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

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Abstract

Separating export supply form import demand shocks is a key difficulty when estimating the impact of trade on labor markets. Recent influential contributions use shift-share designs under estimation strategies that require demand shocks to importing countries to be uncorrelated. We contribute to this literature in three points. First, we document empirical patterns, which strongly suggest that common demand shocks are prevalent. Second, we propose a strategy that directly identifies country-specific supply shocks even in the presence of common shocks to import demand. Third, we apply our new measure of supply shocks in well-established models to estimate the effect of Chinese exports on U.S. labor markets. Our results from reduced form regressions a la Autor et al. (2013) suggest overall larger contractions of manufacturing employment. In the general equilibrium model from Caliendo et al. (2019), our shocks realign the implied sectoral manufacturing employment losses with standard Heckscher-Ohlin-based predictions.

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JEL Classification: F10

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1 Introduction

Since the early neoclassical trade theory we know that international trade can lead to individual income losses, but systematic evidence was elusive until recently.[1] A fast-growing and highly influential literature uses shift-share regression designs to identify adverse effects of trade on manufacturing employment, wages and other labor market outcomes. Often focussing on the likely case of Chinese exports, a number of prominent contributions instrument (China's) sectoral exports to one specific destination with (Chinese) sectoral exports to other, comparable destinations.[2] This strategy identifies causal effects if import demand shocks are uncorrelated across destinations.[3]

The current paper adds to this literature in three points. First, we provide robust evidence from trade data, which suggests that common import demand shocks are prevalent. Second, we develop a strategy to directly identify country-specific supply shocks from readily available sectoral trade data. Finally, we use the thus identified supply shocks to estimate the impact of China-specific supply shocks on U.S. labor markets, replicating reduced form estimates from Autor et al. (2013) and the general equilibrium effects in a calibration of Caliendo et al. (2019).

In the first step, we depart from 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. Thus, the correlation between export growth of China and export growth of its competitors is negative under idiosyncratic Chinese export supply shocks but positive under import demand shocks.

Figure 1 plots Chinese product-level export growth between 1991 and 2007 against corresponding growth of comparable emerging market economies (EMEs).[4] The strong positive correlation in Figure 1 suggests that China-

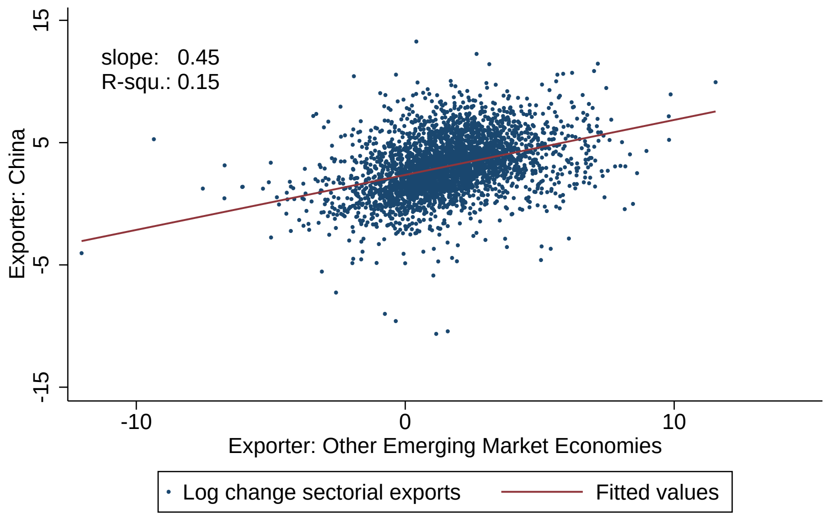
[1] Drawing on Ohlin (1933), among others, Samuelson (1948) observed that the owners of scarce factors may lose "their pre-trade privileged positions and [...] have lower real incomes" (p. 176). The lack of sufficiently granular data was an obstacle to identification in earlier work – see, e.g., Wacziarg and Wallack (2004).

[2] The literature is pioneered by Autor et al. (2013), sparking contributions reviewed below. Starting with Caliendo et al. (2019), the literature studies the China shock in general equilibrium models with labor market frictions. General methodological contribution on shift-share designs have been made, for example, by Adao et al. (2019) and Borusyak et al. (2021).

[3] The literature recognizes "...that in some sectors, import demand shocks may be correlated across countries. This would run counter to our instrumental variables strategy..." Autor et al. (2013) p. 2138.

[4] The choice of period is mainly data-driven as explained below. Comparable EMEs,

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.

specific supply shocks were not the dominant source of Chinese export growth and that, consequently, the assumption underlying the shift-share regression design applied in the recent literature may be violated.[5]

listed in the note to the figure, have a comparative advantage close to China's and are taken from Auer et al. (2013). Exports are reported by nine advanced economies for which the sector breakdown is available – see the note to Figure 1. A parallel figure based on exports to the United States looks very similar. See Appendix B for a detailed discussion of the data and Appendix B1 as to how the emerging market countries were chosen.

[5]Section 2 takes a closer look at the data, showing that the positive correlation in Figure 1 survives various relevant cuts through the data. For example, it is robust when controlling for country and sector effects, persists within the groups of homogenous and differentiated products and largely unrelated with the intensity of imported intermediate inputs.

In our second step, we offer a new identification of the share of Chinese export growth that is accounted for by China-specific supply shocks. We do so based on a parsimonious structural model that encapsulates standard general equilibrium trade models of the Armington type. Our methodology is based on readily available bilateral trade data and disentangles shocks that are specific to Chinese export supply from all other types of shocks.[6] It suggests that China-specific supply shocks account for roughly half of the growth of China's export to the United States for the period 1991 to 2000 and four-fifths for the period 2000 to 2007. This increasing role of supply shocks following 2000 is consistent with decreases in effective trade costs due to China's entry in the World Trade Organization (WTO) and with the accelerated productivity gains in China documented in the literature.[7] Methodologically, we offer a tool that allows direct identification of the supply-induced components of export growth for any sector and any time period. We thus improve upon the indirect approaches previously used.[8]

In the third and final step, we employ the supply shocks identified in the second step for two distinct empirical applications. In the first, we adjust the standard shift-share regression design from Autor et al. (2013), exploiting the variation of supply-driven import penetration across U.S. commuting zones. Our point estimates are broadly in line with the literature and suggest that Chinese import penetration to the United States severely impacted U.S. manufacturing employment.[9]

While reduced-form estimations identify important *differential* effects across commuting zones, they are inept to assess *aggregate* employment

[6]These residual shocks not only include those to U.S. demand but also shocks that are common to supply of all emerging market economies or shocks originating in third countries.

[7]See, e.g., Pierce and Schott (2016) and Handley and Limão (2017). We note that our method implies a higher supply-induced export growth than the one imputed by Autor et al. (2013). This observation does not contradict the positive correlation in Figure 1, as the positive correlation of log changes in Figure 1 may be driven by small sectors and implies little for the importance of the different types of shocks for *aggregate* trade flows. At the same time, we observe that the paramount importance of the sectoral dimension for the analysis in the literature based on shift-share regression design warrants a closer look at the underlying forces of sectoral export growth. See also our discussion in Section 2.5 below.

[8]The indirect approach in Autor et al. (2013) serves as a reference point in our third part and is discussed below.

[9]Our strategy to identify the China-specific export supply shocks is reminiscent of the *gravity estimates* presented in Autor et al. (2013) as a robustness check. As discussed in detail in Section 4.1, our identification differs from the *gravity estimates* in its approach as well as in the practical estimation results.

losses.[10] To assess aggregate effects, our second and main empirical exercise therefore turns to the state-of-the-art dynamic general equilibrium model of trade and labor markets from Caliendo et al. (2019). In this model, Ricardian productivity differences a la Eaton and Kortum (2002) give rise to international and inter-regional trade under an input-output structure as in Caliendo and Parro (2015), while labor market frictions as in Artuç et al. (2010) induce sluggish labor market responses.[11] We follow Caliendo et al. (2019) and assess regional and sectoral employment and welfare effects of Chinese supply shocks – once under the 'China-shock' in its standard identification from Autor et al. (2013) and once based on our own identification. In the former case, the model generates a drop of 0.22 million manufacturing workers in the United States between 2000 and 2007. This number jumps to 0.38 million under our identification.[12] The strong difference in the aggregate response between the two scenarios arises because our strategy attributes a higher share of total Chinese exports to export supply shocks.[13] In addition, the sectoral employment losses are markedly more dispersed under our specification of the China shock.[14] More importantly, they are systematically larger in labor-intensive sectors, which means that our identification realigns the aggregate general equilibrium effects with basic Heckscher-Ohlin intuition.

Our paper contributes to the dynamic literature on the labor market effects of international trade. A large part of the literature employs shift-share regression designs to study the effects of Chinese import penetration on U.S. labor markets technological progress and innovation (Acemoglu et al. 2014

[10]This standard shortcoming of the difference-in-differences approach is largely recognized in the context of the China shock, see, e.g., Adao et al. (2020).

[11]Caliendo and Parro (2021) chose a similar modelling design, adding endogenous capital structure formation and forward-looking location decisions of firms to study the impact of the 2018 U.S. import tariff increases on the location of economic activity.

[12]The corresponding number reported in Caliendo et al. (2019) is 0.55 million, which is due to different in scaling, as explained below in detail.

[13]Regardless of the specific identification strategy, the manufacturing employment losses in the general equilibrium model are much lower than those implied by a naive application of the reduced-form estimations. The latter are, e.g., 1.53 million between 1991 and 2007 according to Autor et al. (2013) and up to 2.4 million between 1999 and 2011 according to Acemoglu et al. (2016). We discuss the reasons and conceptual differences in Section 4.

[14]For example, relative to the standard identification, our China shock implies that employment losses in *Computer and Electronics* are much larger but turn into actual employment *gains* in the *Food* and in the *Petroleum* sector.

and Autor et al. 2016), political voting patterns (Autor et al. 2020, Autor et al. 2017) or the marriage market (Autor et al. 2019). Acemoglu et al. (2016) analyze the effects of China's exports on U.S. employment through up-stream and down-stream connectedness, while other studies assess the impact of Chinese exports on labor markets in Norway (Balsvik et al., 2015), Denmark (Ashournia et al., 2014, Utar, 2018), Germany (Dauth et al., 2014), and France (Malgouyres, 2017).[15] Our paper adds to this literature, first, by establishing a warning that common demand shocks may threaten the standard identification strategy and, second, by proposing an alternative identification strategy that circumvents an identification problem potentially affecting the approach in general.

Closely related work identifies the causal effects of Chinese exports on employment in other economies based on quasi-natural experiments. Thus, Pierce and Schott (2016) assess the effect of trade growth due to the elimination of trade-policy uncertainty (as potential increases of U.S. tariff on Chinese imports were removed).[16] Bloom et al. (2016) rely on the removal of product-specific quotas after China's entry into the WTO in 2001 to document a detrimental effect of Chinese import competition on employment in European countries.[17] Handley and Limão (2017) examine the impact of policy uncertainty on trade, prices, and real income in the United States following China's 2001 WTO accession.[18] By its very design, this literature is unaffected by our concerns but may raise questions about external validity.

Our paper also connects to the recent methodological advances in the shift-share literature that have refined the estimation strategy of Autor et al. (2013). Borusyak et al. (2021), Adao et al. (2019) and Goldsmith-Pinkham et al. (2020) highlight the importance of a priori exogeneity assumptions of shocks (Chinese export growth in the application to the China shock) and exposure shares (the according industry weights), respectively. Borusyak et al. (2021) show under which conditions exogenous shocks allow for identification in the presence of endogenous exposure shares. Our work complements this study by defining an a priori exogenous China shock, which

[15]See Autor et al. (2016) for a recent review of the literature.

[16]The authors identify a trade-induced shift towards less labor-intensive production, thus documenting a link between the two primary suspects of employment losses: trade and technological change. See also Autor et al. (2015), Dauth et al. (2021) on this point.

[17]The authors show that employment losses arise simultaneously with positive reaction of technical change. Parts of Keller and Utar (2016) and Utar, 2018 rely on the same identification strategy.

[18]McLaren (2017) offers an excellent overview of recent contributions. See also Di Giovanni et al. (2014) for the welfare effects of China's integration into the world economy.

can be readily incorporated in the proposed methodology.[19] In the same setup, Adao et al. (2019) show how to correctly compute standard errors if exposure shares are endogenous.[20] On the other hand, Goldsmith-Pinkham et al. (2020) show that the shift-share approach is "numerically equivalent to a generalized method of moments (GMM) estimator with [...] shares as instruments and a weight matrix constructed from" shocks (Goldsmith-Pinkham et al. (2020) p. 2587). The authors thus conclude that the use of the shift-share instruments is valid under an exclusion restriction on the exposure shares.[21] We share the point of departure with Goldsmith-Pinkham et al. (2020) in observing that the shocks traditionally used for identification may be endogenous. Relative to Goldsmith-Pinkham et al. (2020), we offer an alternative remedy to this problem through the structural identification of the China-specific sectoral supply shocks. As stated above, our approach has the advantage that the explicitly defined supply shocks may be incorporated in the framework of Borusyak et al. (2021).

By evaluating the effects of our newly identified China shock in a quantitative trade model, our paper relates to the recent literature that studies the effect of trade shocks in general equilibrium, such as Caliendo et al. (2019), Adao et al. (2020), Galle et al. (2020), and Rodríguez-Clare et al. (2020). In the current paper, we do not aim to develop new features of quantitative trade models and therefore choose to assess the general equilibrium effects of our shock using the framework of the seminal contribution by Caliendo et al. (2019), the only paper in the list above for which replication codes are available. In this growing literature advancing general-equilibrium models, exogenous trade shocks are typically identified as changes in model parameters that generate sectoral export growth predicted by reduced-form regressions.[22] Our paper thus contributes to this literature by providing

[19]Borusyak et al. (2021) "... encourage practitioners to use [their] framework only after establishing an a priori argument for the plausibility of exogenous shocks." Our methodology delivers precisely such exogenous shocks under our own identification assumptions.

