave us with 10 economies, which are China, India, Malaysia, Mexico, Philippines, Poland, Romania, Slovak

Republic, Thailand, and Turkey.

This procedure based on manufacturing export and income performance differs from the classification scheme used by Bernard et al. (2006). They base their selection on a 5% threshold for GDP with respect to the United States. This scheme, which is also used in Bloom et al. (2016) and Khandelwal (2010), comprises over 50 countries in which commodities are often the main export.

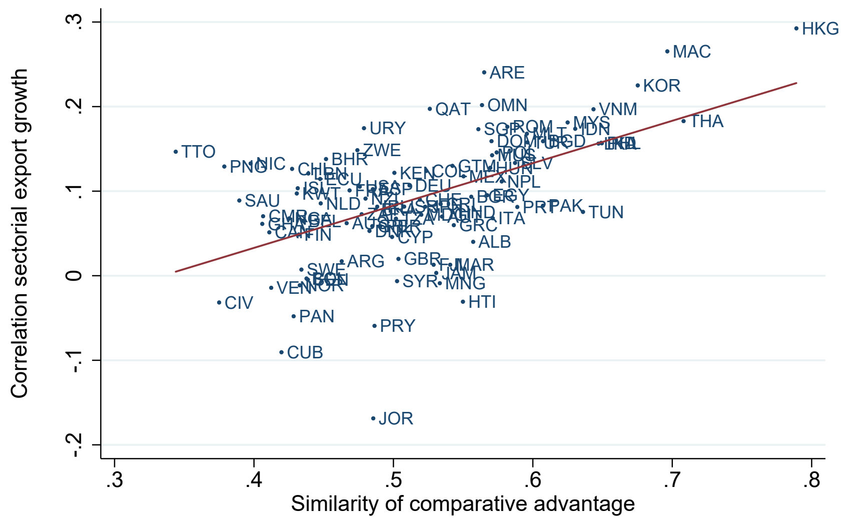
Appendix C: Figures

Figure C1: **Sector export growth of China and other EMEs,** 2000 - 2007



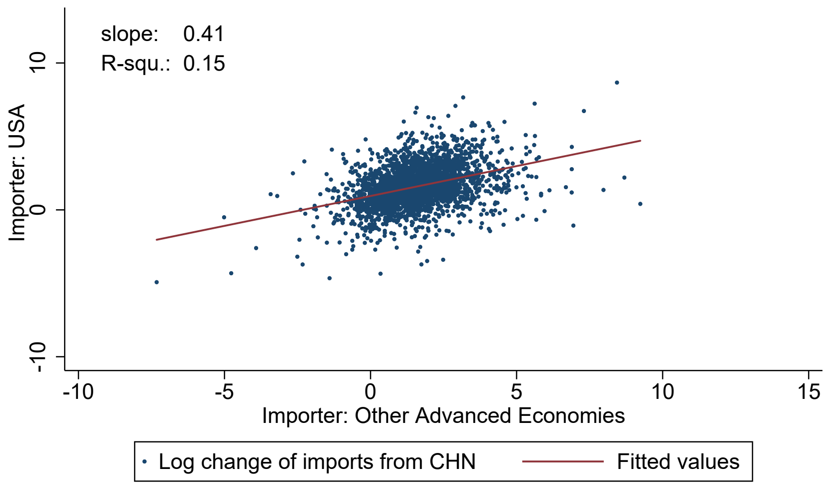
Note: Figure parallel to 1 but for the period 2000 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the Figure. Data source UN Comtrade

Figure C2: Synchronized export growth and similarity of comparative advantage, 2000 to 2007