[20]The authors use a placebo exercise with randomly generated shocks to show that traditional standard errors are too small due to regression residuals that are correlated across regions with similar exposure shares.

[21]Their diagnostics presented in an online appendix cast doubt on the general validity of the traditional shift-share approach in the case of the China shock.

[22]A common praxis rests on fitted values from a regression of Chinese exports to the United States on Chinese exports to other advanced economies, thus following a first-stage of Autor et al. (2013). This approach, pursued in Caliendo et al. (2019), Rodríguez-Clare et al. (2020) and Galle et al. (2020), mechanically attributes roughly the full aggregate trade growth to supply shocks, thus generating an inconsistency to the original decomposition in Autor et al. (2013). Adao et al. (2020), instead, regress sectoral trade growth on sets of exporter- and importer-fixed effects and transform the estimates in a model-

an alternative and, as we argue, improved identification of Chinese supply shocks that is not plagued by concerns about possible demand shocks.[23]

The remainder of our paper is organized as follows. Section 2 takes a critical look at the patterns presented in Figure 1, Section 3 lays out a simple model based on which the China-specific export supply-shocks are identified. Section 4 presents our empirical exercise (reduced form and general equilibrium) and the according results. Section 5 concludes.

2 A close look at sectoral export growth

This section scrutinizes the details of the pattern presented in Figure 1 to avoid premature conclusions from raw correlations.

Our initial observation is that positive China-specific supply shocks expand China's exports at the expense of its competitors' exports suggested and that, therefore, supply shocks generate a *negative* correlation between respective sectoral export growth. While Figure 1 is at odds with this prediction, it does not constitute conclusive evidence that Chinese exports were driven by other types of factors. We therefore review a number of factors that may account for the positive correlation illustrated in Figure 1. We classify these factors into three sets. First, those related to either product-specific effects (e.g., updates of classification and recording practices) or country effects (e.g., differences in economic growth), second, factors related to global values chains (GVC), and third those related to substitution within product classes (e.g., quality substitution and complementarities).

2.1 Sector and country effects

A possible concern is that the correlation in Figure 1 may be driven by the natural fluctuations of global exports not only due to taste shocks but new

consistent way into supply-effects (see Appendix A.4.1 in Adao et al. (2020)). The underlying estimated coefficients, however, are inept to disentangle common demand shocks to all importers from common supply shocks to all exporters by their very construction – they necessarily depend on the exact the choice of exporter- or importer-fixed effect that is dropped in order to avoid collinearity.

[23]We recognize that all of the studies above feature general equilibrium models with complex input-output structures, yet identify Chinese supply shocks ultimately ignoring the input-output structure, as outlined above. We do recognize that our method to identify Chinese supply shocks neglects the potential effects from global value chains as well and is thus not fully consistent with the models of the mentioned literature. Thus, our work improves upon the existing definition of supply shocks for general equilibrium models in one important way but not in all possible dimensions.

inventions or quite profane reasons such as reclassification or technological progress. For example, as products become smaller and lighter, the product *Electric motors and generators of an output not exceeding 37.5 W weighting less than 1 kg* (HS 85011020) may expand at the expense of *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 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.[24]

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 – i.e., the more similar is their comparative advantage.[25]

To assess this hypothesis, we proxy the degree of competition on international markets in two ways: first, through the similarity of the revealed comparative advantage and second, through the similarity of technology, proxied by per-capita income. As the first metric, we define, for country c, $prox_c^{CN}$ as the correlation of China's and country c's sectoral export shares (sector exports over total exports, logged) in the years between 1991 and 1995.[26]

The second metric relies on the relative GDP per capita, which measures 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 ample evidence that product differentiation depends significantly on the source country's capital endowments or income per capita (e.g., Schott 2003, Schott 2004, and Hallak and Schott 2011).

[24]Specifically, if countries with a composition of their export basket close to China's grow above average, the correlation in Figure 1 may arise through a mere composition effect.

[25]Implicitly, we thus assume that goods from destinations with comparable economic development are closer substitutes. We make this argument more explicitly in Section 3 below.

[26]Formally, this is $prox_c = corr(\ln[E_k^c / \sum_j E_j^c], \ln[E_k^{CN} / \sum_j E_j^{CN}])$, where k, j indicate products and c countries. We take five-year averages to address the concern that measurement errors may affect especially initial periods. Ideally, we would use lagged data, but trade data with HS classification was introduced in 1991. 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.

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

When moving to country-sector exports, we can investigate the correlation in Figure 1, while controlling for country- and product-fixed effects, thus addressing potential compositional effects mentioned above. For our formal test, we denote export growth (log difference of real values) of country c in sector j with $\Delta \ln(E_j^c)$. We test whether the conditional correlation between $\Delta \ln(E_j^c)$ and $\Delta \ln(E_j^{CN})$ increases with $prox_c^{CN}$ (induced by demand shocks) or decreases with $prox_c^{CH}$ (induced by Chinese supply shocks). We do so by determining the sign of the coefficient β in the following regression

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

where the *controls* include the base variables $\Delta \ln(E_j^c)$, $prox_c^{CN}$, and a set of dummies. ε_{cj} and is the error term. As explained above, predominant Chinese supply shocks would induce a negative coefficient β, since they make export market shares of close competitors move in opposite directions.

Table 1: Conditional correlation of Chinese and other countries' export growth and the 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1 reports the estimation results. Columns I - III correspond to the specifications where $prox_c^{CN}$ stands for the initial correlation of the log export shares, our measure of the similarity of revealed comparative advantage. 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' sectoral export growth. The point estimates on $proc_c$ and the interaction term imply that for a hypothetical country that is very similar to China's economic structure ($prox_c = 1$), its sectoral export growth moves at the rate of $1.253 - 0.453 = 0.8$ or almost one-to-one with Chinese export growth.[27] At the same time, a country that is maximally different from China has a sectoral export growth that is negatively correlated with China -0.453. Column II of the table refers to a specification that includes fixed effects for each product class, thus controlling for sector-specific export growth, potentially driven by sector-specific technology or demand shocks. While an assessment of the level of the conditional correlation is no longer possible, the point estimate of β confirms the general message conveyed by Figure 1: countries with a comparative advantage close to China's tended to experience more export growth in sectors in which Chinese exports grew most. Finally, Column III adds country fixed effects, controlling for differentials in country growth. Again, the coefficient of interest remains stable and statistically significant. Overall, 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.

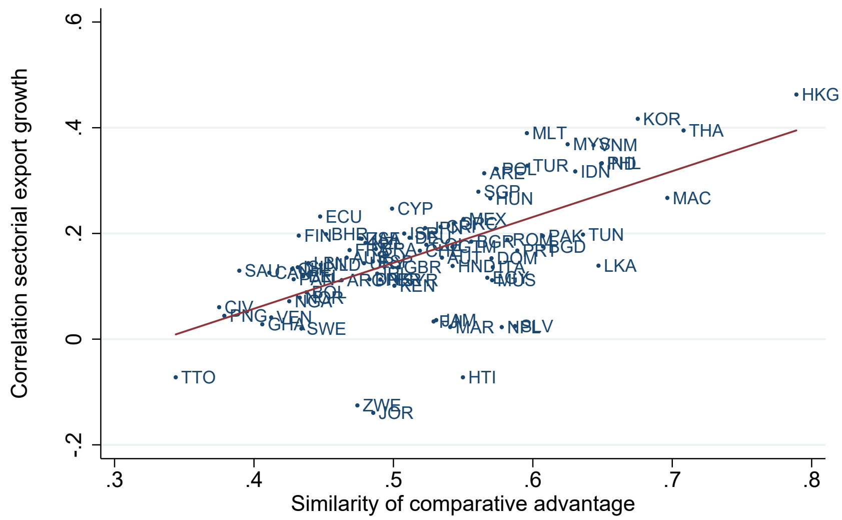
Columns IV to VI of Table 1 refer to specifications where $prox_c$ is defined as the similarity of per-capita income in the initial year 1991. As before, the estimation results document that the stronger a country's initial economic proximity to China, the higher (more positive) is the correlation between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

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 the national trend and above the global sector trend, so did sector exports of its direct competitor countries (and vice versa). These findings corroborate our earlier interpretation that China-specific supply shocks did not dominate Chinese export growth between 1991 and 2007.[28]

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

[28]We also point out that this section's results are consistent with the product cycle

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



Note: The vertical axis shows the correlation of sectoral export growth between China and the indicated country. The reference period is 1991 to 2007, sectoral export growth is defined as log changes of a 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, for the period 2000 to 2007 only.

2.2 Substitution Effects

Another potential concern is that the correlation in Figure 1 is driven by quality substitution. For example, increased supply of Chinese goods forced other EMEs to upgrade the quality of their exports, which increased the value of their exports. Such effects are documented in Brandt et al. (2017).[29]

theory put forward in Vernon (1966). 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. See Eriksson et al. (2021) for direct evidence on the role of the product cycle for Chinese export growth.

[29]See also Hallak and Schott (2011) and Khandelwal et al. (2013) for the role of quality in trade data.

In this case, the positive correlation in Figure 1 may reflect a pure price effect, as other EMEs upgrade their product quality and export more costly products within the same product category in response to Chinese export growth.

We address this concern by investigating the corresponding correlation between the volume exports (measured in kilogram) instead of its values.[30] Specifically, if the positive correlation in Figure 1 were generated by Chinese competitors substituting towards higher quality in other emerging economies, the correlation should turn negative when measuring exports by weight, because increases in export value due to price increases would be removed. Figures C3 and C4 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.

Another concern may be raised related to potential complementarities of varieties within product classes. For example, if China's integration in the world economy raises its supply of cheap tennis rackets to the United States, this could increase U.S. demand for Indian tennis balls.

We address this concern in two ways. First, we refer to the detailed classification of products, which make it unlikely that complements are classified within the same 6-digit HS category.[31] Complementarities cannot affect the correlation in Figure 1 if complementarities arise between different product classes.

Second, we investigate whether the correlation exhibited in Figure 1 holds within a sample of homogeneous and differentiated goods. Specifically, we argue that, in case the positive correlation of Figure 1 were driven by unobserved within-product complementarities, it should surface particularly strongly in a sample of horizontally or vertically differentiated goods, where such complementarities are more likely to be relevant. Conversely, in a sample of homogenous, standardized products, demand complementarities play arguably a minor or negligible role, a negative correlation should emerge due to underlying supply shocks. For a partition into the different sub-samples, we turn to the widely used classifications introduced by Rauch (1999), i.e., we look at the correlation of sectoral export growth of China and the EMEs separately for the three categories of homogeneous goods (least affected by demand complementarities), goods that are trade on or-

[30] Quality correlates with prices and prices correlate with unit values, see e.g., Hallak and Schott (2011), Auer et al. (2018), and prices are proxied by value over volume, see Berman et al. (2012) and the literature in Burstein and Gopinath (2014).

[31] In the specific example above, exports would be classified in two separate HS classes: 950651 for tennis rackets and 950661 for tennis balls.

ganized exchanges, or reference priced, (unlikely to be affected by demand complementarities), and differentiated goods (possibly affected by demand complementarities).

Figure C5 in the Appendix illustrates that, while the number of product classes is by far the largest for differentiated products (bottom panel), the positive correlation is equally present in the sample of homogeneous goods (top panel) and within the sample of reference priced goods (middle panel). Sectoral export growth of China and of other EMEs between 1991 and 2007 seems similarly synchronized within the three samples of goods. Figure C6 also presents the correlation of sectoral export growth for the period 2000 to 2007. Here, while still positive, the correlation for reference-priced goods is the weakest (middle panel). However, neither of the panels exhibits the negative correlation consistent with pure Chinese supply shocks.

Overall, the split of the sample into homogeneous, reference-priced, and differentiated goods gives no indication that the positive correlation from Figure 1 is driven by peculiar characteristics of differentiated goods. This observation, in turn, lets us conclude that demand complementarities are unlikely drivers of the strong positive correlation observed in Figure 1.

2.3 Global Value Chains

Another potential driver of the correlation in Figure 1 could be the Chinese supply of tradable intermediate inputs under intensifying Global Value Chains (GVC). If, for instance, a positive supply shock of Chinese intermediate goods or raw materials to the world market simultaneously spurred sectoral productivity in China and sectoral productivity in other emergent market economies, the supply shock to intermediates could result in a parallel sectoral export growth across all EMEs. The positive correlation in Figure 1 would thus emerge.

To some extent, this concern is addressed with the regressions that control for sectoral effects, reported, i.e., Columns II, III; V and VI from Table 1, as well as in Figure 2. In addition, we address the issue in two related but different ways. First, we regress Chinese export growth to the United States on Other EME's export growth to the United States, including dummies for the 15 manufacturing sectors for which data on input-output relations across the world is available in the WIOD (see Timmer et al., 2015).[32] If the WIOD sectors capture a relevant dimension of the input-output rela-

[32] Sector *Manufacture of coke, refined petroleum products and nuclear fuel* is dropped because of insufficient non-zero trade relations. We also use the data from WIOD in Section 4.2.1 and describe them in more detail in Appendix 5.

tions and if, at the same time, GVC contribute to the positive correlation in Figure 1, the estimated coefficient should drop when dummies for the WIOD sectors are controlled for. This is not the case, however. The coefficient drops from 0.359 in a regression without dummies to 0.312 in the regression that includes the dummies. If we rerun the regressions for each WIOD sector separately, the coefficients lie in the range $[-0.050, 0.631]$ or $[0.198, 0.631]$ when ignoring sectors with less than 100 observations. Neither of these results gives a strong indication that the input-output linkages in the WIOD account a relevant part of the correlation.