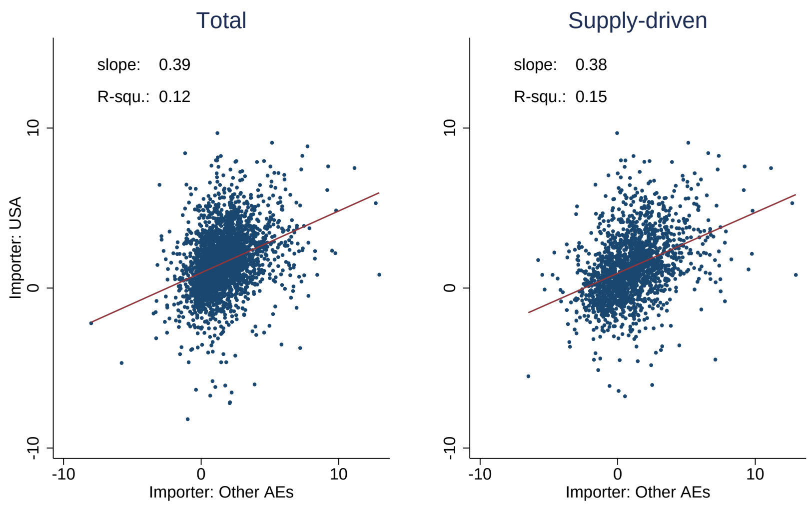
Note: Figure parallel to Figure 2 but for period 2000 to 2007. The similarity of comparative advantage on the horizontal axis is defined based on data of the years 1991 to 1995, described in Figure 2.

Figure C3: China's Sector Export Growth – Common Component with Other EMEs (2000 to 2007)



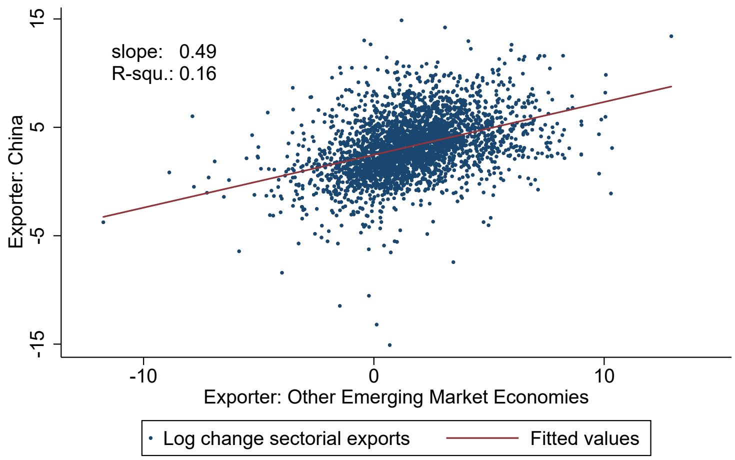
Note: Figure parallel to Figure 3 but for period 2000 to 2007.

Figure C4: **Chinese export growth, total and supply-driven,** 1991 - 2007



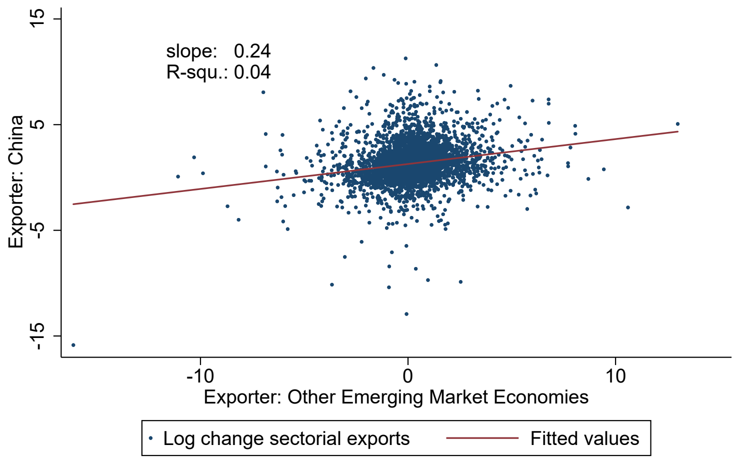
Note: Log changes of Chinese exports between 1991 and 2007 by 6-digit HS class to the U.S. and other advanced countries. Exports are measured in constant 2007 USD; supply-driven exports are defined in equation (5). Other advanced economies are Australia, Denmark, Germany, Finland, New Zealand, Japan, Spain and Switzerland. See also note of Figure 1.

Figure C5: **Sector export growth of China and other EMEs,** by export weight 1991 - 2007



Note: Figure parallel to 1 but for export weights (instead of value), 1991 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the Figure. Data source UN Comtrade

Figure C6: **Sector export growth of China and other EMEs,** by export weight 2000 - 2007



Note: Figure parallel to 1 but for export weights (instead of values) and the period 2000 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the Figure. Data source UN Comtrade

Appendix D: Tables

Table D1: Original and Replication – panel estimations 1991 - 2007

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points)

	(1)	(2)	(3)	(4)	(5)	(6)
	(i) Autor et al. (2013a) original data: 1991-2007 stacked first differences					
(Δ imports from China to US)/ worker	-0.746***	-0.610***	-0.538***	-0.508***	-0.562***	-0.596***
	(0.068)	(0.094)	(0.091)	(0.081)	(0.096)	(0.099)
	(ii) Autor et al. (2013a) original data: First stage estimate					
(Δ imports from China to OTH)/ worker	0.792***	0.664***	0.652***	0.635***	0.638***	0.631***
	(0.080)	(0.089)	(0.094)	(0.094)	(0.091)	(0.091)
R^2	0.544	0.573	0.579	0.585	0.583	0.585
	(iii) Replication data: 1991-2007 stacked first differences					
(Δ imports from China to US)/ worker	-0.703***	-0.538***	-0.472***	-0.444***	-0.501***	-0.533***
	(0.066)	(0.105)	(0.101)	(0.091)	(0.100)	(0.102)
	(iv) Replication data: First stage estimate					
(Δ imports from China to OTH)/ worker	0.763***	0.656***	0.644***	0.630***	0.632***	0.624***
	(0.075)	(0.089)	(0.093)	(0.094)	(0.091)	(0.091)
R^2	0.518	0.542	0.549	0.554	0.552	0.555
N	1444	1444	1444	1444	1444	1444

Notes: Rows (i) and (ii) use Autor et al. (2013a) original data. Rows (iii) and (iv) are our replication. Only the variable of interest is shown here. However, columns (1) to (6) include the identical control variables as in Table 3 from Autor et al. (2013a).
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D2: Original and replication estimates – 2000 to 2007

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points)

	(1)	(2)	(3)	(4)	(5)	(6)
	(i) Autor et al. (2013a) original data: 2000-2007 first differences					
(Δ imports from China to US)/ worker	-0.718***	-0.409***	-0.419***	-0.424***	-0.426***	-0.469***
	(0.064)	(0.107)	(0.120)	(0.127)	(0.116)	(0.123)
	(ii) Autor et al. (2013a) original data: First stage estimate					
(Δ imports from China to OTH)/ worker	0.767***	0.603***	0.584***	0.541***	0.536***	0.528***
	(0.088)	(0.100)	(0.105)	(0.101)	(0.094)	(0.097)
R^2	0.446	0.491	0.506	0.524	0.524	0.527
	(iii) Replication data: 2000-2007 first differences					
(Δ imports from China to US)/ worker	-0.671***	-0.340***	-0.344***	-0.342**	-0.345***	-0.386***
	(0.068)	(0.116)	(0.129)	(0.133)	(0.114)	(0.120)
	(iv) Replication data: First stage estimate					
(Δ imports from China to OTH)/ worker	0.737***	0.599***	0.581***	0.547***	0.544***	0.536***
	(0.084)	(0.102)	(0.106)	(0.105)	(0.099)	(0.102)
R^2	0.432	0.470	0.485	0.502	0.501	0.504
N	722	722	722	722	722	722

Notes: Rows (i) and (ii) use Autor et al. (2013a) original 2000-2007 data. Rows (iii) and (iv) are our replication for this time period. Only the variable of interest is shown here. However, columns (1) to (6) include the identical control variables as in Table 3 from Autor et al. (2013a).
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D3: Replication estimates full set of coefficients – panel 1991 to 2007