In a second step, we take the estimated coefficients corresponding to the separate regressions for each of WIOD sectors and relate them to the change in Chinese input supply. For that purpose, the intensity of Chinese input supply exports is defined as the change of China's market share in EME's imports of intermediate goods. If Chinese intermediate goods or raw materials did generate an export boom for China and in other EMEs, we would expect a positive relation between the estimated coefficient and the intensity of Chinese input supply. In this regression, the coefficient of interest (on the change in Chinese input supply to EMEs) is 0.307 with a standard deviation of 0.921 or, when weighting with the inverse standard error from the first step, 0.12 with a standard error of 0.581. Again, empirical evidence does not support the conjecture that GVC drive the positive correlation in 1.

Overall, we find no indication that GVC account for a substantial part of the positive correlation between Chinese exports and exports from other EMEs.

2.4 Sectoral export growth by destination markets

Our assessment so far casts doubt on the assumption that import demand shocks in high-income countries are uncorrelated. By aggregating data over all importers, however, 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 of the usual shift-share regression approach in Autor et al. (2013) is flawless when import demand shocks of both destinations are uncorrelated.[33] Conversely, the strategy leads to biased estimations if demand shocks between the United States and OAEs are correlated due to the correlation between the instrument and

[33] Autor et al. (2013) 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 does not dependent on individual sectors.

the dependent variable induced through channels other than the postulated Chinese supply shock. We address the question whether demand (or all residual) 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. Next, 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.[34] Finally, we correlate the common components of Chinese export growth to the United States and those to OAEs. Figure 3 plots the according correlation, showing a strong positive correlation between both common components. The figure suggests that residual Chinese export growth to the United States and residual Chinese export growth to OAEs have a strong positive correlation.[35]

Overall, our findings confirm our earlier conjecture based on Figure 1 that the identification strategy in Autor et al. (2013) 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 aim to disentangle the Chinese supply shock from other shocks in the following section next. In a subsequent step, we propose a new identification strategy.

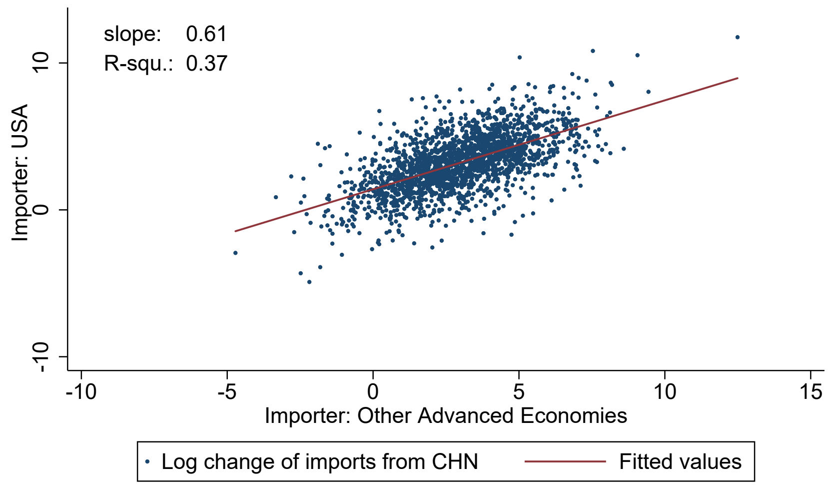
2.5 Discussion

Before proceeding, we clarify two issues to avoid misunderstandings. The first relates to the magnitude of U.S. imports from other EMEs. Autor et al. (2013) stress that over the relevant period 1991 to 2007, U.S. import growth from other EMEs fell short of corresponding imports from China by an order

[34]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. (2013). Therefore, whenever both common components are correlated, they will invalidate the identifying assumption in Autor et al. (2013).

[35]By 'demand-induced' Chinese export growth we mean all Chinese export growth not induced by China-specific supply chocks.

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.

of magnitude.[36] We emphasize that the logic of the argument and our use of exports from other EMEs is unrelated to the latter's absolute weight in the U.S. import basket. Instead, the EMEs importance derives from their role as an indicator of the *nature* of the shocks underlying Chinese export growth. They provide a litmus test, irrespective of their magnitude.

The second issue relates to the implications of the correlation in Figure 1 for aggregate Chinese exports. We stress that the information content of Figure 1 for the importance of China-specific supply shocks for *aggregate* Chinese exports is limited. At the risk of stating the obvious, we observe that, by plotting log differences in Figure 1, the correlation may be driven by very small sectors that barely contributed to aggregate export growth.[37]

[36]Discussing the potential impact of exports from other EMEs on their regression results, Autor et al. (2013) first point out that their increase was relative small in magnitude. They also include import penetration by other EMEs as a control variable.

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

We do not view this fact as a drawback of our strategy, however. Quite the contrary, since the estimation strategy of Autor et al. (2013) 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.

3 Identifying Chinese supply shocks

This section provides a model-based identification of Chinese export growth that is driven by China-specific supply shocks. Specifically, we isolate China-specific supply shocks from sector shocks that are common to all exporters. Based on a simple model, we identify the fraction of Chinese export growth that is driven by China-specific sector supply shocks and then use this fraction to alter and refine the estimation strategy in Autor et al. (2013).

Before we embark, however, we should clarify what this section aims to achieve. We do *not* separate supply and demand shocks. Instead, we will disentangle China-specific supply shocks from the combination of *all* remaining shocks.[38] The collection of all other shocks comprises, e.g., U.S. demand shocks, supply shocks that are not specific to China but common shocks related to technological change and shocks to demand of third countries that affect residual Chinese supply. We remain agnostic about the exact nature and composition of this collection of these other shocks. However, we claim that we can structurally identify China-specific supply shocks.

3.1 A simple theoretical framework

To identify Chinese sector supply shocks, we are guided by a simple Armington-type model with constant demand elasticities. This approach is consistent with a large number of quantitative trade models.[39]

Demand. Demand for product j with world price p_j is defined by

$$q_j^{demand} = a_j p_j^{-\sigma_j}, \tag{1}$$

as arising from preference structures à la Dixit-Stiglitz. The value of supply from country c equals $e_{cj} = p_j q_{cj}$ with $c = CN$ (China), $c = OE$

[38] Motivated by the usual 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. Clearly, there are other types of shocks than these two.

[39] In Appendix A, we spell out such a model in detail.

(Other Emerging Market Economies). The parameter a_j is a product-specific demand-shifter that depends on not only structurally on demand in the importing country, but also collects general equilibrium effects, e.g., driven by supply and demand of other goods that are imperfect substitutes.[40] We will allow a_j to be subject to all shocks that capture time-variation of the general equilibrium effects unrelated to the supply of q_j itself.

Supply. Aggregate supply of q_j is the sum of supply from two origin regions, China and other EMEs:

$$q_j^{supply} = q_{CNj} + q_{OEj}. \tag{2}$$

The quantity q_{CNj} is the quantity exported from China and q_{OEj} is the quantity exported from other EMEs. Specifically, we assume that goods produced in China and other EMEs are perfect substitutes.[41]

Our focus is on the effects of China-specific supply shocks between an initial period $t = 0$ and period $t = 1$. To distinguish the different supply shocks to EMEs, we define shocks that are common to China and all other emerging economies. These shocks will be represented by a factor χ_j that multiplies output of China and all other EMEs: $q_{cj,1} = \chi_j q_{cj,0}$ where $c = CN, OE$. An additional shock that is specific to China, is represented by the factor χ_j^{CN} and multiplies Chinese productivity only.[42] Collecting these supply shocks, we write

$$q_{cj,1} = \begin{cases} \chi_j q_{cj,0} & \text{if } \; c = OE \\ \chi_j^{CN} \chi_j q_{cj,0} & \text{if } \; c = CN. \end{cases} \tag{3}$$

Overall, we thus distinguish three different shocks. First, a shock to the parameter a_j in equation (1), capturing shocks to U.S. demand plus all types of general equilibrium effects unrelated to supply from EMEs (see Appendix A). Second, a common shock to supply of all exporting countries, represented

[40]See Appendix A, where a_j includes shocks to supply of varieties by other non-EME countries and demand for goods from specific regions.

[41]This assumption is a reflection of two observations. First, the 6-digit HS classification categorizes products at a very fine level of disaggregation, which largely excludes strong complementarities of varieties within the same HS-category. Second, the findings in Schott (2003) and Schott (2004) suggest that goods within the same narrow HS class are even closer substitutes 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 other countries.

[42]All factors referred to in the usual narrative of the China shock refer to market-oriented reforms and trade liberalization are represented by such China-specific shocks.

by the factor χ, and an additional China-specific shock represented by the factor χ^{CN}. All three shocks are allowed to be sector-specific.[43]

In the next steps, we aim to identify Chinese export growth stemming from χ_j^{CN}. As a first step, we will use the symbol D to denote changes between period, i.e., $DX_t = X_t - X_{t-1}$. Denoting further export value of country c at time t with $E_{cj,t} = p_{j,t} q_{cj,t}$, we decompose the change in export value into a price change and an exporter-specific supply

$$D\ln(E_j^c) = D\ln(p_j) + D\ln(q_{cj}), \tag{4}$$

where c denotes the exporter country. For notational clarity, we neglect importer indices here, but introduce them later.

We can now isolate the China-specific supply shock, χ_j^{CN}, by taking differences of (4) between China and other EMEs and using (3):

$$D\ln(E_j^{CN}) - D\ln(E_j^{OE}) \quad = \quad \ln(\chi_j^{CN}). \tag{5}$$

We notice that, by taking differences between suppliers, all common shocks – including those to a_j and those that affect the value of supply though prices – drop out in expression (5).

To isolate the change in the value of Chinese exports $E_{j,t}^{CN} = p_j q_{CNj}$ driven by χ_j^{CN}, we compute the partial derivative

$$\frac{\partial \ln(E_j^{CN})}{\partial \chi_j^{CN}} = \left[\frac{p_j'(q_j)}{p_j(q_j)} q_{CNj} + 1\right] \frac{\partial \ln(q_{CNj})}{\partial \chi_j^{CN}},$$

where p_j' is the partial derivative of p_j with respect to q_j. Since the shock to supply makes the equilibrium price slide along the demand curve, the fraction in the squared bracket can be expressed in terms of demand elasticities:

$$\frac{\partial \ln(E_j^{CN})}{\partial \chi_j^{CN}} = \left[1 - \frac{1}{\sigma_j} \frac{E_{j,0}^{CN}}{E_{j,0}^{OE} + E_j^{CN} j, 0}\right] \frac{\partial \ln(q_{CNj})}{\partial \chi_j^{CN}}. \tag{6}$$

Here, we have used (1) to replace $p_j'(q_j)/p_j(q_j) = -1/(\sigma_j q_j)$ and (2) to replace $q_{CNj}/q_j = E_j^{CN}/(E_j^{OE} + E_j^{CN})$.

Equation (6) delivers an expression for our object of interest – the response of Chinese exports to China-specific shocks – in marginal terms. We

[43] Chinese productivity gains resulting from trade liberalization are captured by the reduced form factor χ^{CN} specified in equation (3).

will now approximate the last term in (6), $\partial \ln(q_{CNj})/\partial \chi_j^{CN}$, with differences using (3):

$$\frac{\partial \ln(q_{CNj})}{\partial \chi_j^{CN}} = \frac{\ln(\chi_j^{CN}) - \ln(1)}{\chi_j^{CN} - 1} = \frac{\ln(\chi_j^{CN})}{\chi_j^{CN} - 1}.$$

To compute now the total response of exports, we need to multiply the expression for the marginal response, (6), with the magnitude of the shock, i.e., the term $\chi_j^{CN} - 1$. Replacing log differences with percentage changes also on the left hand side and combining all elements, we rewrite (6) as

$$\frac{\widehat{\Delta E}_j^{CN}}{E_{j,0}^{CN}} = \left[1 - \frac{1}{\sigma_j} \frac{E_{j,0}^{CN}}{E_{j,0}^{OE} + E_{j,0}^{CN}}\right] \ln(\chi_j^{CN}),$$

where we have indicated changes of export due to the China-specific shock with *hats*. Finally, we use equation (5) to replace the term $\ln(\chi_j^{CN})$. Doing so and replacing again log differences with percentage changes, we obtain:

$$\widehat{\Delta E}_j^{CN} = E_{j,0}^{CN} \left[1 - \frac{1}{\sigma_j} \frac{E_{j,0}^{CN}}{E_{j,0}^{OE} + E_{j,0}^{CN}}\right] \left[\frac{E_{j,1}^{CN}}{E_{j,0}^{CN}} - \frac{E_{j,1}^{OE}}{E_{j,0}^{OE}}\right]. \tag{7}$$

Equation (7) reflects the component of Chinese export growth in product class j that is induced by a China-specific sectoral shock. This specific component is our formal definition of what Autor et al. (2013) refer to as the 'China shock', i.e., China's increase in exports driven by the combination of China-specific factors, such as reforms towards a market economy, the reductions of trade barriers and further trade-facilitating factors related to its accession to the WTO.