	Replication: 1991-2007 stacked first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/ worker	-0.703***	-0.538***	-0.472***	-0.444***	-0.501***	-0.533***
	(0.066)	(0.105)	(0.101)	(0.091)	(0.100)	(0.102)
Percentage of employment in manufacturing$_{-1}$		-0.045*	-0.062***	-0.072***	-0.066***	-0.051***
		(0.025)	(0.023)	(0.020)	(0.019)	(0.016)
Middle atlantic dummy			0.191	-0.157	0.406**	0.326
			(0.200)	(0.192)	(0.173)	(0.287)
East north central dummy			0.954***	0.715**	1.245***	1.332***
			(0.273)	(0.300)	(0.279)	(0.344)
West north central dummy			1.740***	1.711***	1.512***	1.652***
			(0.474)	(0.544)	(0.411)	(0.383)
South atlantic dummy			-0.138	-0.468	-0.328	-0.321
			(0.275)	(0.298)	(0.272)	(0.256)
East south central dummy			1.095***	0.420	0.914***	1.074***
			(0.279)	(0.295)	(0.230)	(0.330)
West south central dummy			1.154***	0.536**	0.794***	0.743***
			(0.158)	(0.217)	(0.158)	(0.232)
Mountain dummy			0.768***	0.448	0.388*	0.401
			(0.256)	(0.283)	(0.225)	(0.261)
Pacific dummy			0.594***	0.301	0.488***	0.050
			(0.139)	(0.209)	(0.171)	(0.191)
Percentage of college-educated population$_{-1}$				-0.011		0.012
				(0.016)		(0.012)
Percentage of foreign-born population$_{-1}$				-0.009		0.031***
				(0.008)		(0.011)
Percentage of employment among women$_{-1}$				-0.054**		-0.003
				(0.025)		(0.024)
Percentage of employment in routine occupations$_{-1}$					-0.232***	-0.247***
					(0.065)	(0.066)
Average offshorability index of occupations$_{-1}$					0.196	-0.117
					(0.253)	(0.240)
First stage R^2	0.52	0.54	0.55	0.55	0.55	0.55
First stage F-stat	104.12	53.96	47.94	45.28	48.71	46.62
N	1444	1444	1444	1444	1444	1444

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points).
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Replication estimates full set of coefficients – panel 1991 to 2007, first stage

	Replication: First stage estimates					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to OTH)/ worker	0.763***	0.656***	0.644***	0.630***	0.632***	0.624***
	(0.075)	(0.089)	(0.093)	(0.094)	(0.091)	(0.091)
Percentage of employment in manufacturing$_{-1}$		0.039***	0.038***	0.047***	0.042***	0.049***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Middle atlantic dummy			-0.307**	-0.236	-0.282*	-0.197
			(0.124)	(0.178)	(0.157)	(0.209)
East north central dummy			-0.241	-0.155	-0.210	-0.104
			(0.166)	(0.176)	(0.202)	(0.214)
West north central dummy			-0.089	-0.009	-0.054	-0.017
			(0.158)	(0.171)	(0.161)	(0.163)
South atlantic dummy			-0.278	-0.157	-0.235	-0.152
			(0.220)	(0.257)	(0.224)	(0.255)
East south central dummy			0.118	0.369*	0.193	0.403*
			(0.183)	(0.200)	(0.195)	(0.219)
West south central dummy			-0.087	0.095	-0.027	0.096
			(0.166)	(0.174)	(0.152)	(0.171)
Mountain dummy			-0.328**	-0.216	-0.300*	-0.230
			(0.158)	(0.172)	(0.162)	(0.168)
Pacific dummy			0.068	-0.014	0.009	-0.043
			(0.137)	(0.160)	(0.145)	(0.169)
Percentage of college-educated population$_{-1}$				0.009		0.010
				(0.016)		(0.014)
Percentage of foreign-born population$_{-1}$				0.011**		0.013**
				(0.004)		(0.006)
Percentage of employment among women$_{-1}$				0.010		0.013
				(0.014)		(0.014)
Percentage of employment in routine occupations$_{-1}$					-0.022	-0.029
					(0.057)	(0.054)
Average offshorability index of occupations$_{-1}$					0.319	0.073
					(0.296)	(0.264)
R^2	0.52	0.54	0.55	0.55	0.55	0.55
N	1444	1444	1444	1444	1444	1444

Dependent variable: (Δ imports from China to US)/worker.
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D5: Replication estimates full set of coefficients – cross section 2000 to 2007