Importantly, by formulating (7), we have expressed this specific component in terms of readily observable variables – mainly bilateral trade values and the demand elasticities σ_j, which can be taken from Broda and Weinstein (2004).[44]

Finally, we stress that we have not restricted the parameters a_j and χ_j to be constant. Any shock to these varieties is differenced out in equation (5), either directly (in the case of χ_j) or indirectly through the price p_j (in the case of a_j). Thus, our identification of Chinese export growth due to

[44]Export growth in equation (7), $E_{j,1}^{CN}/E_{j,0}^{CN}$ and $E_{j,1}^{OE}/E_{j,0}^{OE}$, respectively, is defined for generalized HS classes. The elasticities from Broda and Weinstein (2004) are defined as weighted averages, when generalized HS classes comprises more than one of the classes in the HS revision 1. Weights are proportional to overall imports to all nine AEs. In order to limit the influence of outliers, we also restrict the elasticities to be larger or equal to 1. This restriction affects about one percent of all generalized HS classes.

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 USD. Source: UN Comtrade and own calculations.

China-specific supply shocks allows for simultaneous shocks to U.S. demand, foreign competitors, third-country demand (through the parameter a) as well as supply shocks common to all EMEs (through the parameter χ).

3.2 Supply-driven Chinese export growth

Applying this procedure separately for Chinese exports to the United States and Chinese exports to OAEs, we can identify the supply-driven component of sectoral Chinese export growth to the United States and to OAEs, respectively. Summing over all sectors then gives the corresponding aggregates, which are reported in the first two columns in Table 2, expressed in USD 2007 billion. The last column reports the component of Chinese export growth that is explained by China-specific shocks, expressed as a share of total Chinese export growth. Specifically, our decomposition shows that 45.2% of the increase in Chinese exports to the United States from 1991 to 2000 was driven by China-specific supply shocks. This share increases to 79.2% for the consecutive period 2000 to 2007. Similarly, Chinese supply induced export growth to Other Advanced Economies is also large in that it explains more than half of total Chinese export growth over the two decades.

Two observations regarding the numbers in Table 2 are in order. First, the supply-induced Chinese export growth to the United States is considerably larger for the second period 2000 to 2007 than for the initial period 1991 to 2000. This fact is consistent with the common view expressed, among others, in Pierce and Schott (2016), Handley and Limão (2017), Bloom et al. (2016), and Caliendo et al. (2019), who argue that China's entry into the WTO and productivity gains accelerated its export growth to the United States but differently across sectors. The observation also corresponds to the more pronounced manufacturing job losses for the United States during the post-WTO period, which are typically reported in the literature.[45] Second, the decomposition into the supply-induced component and a residual by destination country also suggests that China's WTO accession increased Chinese exports to the United States much more than those to OAEs. This statement applies both to the dollar value of trade as well as to the share of trade growth explained by supply factors. This second observation can be attributed to the trade integration of Eastern Europe, which, as a low-wage competitor of China, was more important for Western European countries due to geographic proximity. It also resonates with the more pronounced job losses in the United States, relative to those in Other Advanced Economies (see, e.g., Dauth et al. 2014).

We argue that the identification of the supply-driven component of China's export growth reported in Table 2 already constitutes a contribution *per se*. First and foremost, it is directly applicable to different periods and regions. By comparison, the indirect decomposition in Autor et al. (2013) that rests on the different estimates in the OLS and 2SLS and does not apply separately to the sub-periods.[46] Moreover, the decomposition allows to estimate the impact of Chinese export supply on U.S. employment without the need to instrument due to endogeneity concerns. For example, referring to such a decomposition, Feenstra and Sasahara (2018) write that it "would be preferable to isolate the portion of such changes that could be viewed as exogenous to the United States..." to conduct their exercise of identifying trade effects on trade labor demand in a global value chain.

Before closing this section, we observe that our choice of a model-based identification of the Chinese trade shock does require two different assumptions. First, we rely on the arguably simple modelling choice of the Armington type. We make this assumption deliberately to stay close to the theoretical part in Autor et al. (2013), our main benchmark. Second, we assume, somewhat specifically, that within the same 6-digit HS categories, products

[45] At this point, we should point out that our theory does not require or predict any size of the supply-induced shock. In particular, trade growth for any sector, determined by equation (7), can be any real number and may, in particular, be either positive or negative. It is negative if exactly one of the cases applies: Chinese export growth falls short of export growth from other emerging economies or initial Chinese exports, measured as a share of total exports from emerging economies, is larger that the demand elasticity.

[46] In principle, the decomposition in Autor et al. (2013) could be applied separately based on OLS and 2SLS regressions from both sub-periods. In practice, however, Autor et al. (2013) argue that their panel regression that pools both sub-periods renders the most reliable estimates and is thus the preferable specification. Section 4 discusses the issue in more detail.

from EMEs are close substitutes among each other (see equation (2)). This assumption, in turn, is consistent with evidence prominently presented in Schott (2003) and Schott (2004), where the substitutability of goods within product-classifications is strong within countries grouped by their degree of economic development. In addition, we argue that the robustness of the patterns across product groups with apparent higher and lower within-product substitutability (see the split between homogenous, reference-priced and differentiated goods in Figure C5) indicates that the correlation of sectoral growth across countries, used in equation (7) and plotted in Figure 1, is unrelated to complementarities within product classes.

In sum, we argue that our decomposition of Chinese export growth rests on solid theoretical foundations and produces empirically sensible patterns that are well in line with common views on the main factors of Chinese export growth. In the next section, we will use our decomposition to identify the causal impact of Chinese exports on U.S. labor markets.

4 Applications of the China shock

This section describes the strategy and the results, when we use our identification of the Chinese supply shock to assess the labor market consequences of trade. We first adapt the strategy from Autor et al. (2013), running reduced-form regressions and subsequently turn to Caliendo et al. (2019) to assess the full general equilibrium effects of the Chinese supply shock.

4.1 Reduced-form regressions

Autor et al. (2013) assess the effect of import penetration on manufacturing employment by estimating

$$\Delta L_{i,t}^{m} = \gamma_t + \beta \cdot \Delta IPW_{i,t}^{CN,US} + X_{i,t}'\lambda + \varepsilon_{i,t}, \tag{8}$$

where $\Delta L_{i,t}^{m}$ is the decadal change in the manufacturing employment share of the working-age population in commuting zone i in the United States between period t and $t+1$. The main independent variable is *import penetration per worker*, defined as

$$\Delta IPW_{i,t}^{CN,US} = \sum_{j} l_{ij,t} \frac{\Delta E_{j,t}^{CN,US}}{L_{j,t}}, \tag{9}$$

where j identifies sectors and i commuting zones, $\Delta E_{j}^{CN,US}$ is the increase in sectoral exports from China to the United States between period t and

$t+1$, measured in constant 2007 USD. The variable $l_{ij,t} = L_{ij,t}/L_{i,t}$ stands for sector j's employment in commuting zone i ($L_{ij,t}$), expressed as a share of the local employment $L_{i,t}$. Finally, $L_{j,t}$ is total U.S. employment in sector j in the initial period t.

To identify the causal effects of Chinese export supply on U.S. labor markets, Autor et al. (2013) instrument the variable $\Delta IPW_i^{CN,US}$ with

$$\Delta IPW_{i,t}^{CN,AE} = \sum_j l_{ij,t-1} \frac{\Delta E_{j,t}^{CN,AE}}{L_{j,t-1}}. \tag{10}$$

where lagged employment variables are used to avoid a simultaneity bias.

We could use the supply-induced component of Chinese exports to the U.S. to adapt the regression (8) by replacing the key regressor (9) directly with the supply-induced component. Concerned about potential attenuation bias due to measurement errors, however, we instrument $\Delta IPW_{i,t}^{CN,US}$ in (8) by the equivalent of (10), defined with the supply-induced change in import penetration per worker

$$\widehat{\Delta IPW}_{i,t}^{CN,AE} = \sum_j l_{ij,t-1} \frac{\widehat{\Delta E}_{j,t}^{CN,AE}}{L_{j,t-1}}, \tag{11}$$

where $\widehat{\Delta E}_{j,t}^{CN,AE}$ is from (7). Overall, we thus follow closely the IV strategy from Autor et al. (2013), but for the first stage, where (10) is replaced by (11):

$$\widehat{\Delta IPW}_{i,t}^{CN,US} = \sigma \cdot \widehat{\Delta IPW}_{i,t}^{CN,AE} + X_{i,t}'\lambda + \nu_{i,t}. \tag{12}$$

The second stage is defined by (8).[47]

4.1.1 Main Results

Table 3 summarizes our estimation results corresponding to the panel regressions based on the stacked panel with changes between 1991 - 2000 and 2000 - 2007. The six columns correspond to Table 3 in Autor et al. (2013) and refer to specifications with an expanding set of control variables. To save space, however, we only report on the coefficient of interest for the variable,

[47] We also perform OLS estimates, which are somewhat smaller in magnitude, consistent with the concern regarding an attenuation bias, as discussed in an earlier version of this paper.

Table 3: Baseline Estimates, Balanced Panel 1991-2007

Dep Var: 10x Annual Change in Manufacturing Empl./Working-Age Population (in PP)	(1)	(2)	(3)	(4)	(5)	(6)
	(i) Replication ADH, 2SLS					
$\Delta IPW^{CN,US}$	-0.703***	-0.538***	-0.472***	-0.444***	-0.501***	-0.533***
	(0.066)	(0.105)	(0.101)	(0.091)	(0.100)	(0.102)
1st Stage F-Stat.	104.120	53.965	47.937	45.279	48.714	46.619
	(ii) Instrument: Supply-Induced exports to OAE					
$\Delta IPW^{CN,US}$	-0.629***	-0.491***	-0.438***	-0.591***	-0.489***	-0.519***
	(0.070)	(0.117)	(0.115)	(0.077)	(0.119)	(0.121)
1st Stage F-Stat	35.718	27.526	24.133	35.839	25.862	25.256

Columns (1) to (6) correspond to those of Table 3 of ADH successively including the control variables. These 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. Panel (i) reports regression results based on our replication of the 2SLS-estimates of ADH. Panel (ii) reports 2SLS regressions instrumenting the supply-induced measures with the measure based on supply-induced Chinese export growth to other advanced economies. Robust standard errors clustered on the state level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

$\Delta IPW_{i,t}^{CN,US}$.[48] The fully controlled specification reported in Column (6) is the specification preferred by Autor et al. (2013) and will be our relevant benchmark.

For comparison with the original estimates, Panel (i) of Table 3 reports the estimates from the two-stage estimation strategy in Autor et al. (2013). The estimated coefficient in the fully controlled specification of Column (6) is -0.533.[49] Panel (ii) reports the results from our adjusted specification, where $\Delta IPW_i^{CN,US}$ from (9) is instrumented by $\widehat{\Delta IPW}_i^{CN,AE}$ from (11). The point estimates are very similar in magnitude and do not differ in a statistical sense. The F-statistics indicate acceptable relevance of the instrument.

Table D3 in Appendix D reports the results for the period 2000 to 2007 in the same format as Table 3.[50] As in Autor et al. (2013), the cross-section es-

[48]The complete estimation results with the full set of dependent variables are reported in Tables D1 - D5 in the Appendix.

[49]Our estimates differ somewhat from those in Autor et al. (2013), as our variables are constructed with publicly available data from UN Comtrade. In particular, our estimates are slightly lower – the original estimate in Autor et al. (2013) corresponding to our Column (6) in Panel (i) is -0.596. We view this difference not as a problem for the original estimation strategy but rather as a confirmation of a robustness of the results across slightly distinct data sets.

[50]While Autor et al. (2013) stress that panel regressions are generally preferable, we concur with Feenstra et al. (2017) who regard the cross-section specification for the 2000 - 2007 period as the more meaningful, because the more substantive increase of Chinese import penetration to the United States occurred after China's accession to the WTO in

timates reported in Table D3, Panel (i) drop in absolute magnitudes relative to the one reported in Table 3. By comparison, the estimated coefficients of interest of our adjusted specification (the respective Panels (ii)) barely change. Autor et al. (2013) argue that the specification based on the full period 1990 - 2007 is preferable on econometric grounds, while the restriction to the period 2000-2007 has the advantage that variation of Chinese export growth stems from the period following China's accession to the WTO. Our identification strategy produces relatively stable estimates across periods.

4.1.2 Discussion and further results

Overall, our estimation strategy produces similar point estimates as the original strategy. Does this imply that our adaptation of the estimation strategy is technically correct but economically unsubstantial? Not quite – as the following naive computation of total job losses suggests.

To gauge the impact of supply-induced export growth on U.S. manufacturing employment, Autor et al. (2013) use the point estimates with export values to infer the number of job losses due to the China shock. We can follow this strategy, taking advantage of the fact that our identification strategy directly separates the value of supply-induced Chinese export growth from the part that was driven by other factors (see Section 3). Specifically, we combine the coefficient -0.519 (Panel (ii), Column 6 of Table 3) and the supply-induced share 0.792 (Table 2), with export growth of USD 1,839 per worker between 2000 and 2007 and U.S. mainland working-age population of 178.7, and 194.3 million in 2000, and 2007 (latter numbers from Census/ACS data, as reported in Autor et al. 2013). Together, these numbers imply 1.41 million manufacturing job losses between 2000 and 2007 ($1.839 * 0.792 * (178.7 + 194.3)/2 * 0.519/100 = 1.411$) in response to the Chinese export supply shock.[51] Our identification would thus imply an upward correction of manufacturing employment losses from roughly 0.98 million reported in Autor et al. (2013) for the period 2000 to 2007 – an increase of 43.7%.

These computations do suggest differences in our approach and the one

2001.

[51]The computation assumes a share of supply-induced Chinese export growth of 0.48. For the full period, the numbers are $[(157.6 + 178.7)/2 * 1.14 * 0.452 * 0.519/100 + (178.7 + 194.3)/2 * 1.839 * 0.792] = 0.450 + 1.411 = 1.861$ for our identification of the shock and $[(157.6 + 178.7)/2 * 1.140 + (178.7 + 194.3)/2 * 1.839] * (0.00596 * 0.48) = -1.53$ for the original – see footnote 31 in Autor et al. (2013).

from Autor et al. (2013).[52] But we treat them with caution and deliberately called them naive because the estimated coefficients presented in Tables 3 and D3 merely uncover *differential* employment effects between commuting zones. Inferring aggregate employment losses from these estimates makes the implicit assumption that commuting zones with zero change of import penetration per worker experienced zero employment effects. This assumption cannot be verified in partial equilibrium.[53] Instead, reliable information about total manufacturing employment losses must be based on a full general equilibrium model. Accordingly, we turn to such a model in the next section.

Before closing this section, we point out that our identification of the China-specific supply shocks is reminiscent of a specific robustness check in Autor et al. (2013). The authors design this robustness check based on a gravity estimation (abbreviated as *gravity estimates*) and is constructed as follows. Log differences between Chinese and U.S. exports to third markets are regressed on time-invariant sector and destination fixed effects. The time differences of the residuals are interpreted as the increase of Chinese exports driven by Chinese supply shocks relative to U.S. supply shocks, because demand and other common shocks are differenced out. These changes are then used to define a supply-induced change in import penetration, parallel to (10). Despite the similarity of our structural approach and the *gravity estimates*, there are important conceptual differences. First, since the approach of the *gravity estimates* in Autor et al. (2013) "captures changes in the productivity or transport costs of Chinese producers relative to U.S.," it rests on the changing supply conditions between China and the U.S., instead of those between China and other emerging markets. This has two undesirable implications. On the one hand, it may well pick up potential supply shocks common to emerging markets, the presence of which would be consistent with the correlation in Figure 1. On the other hand, the *gravity estimates* are prone by construction to bias estimations whenever the mechanics of the international product cycle are operating. According to these mechanics, ongoing innovation and standardization of production processes in advanced economies makes production continuously transit from advanced to emerging economies.[54] The effect of these forces is then counted twice (once as

[52] In Appendix D, we report that for some labor market segments – defined by gender and skill level – our identification strategy produces results that are qualitatively different from those in Autor et al. (2013).

[53] For example, Magyari (2017) documents positive employment effects for the U.S. economy.

[54] See Vernon (1966), Krugman (1979), Flam and Helpman (1987), and Eriksson et al.

the drop of U.S. export and another time as the increase in Chinese exports) thus artificially increasing the value of trade attributed to improving Chinese technology. As a second conceptual difference, taking difference between the technology change in China and the United States implies that the *gravity estimates* rest on the comparison of potentially very dissimilar products. As argued in Section 3 based on the findings in Schott (2003) and Schott (2004), goods within the same narrow are closer substitutes if they are produced in countries of similar economic development. Third, by imposing mild additional structure on the model (substitutability of products produced in EMEs), we are able to directly identify the supply-induced component of Chinese export growth and, in addition, exploit variation stemming from differences in sector-specific demand elasticities σ_j across products, as illustrated in equation (7). Finally, a direct comparison of the resulting estimates shows that the coefficients emerging from the *gravity estimates* are about half the size of those reported in Table 3 documenting stark differences from a practical point of view.[55]

4.2 General equilibrium analysis

While the reduced-form regressions from Autor et al. (2013) identify the differential effect across local labor market, the assessment of aggregate employment losses in response the China trade shock requires a general equilibrium approach. For that purpose, we turn to the model developed in Caliendo et al. (2019). This dynamic quantitative general equilibrium trade model suits our purpose because of the following three defining elements. First, it features segmented labor markets along sector and regional lines, thus capturing the dimensions along which the effects in Autor et al. (2013) operate. Second, it explicitly models worker's migration choice, thereby allowing for a comprehensive welfare analysis. Third, it features the full global value chain and thus captures not only the direct effects of imports on labor markets, but also indirect effects through access to imported inputs.[56]

In their assessment of the China shock, Caliendo et al. (2019) proceed as follows. They calibrate their model to bilateral sectoral trade from WIOD (Timmer et al., 2015) and regional employment data from the U.S. Census Bureau for the period 2000 to 2007. Given the thus defined baseline, the

(2021).

[55] The according coefficient is -0.29 in Panel E of Table 10 in Autor et al. (2013).

[56] Indirect effects are addressed in Magyari (2017) and Acemoglu et al. (2016), Feenstra and Sasahara (2018).

authors infer the Chinese sectoral productivity growth rates that account for the supply-induced sectoral export growth from China to the United States using the identification strategy from Autor et al. (2013). Finally, the consequences of the China shock are defined as the differential employment (welfare) between the model's baseline and its prediction *in the absence* of the inferred Chinese sectoral productivity changes.[57]

We follow this approach closely, only recalculating the Chinese productivity changes compatible with our own China-specific supply shock in the second step.[58] In the next subsection, we document the employment shifts and welfare changes due to our China shock. The comparison to the approach from Autor et al. (2013) used in Caliendo et al. (2019) documents that our approach produces larger results – both, in terms of aggregate employment losses and in terms of sectoral distribution.

4.2.1 Results

We now present the different predictions of the model from Caliendo et al. (2019) when the China shock is defined according to our definition and the definition in Autor et al. (2013). To compute the latter, we use, just as Caliendo et al. (2019), the first-stage regression from Autor et al. (2013), i.e., a regression of sectoral import growth to U.S. imports from China on Other Advanced Economies' imports from China, to predict U.S. import growth from China. Observing with Autor et al. (2013) that only 44% of U.S. imports from China are supply-driven, we re-scale the resulting prediction so that aggregate predicted trade growth equals 44% of total trade growth. The according results from the calibration serve as our point of comparison.[59]

The aggregate response in Manufacturing Employment. Figure 4 replicates Figure 1 from Caliendo et al. (2019) for our calibrations. It plots the response of aggregate employment in manufacturing (top left panel), services (top right), wholesale & retail (bottom left), and construction (bot-

[57] Appendix E provides an short overview of the model in Caliendo et al. (2019).

[58] To calculate the implied productivity changes we use a code that is not part of the replication package of Caliendo et al. (2019). We thank Fernando Parro for providing the code and for his patience with our related questions.

[59] The original number of 0.48 reported in Autor et al. (2013) on p. 2164 has been recently revised to 0.44. As we discuss in Appendix E, Caliendo et al. (2019) do not re-scale the predicted trade growth after the first-stage regression in Autor et al. (2013), which generates a predicted increase in U.S. imports from China that aggregates essentially to the entire aggregate import growth observed in the data. Their resulting effects are necessarily larger.

tom right) under the definition of the shock according to Autor et al. (2013) (blue lines) and according to our own identification (green lines). The vertical axis plots percentage points of initial manufacturing employment. Under our identification of the supply-induced Chinese export growth, the response is much larger than under the definition from Autor et al. (2013), owing to the fact that the aggregate changes are substantially larger under our definition (USD 147 billion instead of USD 94 billion). Translated to absolute numbers, however, the aggregate employment losses implied by our China shock are small (-0.38 million), when compared to the numbers from a naive application of the differential effect across commuting zones (-1.41 million).

As under the identification of Autor et al. (2013), a large part of the employment losses in the manufacturing sector are compensated by employment gains in services. The employment gains in the wholesales and retail and in the construction sector are smaller by an order of magnitude (in our identification of the China shock, the rate of non-employed actually drops by 0.15 percentage points in the long run – compare Figure 9 in Caliendo et al. 2019). In all of the four broader sectors, the response is more pronounced under our identification of the China shock than under the definition from Autor et al. (2013).

The Sectoral Dimension. The difference between our identification of the China shock and that from Autor et al. (2013) is also apparent when decomposing the overall manufacturing employment loss into its sectoral contributions. Figure 5 plots the sectoral contributions in percent (which, respectively, sum to 100 percent by definition) for the identification according to Autor et al. (2013) (blue bars) and for our identification (green bars). Two important facts stand out. First, there are clear differences of the sectoral contributions between the two approaches. For example, the sectors *Textiles*, *Computers and Electronics* and *Furniture* contribute much more to the aggregate according to our approach, while *Chemicals*, *Metal* and *Transport Manufacturing* contribute less.

Second, employment does not decrease universally across sectors. Indeed, the response of the *Food* and *Petroleum* sectors illustrates that manufacturing employment may actually *rise* in response to import competition even within broadly defined sectors.[60] This suggests that price drops due to imported intermediate inputs spur the output and employment of local

[60] For comparison, the reduced form regressions in Section 4.1 and in Autor et al. (2013) and Acemoglu et al. (2016) rely on 397 4-digit SIC industries.

Figure 4: Aggregate Response in Broad Sectoral Employment to the China Shock

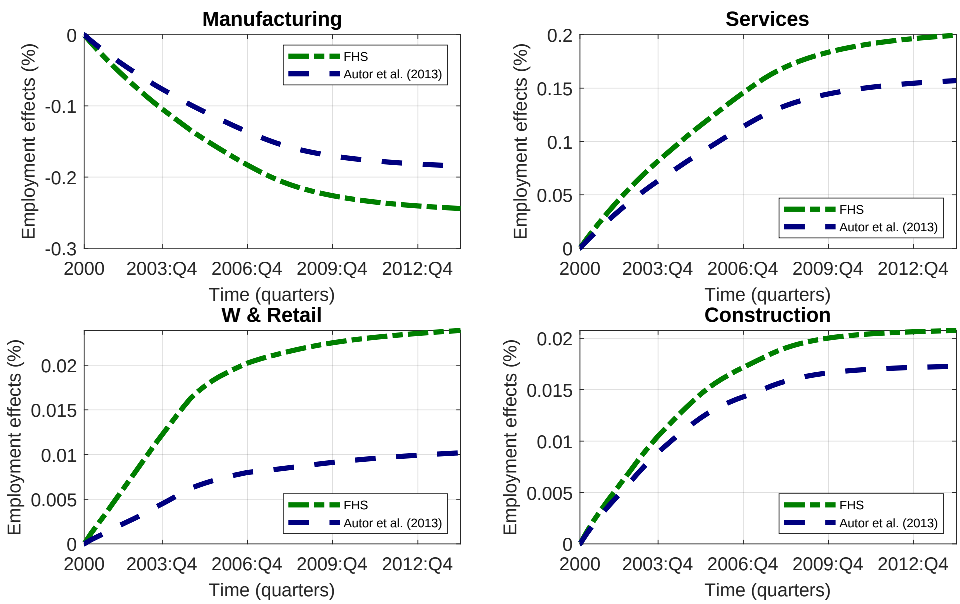
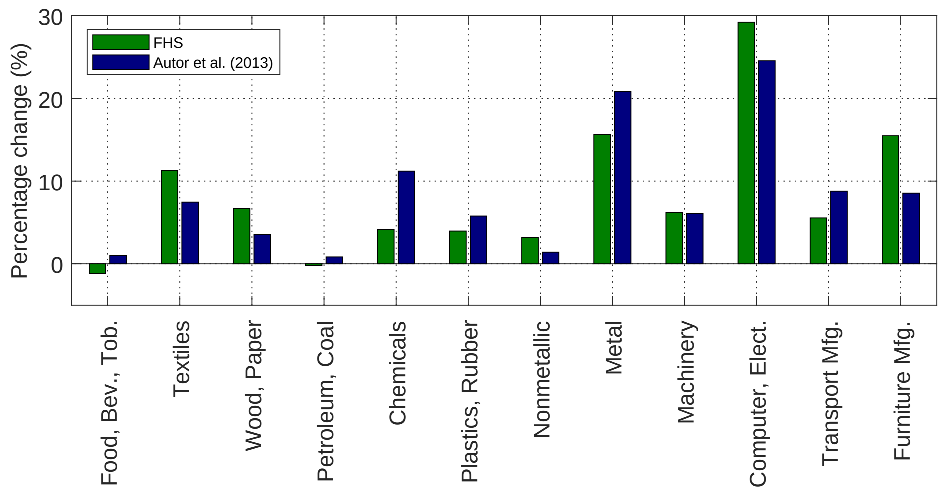


Figure 5: Sectoral Contributions to Manufacturing Employment Losses (% of total)

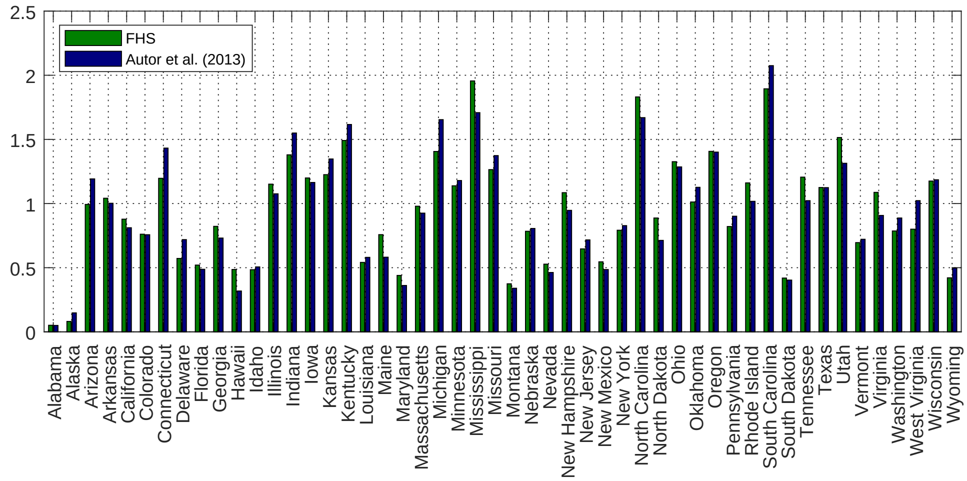


industries, as argued, e.g., by Magyari (2017) and Feenstra and Sasahara (2018).