	Replication: 2000-2007 first differences					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to US)/ worker	-0.671***	-0.340***	-0.344***	-0.342**	-0.345***	-0.386***
	(0.068)	(0.116)	(0.129)	(0.133)	(0.114)	(0.120)
Percentage of employment in manufacturing$_{-1}$		-0.112***	-0.111***	-0.120***	-0.118***	-0.104***
		(0.030)	(0.033)	(0.036)	(0.031)	(0.028)
Middle atlantic dummy			0.275	0.097	0.381	0.465
			(0.267)	(0.323)	(0.342)	(0.444)
East north central dummy			0.160	0.128	0.331	0.590
			(0.453)	(0.436)	(0.545)	(0.512)
West north central dummy			1.360**	1.377**	1.294**	1.316***
			(0.589)	(0.608)	(0.580)	(0.507)
South atlantic dummy			-0.256	-0.385	-0.349	-0.194
			(0.366)	(0.399)	(0.397)	(0.401)
East south central dummy			0.799**	0.717*	0.734**	1.398***
			(0.322)	(0.389)	(0.357)	(0.433)
West south central dummy			1.240***	1.048***	1.042***	1.261***
			(0.265)	(0.362)	(0.315)	(0.378)
Mountain dummy			0.532	0.516	0.362	0.561
			(0.379)	(0.427)	(0.400)	(0.448)
Pacific dummy			1.108***	0.935**	1.098***	0.876**
			(0.249)	(0.383)	(0.302)	(0.374)
Percentage of college-educated population$_{-1}$				-0.031		-0.002
				(0.024)		(0.020)
Percentage of foreign-born population$_{-1}$				0.013		0.056***
				(0.010)		(0.013)
Percentage of employment among women$_{-1}$				0.014		0.069*
				(0.040)		(0.038)
Percentage of employment in routine occupations$_{-1}$					-0.104	-0.135
					(0.103)	(0.092)
Average offshorability index of occupations$_{-1}$					-0.091	-0.798**
					(0.356)	(0.330)
First stage R^2	0.43	0.47	0.49	0.50	0.50	0.50
First stage F-stat	77.39	34.74	29.96	27.36	30.24	27.90
N	722	722	722	722	722	722

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points).
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D6: Replication estimates full set of coefficients – cross section 2000 to 2007, first stage

	Replication: First stage estimates					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports from China to OTH)/ worker	0.737***	0.599***	0.581***	0.547***	0.544***	0.536***
	(0.084)	(0.102)	(0.106)	(0.105)	(0.099)	(0.102)
Percentage of employment in manufacturing$_{-1}$		0.063***	0.065***	0.091***	0.084***	0.092***
		(0.015)	(0.014)	(0.017)	(0.016)	(0.019)
Middle atlantic dummy			-0.295	-0.157	-0.218	-0.169
			(0.236)	(0.334)	(0.319)	(0.371)
East north central dummy			-0.386	-0.272	-0.361	-0.274
			(0.272)	(0.274)	(0.352)	(0.349)
West north central dummy			-0.258	-0.165	-0.175	-0.149
			(0.309)	(0.310)	(0.317)	(0.317)
South atlantic dummy			-0.159	0.087	-0.029	0.044
			(0.377)	(0.432)	(0.398)	(0.426)
East south central dummy			0.311	0.829***	0.562*	0.764**
			(0.245)	(0.279)	(0.313)	(0.325)
West south central dummy			0.006	0.378	0.217	0.306
			(0.291)	(0.306)	(0.260)	(0.286)
Mountain dummy			-0.486*	-0.260	-0.362	-0.307
			(0.251)	(0.275)	(0.266)	(0.277)
Pacific dummy			0.285	0.132	0.148	0.057
			(0.249)	(0.276)	(0.270)	(0.317)
Percentage of college-educated population$_{-1}$				0.022		0.013
				(0.025)		(0.022)
Percentage of foreign-born population$_{-1}$				0.023***		0.016*
				(0.008)		(0.009)
Percentage of employment among women$_{-1}$				0.021		0.012
				(0.021)		(0.024)
Percentage of employment in routine occupations$_{-1}$					-0.035	-0.038
					(0.114)	(0.105)
Average offshorability index of occupations$_{-1}$					0.701	0.392
					(0.529)	(0.491)
R^2	0.43	0.47	0.49	0.50	0.50	0.50
N	722	722	722	722	722	722

Dependent variable: (Δ imports from China to US)/worker.
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D7: OLS estimates with Supply-induced exports full set of coefficients – panel 1991 to 2007