The Geographic Dimension. The sectoral differences in manufacturing employment losses from Figure 5 translate into geographical differences, plotted in Figure 6. Here again, some differences emerge between our identification and the one based on Autor et al. (2013). On the one hand, under our identification strategy, employment losses are larger in Maine, Maryland, North Dakota, Tennessee, Utah and Virginia. On the other hand, losses are smaller in Arizona, Connecticut, Michigan and West Virginia. Overall, however, the differences in the regional employment response produced by the two approaches are relatively mild when compared to the pronounced differences in sectoral employment growth.

Welfare Effects. Next, we turn to an analysis of the welfare effects implied by our identification of the China shock. We follow Caliendo et al. (2019) and measure the welfare effect of the China shock as the change in discounted lifetime utility of a representative agent living and working in a

Figure 6: Regional Contributions to Manufacturing Employment Losses (normalized by initial employment shares)

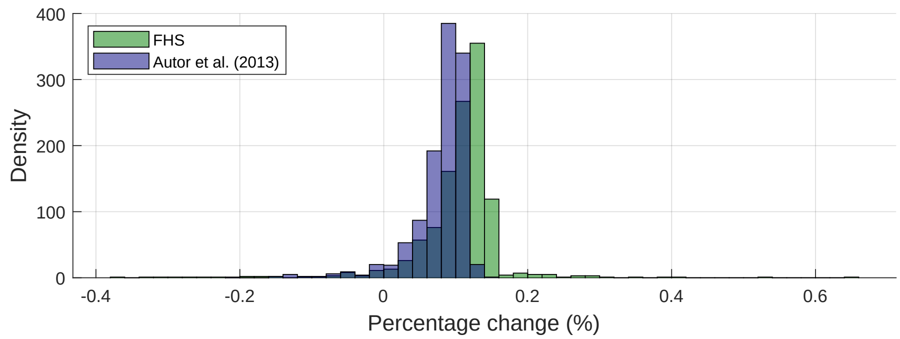


particular labor market (a sector-state combination) between the baseline scenario and the counterfactual. The change in lifetime utility comprises the evolution of differences in real consumption as well as differences in the option values of moving to a different sector-state. While a positive foreign technology shock such as the China shock always induces an increase in real consumption in a Ricardian setup without labor market frictions, this unambiguously positive effect may be overturned under segmented labor markets.

Figure 7 shows the distribution of the sector-state level changes in welfare for all sectors of the economy. Under our identification, workers in the median labor market gain 0.12% due to the China shock, 33% more than under the identification by Autor et al. (2013) (0.09%). This pattern also holds at the mean: we find a 0.11% welfare gain in our case compared to 0.08% for Autor et al. (2013). The aggregate statistics also hide more heterogeneity in the case of our identification: while the identification from Autor et al. (2013) implies a standard deviation of 0.04, our results imply a standard deviation of 0.07.[61] Figure 8 plots the welfare changes at the sector-state level for manufacturing industries only. While the absolute magnitude

[61] The skewness of the distribution of welfare effects is slightly positive (0.3584) under our identification, while the identification based on Autor et al. (2013) implies a skewness of -4.84. This is reflected in the observation that the distribution under the identification according to Autor et al. (2013) has a fatter left tail in Figure 7.

Figure 7: Regional Welfare Effects - All Sectors



Note: The horizontal axis shows model-implied welfare changes at the sector-state level in percent due to the China shock. The welfare measure is based on all industries.

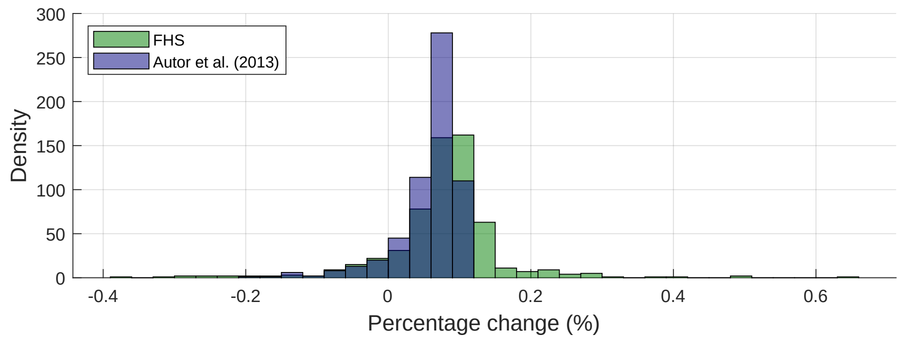
of the welfare effects falls slightly, we still observe that welfare effects are larger under our identification. We find a median welfare gain of 0.09% (0.07% under Autor et al., 2013), a mean welfare gain of 0.09% (0.06%) as well as a standard deviation of 0.09% (0.05%).

Another useful benchmark for our welfare analysis is provided by Galle et al. (2020). The authors evaluate the welfare consequences of the China shock in a static Ricardian general equilibrium model in which workers have different individual effective labor supply across sectors, but are immobile across commuting zones. The welfare measure in Galle et al. (2020) is specific to the labor force of a commuting zone and combines the change in real consumption due to the China shock with a measure of specialization of those workers across sectors. Whether specialization within a commuting zone rises or falls in response to a foreign shock depends on how the commuting zone's pattern of comparative advantage across sectors relates to the pattern of the country as a whole. A loss in commuting-zone-level specialization following an increase in Chinese productivity may overturn the positive impact on real consumption.

In their preferred specification, Galle et al. (2020) report aggregate welfare gains for the United States of 0.22%, which are larger than the aggregate U.S. welfare gains of 0.12% under our identification and those of 0.09% under the Autor et al. (2013) specification.[62] Similar to Galle et al. (2020), we

[62]This difference of the aggregate numbers stems from the fact that Galle et al. (2020), just as Caliendo et al. (2019), take the predicted values from the Autor et al. (2013) first stage as the supply-induced export growth, while we correct these values with the

Figure 8: Regional Welfare Effects - Manufacturing Only



Note: The horizontal axis shows model-implied welfare changes in percent at the sector-state level due to the China shock. The welfare measure is based on manufacturing industries.

find that the worst-off labor market loses about 5 times the average gain, which is about 0.5% of its real income in our case. In contrast to Galle et al. (2020), however, we find larger dispersion of gains at the top end: the best-off labor market gains about 10 times the average gain, about 1%, while in Galle et al. (2020), the best-off commuting zone gains about 6 times the average gain. In sum, we find that 96.4% of labor markets representing 99% of the initial population record a welfare gain from the China shock, while Galle et al. (2020) find that this is true for 85% of commuting zones covering 84% of the population.

The Role of Skill Intensity In a final exercise, we take a look at the relation between employment losses and skill intensity at the sector level. The limited number of broadly defined manufacturing sectors clearly impedes a fully-fledged statistical analysis. With that limitation in mind, we plot the intensity of low-skilled labor and overall labor (defined as the sec-

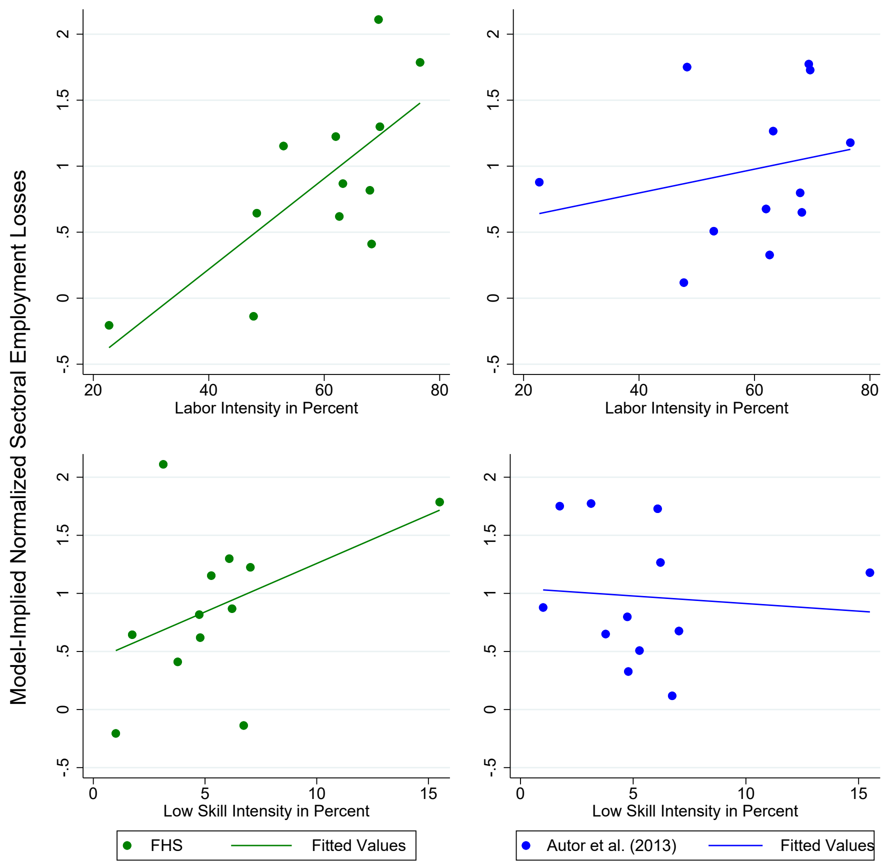
factor 0.44, as argued by Autor et al. (2013). Consequently, the mean commuting zone records a welfare gain of 0.27% in Galle et al. (2020), about 2.7 times the mean from our values considering all sectors. – When interpreting these numbers, we point out that the numbers in Galle et al. (2020) denote the welfare gain from the China shock for an entire commuting zone. It thus averages over all the workers in the group, within which some individual workers still potentially lose, e.g., if they stay in a shrinking sector. In our case, however, the unit of observation is a sector-state, and a welfare gain in a labor market in our setting implies that all workers in the labor market gain as they receive the same wage. With a value of 1.16, Galle et al. (2020) also report a larger coefficient of variation than we do (0.65).

toral wage bill of low skill labor or total labor as a share of value added in the United States in 2000) against the model-implied sectoral employment losses (in percent of total losses) normalized by initial manufacturing employment shares. The normalization corrects for initial sector size. Sectors with values above 1 therefore contribute more than proportionally to overall employment losses.

Given the abundance of (low-skilled) labor in the Chinese economy (see, e.g., Auer et al., 2013), a Heckscher-Ohlin-based argument strongly suggests that employment losses are more pronounced in sectors intensive in (low-skill) labor. Figure 9 plots the employment losses against the respective intensities for the twelve manufacturing sectors. The top left panel shows a strong positive correlation between the normalized model-implied sectoral employment losses (the same measure as in Figure 6, but at the sectoral level) and labor intensity of the sector, where we measure labor intensity as the share of labor compensation in total value added in the United States in the year 2000, i.e., before the China shock. The slope is significant at the 1%-level. The top right panel shows the correlation between model-implied employment losses and U.S. labor intensity for the counterfactual based on the specification from Autor et al. (2013). While the slope is positive, it cannot be distinguished from zero at conventional levels of statistical significance. In the two bottom plots, we repeat the exercise with low-skill intensity on the horizontal axis. We measure low-skill intensity as the share of low-skill labor compensation in total value added in the United States in 2000. Again, the slope is positive and significant at the 5%-level when we consider our counterfactual, while it turns negative and insignificant for the counterfactual from Autor et al. (2013). With the caution needed when interpreting patterns from twelve observations only, the figure suggests that our identification of the China shock generates labor market responses that are more in line with the factor proportions theory of trade.

Summing up, within the framework of Caliendo et al. (2019), our identification of the Chinese supply shock is different to the identification by Autor et al. (2013) in three dimensions. First, the implied manufacturing employment losses are higher and more dispersed. Second, welfare gains are larger and more heterogeneous. Third and finally, labor market responses are realigned with Heckscher-Ohlin-based expectations.

Figure 9: Model-Implied Normalized Sectoral Employment Losses and Initial U.S. Low Skill and Labor Intensity



Note: The vertical axis shows model-implied sectoral employment losses as a share of total losses normalized by initial employment shares. The horizontal axis measures low-skill intensity and labor intensity in percent as the share of low-skill labor compensation in value added and the share of overall labor compensation in value added, respectively. The slope coefficients for the FHS panels are 0.034 (significant at the 1%-level) in the upper panel and 0.083 (significant at the 5%-level) in the lower panel. For the Autor et al. (2013) panels, the slope coefficients are 0.009 (not significant) in the upper panel and -0.013 (not significant) in the lower panel.

5 Conclusion

The seminal paper by Autor et al. (2013) 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 in the United States and Other Advanced Economies. The present paper documents robust empirical patterns that are inconsistent with the identification assumption in Autor et al. (2013). Our paper thus uncovers a potential problem and calls for a mindful use of the identification strategy from Autor et al. (2013) that has enjoyed high popularity in recent years.[63]

To alleviate the documented problem, we propose a simple structural model to identify sector-specific Chinese supply shocks. Our approach allows a direct decomposition of Chinese exports into a supply-driven component and a residual for any given time-period. According to this method, almost 80% of aggregate Chinese exports to the United States between 2000 and 2007 were supply-driven, while Autor et al. (2013) infer a share of 44%.