	Supply-induced: OLS regression					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports CN to US)/ worker	-0.390***	-0.207***	-0.190***	-0.148***	-0.176***	-0.185***
	(0.062)	(0.048)	(0.052)	(0.048)	(0.039)	(0.038)
Percentage of employment in manufacturing$_{-1}$		-0.083***	-0.094***	-0.109***	-0.105***	-0.096***
		(0.018)	(0.018)	(0.017)	(0.014)	(0.014)
Middle atlantic dummy			0.452**	0.071	0.652***	0.540*
			(0.209)	(0.193)	(0.184)	(0.275)
East north central dummy			1.316***	1.022***	1.592***	1.617***
			(0.248)	(0.287)	(0.248)	(0.324)
West north central dummy			2.035***	1.943***	1.811***	1.933***
			(0.487)	(0.568)	(0.430)	(0.425)
South atlantic dummy			0.186	-0.214	-0.004	-0.031
			(0.328)	(0.366)	(0.328)	(0.325)
East south central dummy			1.195***	0.382	0.969***	0.977***
			(0.298)	(0.326)	(0.246)	(0.357)
West south central dummy			1.423***	0.705***	1.052***	0.935***
			(0.163)	(0.227)	(0.180)	(0.244)
Mountain dummy			1.064***	0.671**	0.705***	0.680**
			(0.256)	(0.274)	(0.242)	(0.257)
Pacific dummy			0.783***	0.535**	0.729***	0.363*
			(0.147)	(0.216)	(0.179)	(0.197)
Percentage of college-educated population$_{-1}$				-0.014		0.007
				(0.013)		(0.010)
Percentage of foreign-born population$_{-1}$				-0.016*		0.019*
				(0.008)		(0.011)
Percentage of employment among women$_{-1}$				-0.059**		-0.013
				(0.023)		(0.025)
Percentage of employment in routine occupations$_{-1}$					-0.201***	-0.209***
					(0.060)	(0.062)
Average offshorability index of occupations$_{-1}$					-0.055	-0.200
					(0.287)	(0.248)
N	1444	1444	1444	1444	1444	1444
R^2	0.12	0.25	0.35	0.39	0.44	0.44

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points).
Clustered standard errors in parentheses. Regressions include t2 fixed effect.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D8: OLS estimates with Supply-induced exports full set of coefficients – cross section 2000 to 2007

	Supply-induced: OLS regression					
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ imports CN to US)/ worker	-0.420***	-0.143**	-0.172**	-0.151**	-0.135**	-0.154**
	(0.066)	(0.054)	(0.074)	(0.074)	(0.057)	(0.059)
Percentage of employment in manufacturing$_{-1}$		-0.145***	-0.142***	-0.161***	-0.159***	-0.153***
		(0.020)	(0.024)	(0.028)	(0.024)	(0.025)
Middle atlantic dummy			0.479*	0.269	0.535	0.636
			(0.267)	(0.330)	(0.347)	(0.433)
East north central dummy			0.418	0.356	0.563	0.813
			(0.423)	(0.426)	(0.509)	(0.486)
West north central dummy			1.619***	1.595**	1.527**	1.549***
			(0.575)	(0.618)	(0.573)	(0.515)
South atlantic dummy			-0.042	-0.244	-0.183	-0.025
			(0.408)	(0.467)	(0.452)	(0.470)
East south central dummy			0.848**	0.609	0.661	1.260**
			(0.351)	(0.436)	(0.395)	(0.491)
West south central dummy			1.409***	1.112***	1.138***	1.360***
			(0.261)	(0.385)	(0.334)	(0.405)
Mountain dummy			0.757*	0.680	0.564	0.775*
			(0.377)	(0.433)	(0.413)	(0.455)
Pacific dummy			1.228***	1.116***	1.258***	1.130***
			(0.267)	(0.400)	(0.326)	(0.392)
Percentage of college-educated population$_{-1}$				-0.039*		-0.007
				(0.023)		(0.019)
Percentage of foreign-born population$_{-1}$				0.006		0.049***
				(0.008)		(0.012)
Percentage of employment among women$_{-1}$				0.011		0.068*
				(0.037)		(0.035)
Percentage of employment in routine occupations$_{-1}$					-0.071	-0.097
					(0.099)	(0.087)
Average offshorability index of occupations$_{-1}$					-0.402	-1.028***
					(0.409)	(0.344)
N	722	722	722	722	722	722
R^2	0.16	0.46	0.55	0.57	0.58	0.61

Dependent variable: 10 × annual change in manufacturing emp/working-age pop (in % points).
Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$