Next, we use the resulting supply-induced Chinese exports to assess its impact on the U.S. labor market, first with reduced-form regressions and, second, in general equilibrium. In the first exercise, we adapt the estimation strategy in Autor et al. (2013) to our identification, which largely preserves the point estimates in the baseline from Autor et al. (2013). However, when we assess labor market consequences in general equilibrium with the state-of-the-art model from Caliendo et al. (2019), we document much larger aggregate manufacturing employment losses, a greater dispersion of sectoral employment responses and welfare changes and, finally, a realignment of the employment losses with standard Heckscher-Ohlin-based intuition.

[63]See. e.g., Ashournia et al. (2014), Balsvik et al. (2015), Dauth et al. (2014), Autor et al. (2014), Malgouyres (2017), Autor et al. (2020), Autor et al. (2019), Bloom et al. (2019) and Albouy et al. (2019).

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Appendix A: Nested CES Model

In this section, we motivate our choice of the reduced-form model in Section 3.1, 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

$$X = \left[\sum_{g=1}^{G} \gamma_g \left(\sum_{k \in S_g} x_{gk}^{1-1/\eta_g} \right)^{\frac{\eta_g}{\eta_g - 1} \frac{\sigma - 1}{\sigma}} \right]^{\sigma/(\sigma-1)} \tag{13}$$

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, $g = 1$ w.l.o.g.

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

$$\alpha_g x_g^{-1/\sigma} \left[\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)} \right]^{\sigma/(\sigma-1)-1} = \lambda p_g \tag{14}$$

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 (14) therefore becomes

$$\alpha_g x_g^{-1/\sigma} = \frac{p_g}{E} \sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)} \tag{15}$$

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[64]

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

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

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

[64]For the more general case, where E is a function of prices, 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

$$\sum_k x_{1k} = \Lambda p_1^{-\bar{\varepsilon}_1} \tag{16}$$

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 3.1. 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.

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. (2013). 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. (2013), we rely on publicly available trade data instead of mildly processed and cleaned ones, which results in slightly lower aggregates than those reported by Autor et al. (2013), 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. (2013), 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. (2013), 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. (2013) 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

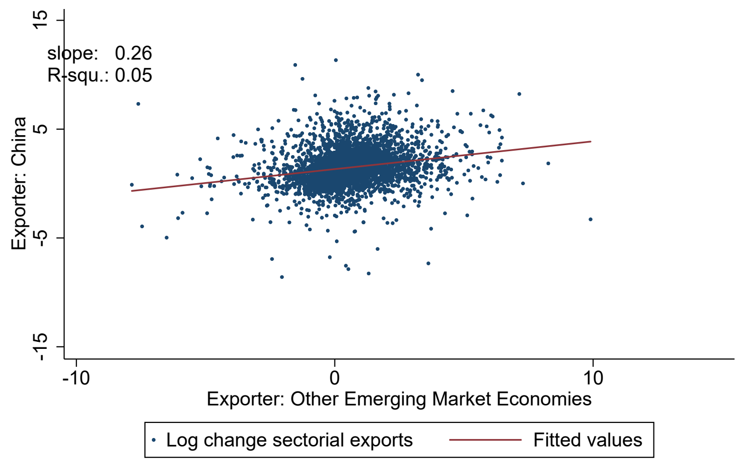
In identifying EMEs, we follow Auer et al. (2013), who define a country to be other emerging market economies if a nation's average GDP per capita (averages from 1995 to 2008) is less than 25% of the average GDP per capita (in current U.S. dollars) for Italy, Germany, France, Sweden, and the United Kingdom (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.

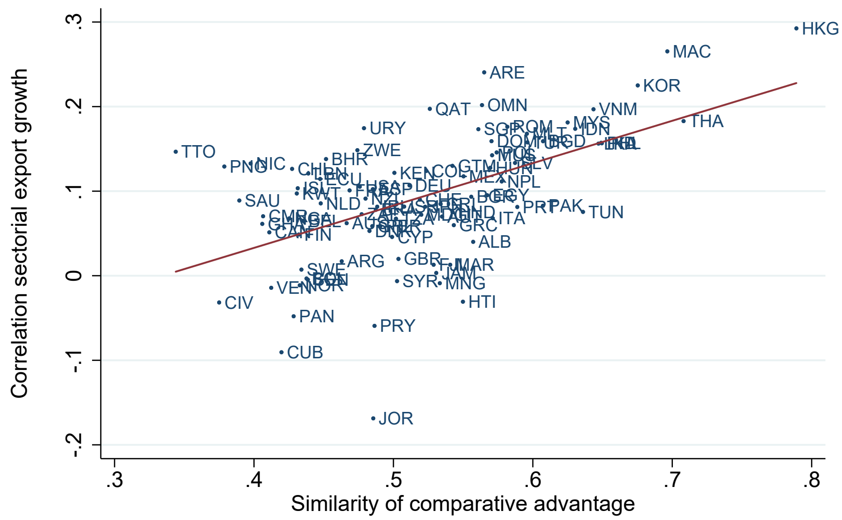
Appendix C: Figures

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



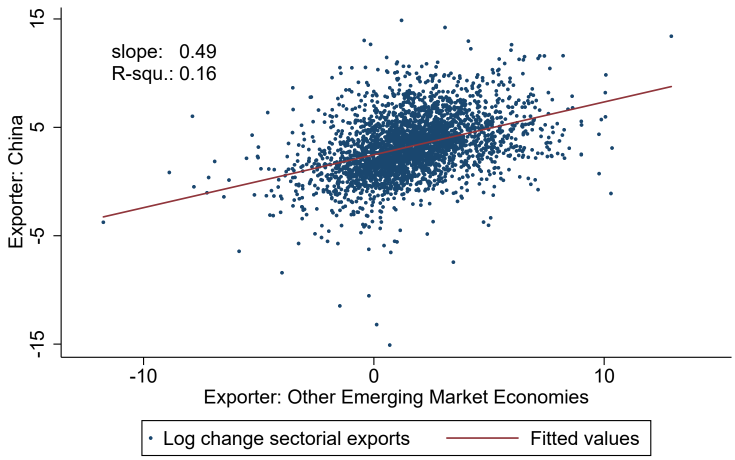
Note: Figure parallel to Figure 1 but for the period 2000 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the Figure. Data source UN Comtrade.

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



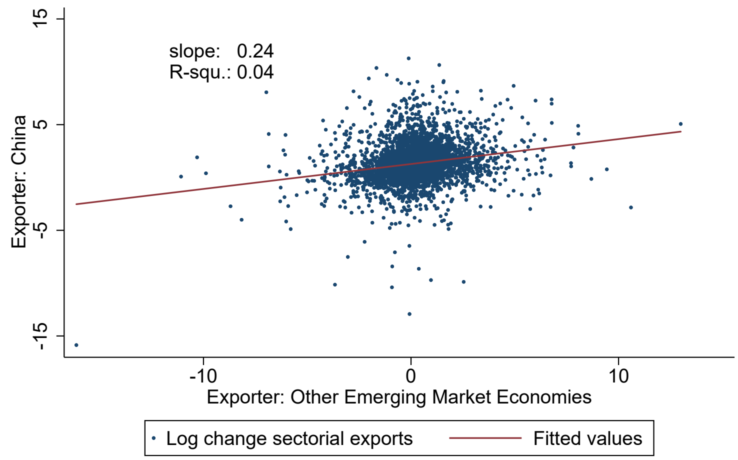
Note: Figure parallel to Figure 2 but for period 2000 to 2007. The similarity of comparative advantage on the horizontal axis is defined based on data of the years 1991 to 1995, described in Figure 2.

Figure C3: **Export weight: sectoral export growth of China and other EMEs,** 1991 - 2007



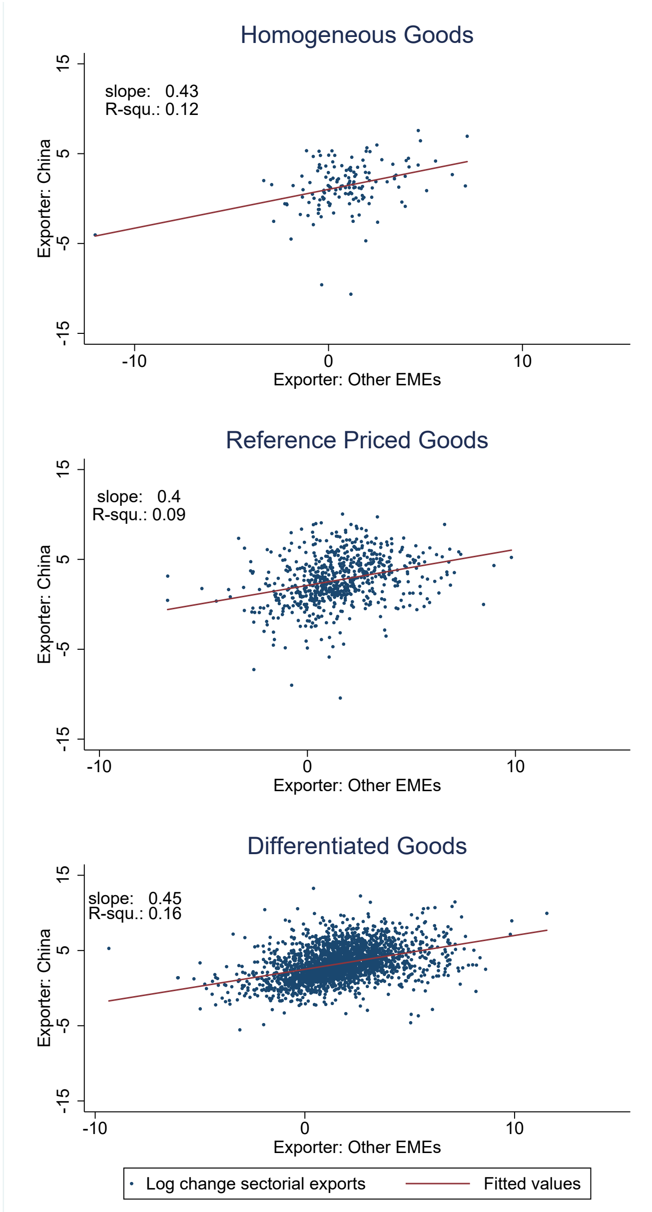
Note: Figure parallel to Figure 1 but for export weights (instead of value), 1991 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the Figure. Data source UN Comtrade.

Figure C4: **Export weight: sectoral export growth of China and other EMEs,** 2000 - 2007



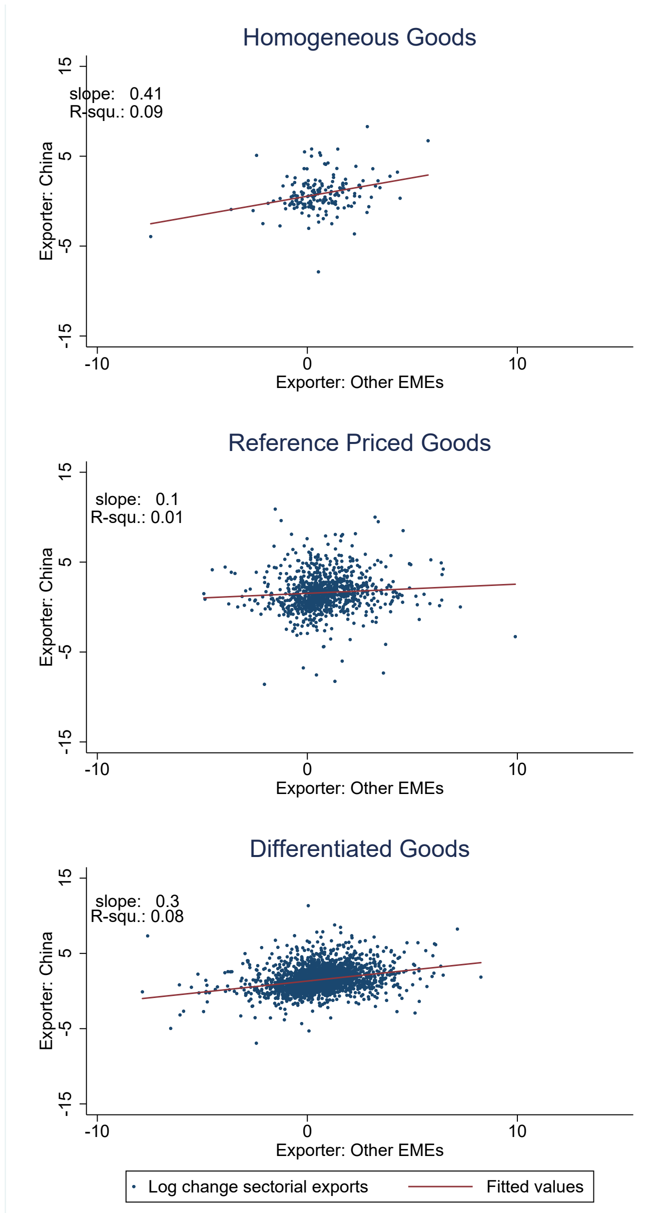
Note: Figure parallel to Figure 1 but for export weights (instead of values) and the period 2000 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the Figure. Data source UN Comtrade.

Figure C5: **Homogeneous and Differentiated Goods: China's Sectoral Export Growth**, 1991 to 2007



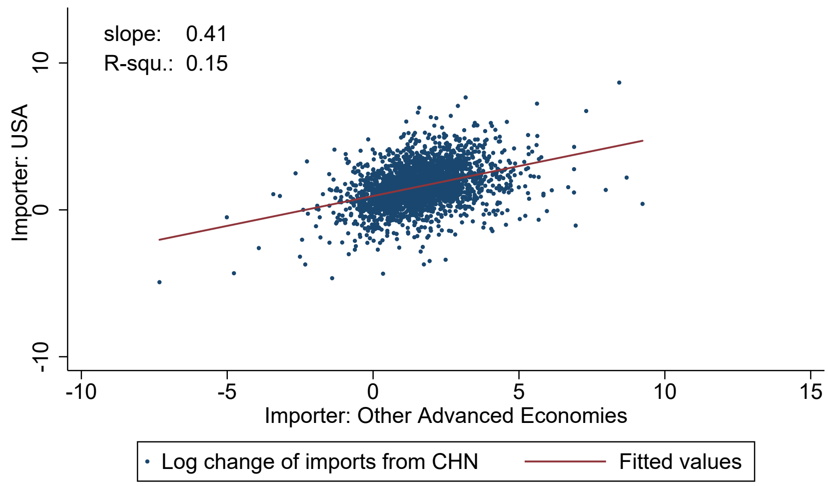
Note: Figure parallel to Figure 1 by product classification according to Rauch (1999).

Figure C6: **Homogeneous and Differentiated Goods: China's Sectoral Export Growth**, 2000 to 2007



Note: Figure parallel to Figure 1 by product classification according to Rauch (1999).

Figure C7: China's Sectoral Export Growth – Common Component with Other EMEs (2000 to 2007)



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

Appendix D: Tables

This section provides additional tables and discusses some of the results, comparing them to the original findings in Autor et al. (2013).

The first part of this appendix provides tables of regression results underlying Table 3, reporting the full set of estimated coefficients (Tables D1 and D2), a replication for Table 3 but with data for the period 2000-2007 (Table D3), and the according tables with the full set of estimated coefficients (Tables D4 and D5).

An important part of the analysis in Autor et al. (2013) focuses on specific segments of the U.S. labor market differentiated by gender, education and (non-)manufacturing sector. The second part of this appendix presents Tables D6 and D7 that report regression results by gender and education level and by manufacturing and non-manufacturing sector – corresponding to Tables 6 and 7 in Autor et al. (2013). This part shows that the estimates based on our identification somewhat qualify the message from Autor et al. (2013).

Thus, Column (1) of Table D6 reports that Chinese supply-induced exports have a slightly smaller impact on the average weekly wages in the United States than originally estimated by Autor et al. (2013). Especially for workers without College education, the point estimate drops along with the significance levels. These moderate effects on average wage are in line with the finding from by Panel (iv) of Table D7 in the Appendix, which reports no significant wage decreases across manufacturing (Columns (1)-(3)) and non-manufacturing (Columns (4)-(6)) sector, irrespective of the education level. The wage change of college-educated workers in the manufacturing sector are actually positive and marginally significant at the 10 % level (Column 2 of Panel (iv) in Table D6), which points to a potential selection effect through which the less productive workers in that segment lose their job.

These muted wage reactions are consistent with the strong contraction in employment, reported in Panel (ii) of Table D7 as changes in quantities tend to mitigate price reactions.[65] In particular, the reduction of employment is consistent with migration of college-educated workers out of those regions

[65] Associating high- and low-wages segments with education levels, Autor et al. (2014) use worker-level data to document that "low- and middle-wage workers experience substantial declines in earnings per year both at the initial firm and at subsequent employers. High-wage workers, by contrast, exhibit no adverse earnings effects, even as they move across firms and sectors". The same study also observes that "[i]mport exposure does in-

and sectors that are heavily affected by import penetration, as documented in Autor et al. (2014) with worker-level data. Further, it is also consistent with migration of non-college-educated workers into unemployment and with the drop of yearly earning losses reported in Autor et al. (2014).[66]

Returning to Table D6, the estimates in Columns (2) and (3) document that the impact on wages of female workers is less pronounced than reported in Autor et al. (2013). In view of the dichotomy between the reaction of wages and employment, this observation could point to especially severe employment losses of female workers. Our estimates thus emphasise the differences in the reaction of gender wages, contrary to Autor et al. (2013)[67] and to Dauth et al. (2014) who find, "by and large, homogeneous effects" across gender groups.

Specifically, the estimated effects of trade on wages we report in Table D6 indicate that male college educated seem to suffer wage losses most prominently – in absolute terms but also relative to female workers and to non-college-educated workers. While Autor et al. (2013) report wage losses to be -0.757 log points for all college-educated workers, -0.991 for male-college educated and (marginally significant) -0.525 for college-educated female workers.[68] By contrast, our corresponding estimates are -0.542, -0.781, and (insignificant) a much smaller value of -0.300. At the same time, we estimate that wage losses for male workers without college education to be much smaller (-0.382) and statistically insignificant (Panel (vi) in Table D6). These findings differ from those in Autor et al. (2013). Our identification strategy implies a sharper separation of the effects by gender, which would suggest, in particular, stronger employment losses for college-educated

deed shift the employment of high-wage workers from the initial CZ toward other regions" but do not observe similar patterns for workers with middle or low wages.

[66]The strong dichotomy between reaction in wages and in employment may be amplified by the fact that information in the employed census data refers to a specific reference week, for which weekly earnings and employment status are recorded – see footnote 38 in Autor et al. (2014) for a discussion. The authors conjecture that "the fall in within-year earnings [...] is reflected primarily in a rise in the odds of nonparticipation during the survey reference week in the census and American Community Survey data used in the Autor, Dorn, and Hanson (2013a) analysis".

[67]Autor et al. (2013) state that their "point estimates are somewhat larger overall for males than for females, with the largest declines found among college males and noncollege females, we do not have sufficient precision to reject the null hypothesis that impacts are uniform across demographic groups."

[68]These numbers are reported in Table 6 in Autor et al. (2013). Again, our estimates based on the original strategy in Autor et al. (2013) are somewhat smaller, see panels (i), (iii) and (v) of Table D6 in the appendix.

women.[69] Conversely, our estimates shine the spotlight on wage losses of college educated workers.

Distinguishing, in addition, the labor market effects in the manufacturing and the non-manufacturing sector (results are reported in Table D7), we find partial agreement with Autor et al. (2013). Thus, we confirm that employment losses are more pronounced within the manufacturing sector (Panels (i) and (ii)) but are not accompanied by wage losses (Panels (iii) and (iv)), which indicates the presence of selection effects.[70] Autor et al. (2013) conjecture "...that the most productive workers retain their jobs in manufacturing, thus biasing the estimates against finding a reduction in manufacturing wages." In contrast to Autor et al. (2013), our estimates suggest that these compositional effects were strong enough to generate *increases* of the average wage within manufacturing workers in reaction to supply-driven Chinese import penetration.

Finally, our estimated wage changes in the non-manufacturing sector (Panels (iii) and (iv) of Table D7) provide a different image than Autor et al. (2013). While Autor et al. (2013) detect substantial and statistically significant declines in the wage across education levels (point estimates for all, college and non-college are, respectively, -0.761, -0.743 and -0.822, see Table 7 in Autor et al. 2013), our supply-induced identification produces more moderate and insignificant estimates for all (-0.365), college workers (-0.432) and non-college workers (-0.256). Our results thus point at a stronger segmentation of manufacturing and non-manufacturing sector at the regional level.

Overall, our estimations in Tables D6 and D7 refine the findings from Autor et al. (2013), clearly focussing on the adverse effects for specific labor market segments: male vs. female, college-educated vs. non-college-educated workers, and manufacturing vs. non-manufacturing sector.

How do our findings relate to existing studies? First, they are in line with the literature which indicates that higher mobility of high-skilled workers shields them from adverse effects or enables them to reap benefits in response to structural change – either under trade shocks (e.g., Autor et al. 2014 and

[69] Autor et al. (2013) state that "relative employment declines are larger among females" but do report the trends separately by education level.

[70] As Autor et al. (2013), our estimated employment losses seem to be pronounced in the manufacturing sector. The point estimates for the sample of manufacturing workers reported in Autor et al. (2013) are -4.231 for all, -3.992 for college and -4.493 for non-college workers. They are somewhat lower than our estimates of -4.948, -5.182 and -4.761.

Bloom et al. 2019) or in the context of offshoring (e.g., Hummels et al. (2014) and Carluccio et al. (2019).[71]

Our findings that trade exposure may generate marginal gains for college educated workers (Panel (iv) in Table D7) are also consistent with studies on the impact of Chinese trade on employment along the firm dimension, such as Magyari (2017), who reports that "firms expanded skilled employment by taking advantage of falling production costs due to increased offshoring" and Bloom et al. (2019), who report that the Chinese trade shock reallocated "jobs from manufacturing in lower income areas to services in higher income areas".[72]

Ultimately, the exact reasons for the wage changes in Tables D6 and D7 (increased competition versus compositional effects) and analyses of the reallocation across- and within regions, sectors and skill groups must be based on worker-level data, as done in Autor et al. (2014) and Bloom et al. (2019). While such exercises are beyond the scope of the present study, we reiterate the need of a clean identification strategy of such studies based on supply-induced Chinese exports.[73]

[71]Hummels et al. (2014), who document wage premia for highly educated workers at Danish firms that engage in offshoring, Carluccio et al. (2019) study the issue for French firms.

[72]Magyari (2017) investigates within-firm and between-establishment reallocation and finds that, by reducing costs at the firm level, offshoring leads to an increase in total manufacturing employment in those industries in which the United States has a comparative advantage. In a related study, Bernard et al. (2016) document that the decline in Danish manufacturing employment is largely accounted for by firm exit and reorientation of manufacturing firms towards the service sector. Relatedly, Fort et al.(2018) document that a large U.S. firms simultaneously operate establishments in the manufacturing and non-manufacturing sectors and that these multi-sector firms have expanded their non-manufacturing employment in services and wholesale.

[73]Such further work may also relate to the literature on wage polarization. E.g., Autor and Dorn (2009) document that "middle-skill, routine task-intensive" workers have migrated "toward the tails of the occupational skill distribution," i.e., either towards the high-income or towards the low income segments of labor markets.

Table D1: Replication ADH – panel 1991 to 2007

	Replication of ADH 2SLS (corresponds to Table 3, Panel (i))					
	(1) ΔL^m	(2) ΔL^m	(3) ΔL^m	(4) ΔL^m	(5) ΔL^m	(6) ΔL^m
$\Delta IPW^{CN,US}$	-0.703***	-0.538***	-0.472***	-0.444***	-0.501***	-0.533***
	(0.066)	(0.105)	(0.101)	(0.091)	(0.100)	(0.102)
Perc. of empl. in manufacturing		-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)
Perc. of college-educated population				-0.011		0.012
				(0.016)		(0.012)
Perc. of foreign-born population				-0.009		0.031***
				(0.008)		(0.011)
Perc. of empl. among women				-0.054**		-0.003
				(0.025)		(0.024)
Perc. of empl. in routine occupations					-0.232***	-0.247***
					(0.065)	(0.066)
Average offshorability index of occupations					0.196	-0.117
					(0.253)	(0.240)
fsf	104.120	53.965	47.937	45.279	48.714	46.619

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D2: 2SLS with Supply-induced exports – panel 1991 to 2007

	Supply Induced 2SLS (corresponds to Table 3, Panel (iii))					
	(1) ΔL^m	(2) ΔL^m	(3) ΔL^m	(4) ΔL^m	(5) ΔL^m	(6) ΔL^m
$\Delta\widehat{IPW}^{CN,US}$	-0.905***	-0.633***	-0.552***	-0.454***	-0.653***	-0.691***
	(0.106)	(0.156)	(0.151)	(0.142)	(0.187)	(0.188)
$\Delta IPW^{\mathrm{L},\ CN,US,res}$	-0.160	-0.081	-0.058	-0.004	-0.087	-0.093
	(0.109)	(0.097)	(0.093)	(0.084)	(0.121)	(0.121)
Perc. of empl. in manufacturing		-0.062***	-0.076***	-0.087***	-0.077***	-0.061***
		(0.023)	(0.021)	(0.020)	(0.018)	(0.015)
Middle atlantic dummy			0.339*	0.005	0.568***	0.503*
			(0.200)	(0.188)	(0.168)	(0.283)
East north central dummy			1.123***	0.877***	1.429***	1.510***
			(0.257)	(0.291)	(0.257)	(0.328)
West north central dummy			1.898***	1.875***	1.666***	1.818***
			(0.496)	(0.559)	(0.438)	(0.415)
South atlantic dummy			0.052	-0.271	-0.133	-0.107
			(0.275)	(0.309)	(0.261)	(0.239)
East south central dummy			1.208***	0.506*	1.062***	1.198***
			(0.259)	(0.292)	(0.199)	(0.312)
West south central dummy			1.357***	0.717***	1.016***	0.968***
			(0.145)	(0.210)	(0.150)	(0.209)
Mountain dummy			0.949***	0.608**	0.562**	0.560**
			(0.246)	(0.275)	(0.220)	(0.252)
Pacific dummy			0.834***	0.518**	0.728***	0.307*
			(0.137)	(0.208)	(0.177)	(0.184)
Perc. of college-educated population				-0.007		0.018
				(0.016)		(0.012)
Perc. of foreign-born population				-0.011		0.027**
				(0.008)		(0.011)
Perc. of empl. among women				-0.059**		-0.011
				(0.025)		(0.026)
Perc. of empl. in routine occupations					-0.251***	-0.264***
					(0.060)	(0.062)
Average offshorability index of occupations					0.339	0.052
					(0.240)	(0.258)
fsf	43.819	32.332	30.262	29.961	28.571	27.448

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D3: Baseline Estimates, Cross-Section 2000-2007

Dep Var: 10x Annual Change in Manufacturing Empl./Working-Age Population (in PP)	(1)	(2)	(3)	(4)	(5)	(6)
	(i) Replication ADH, 2SLS					
$\Delta IPW^{CN,US}$	-0.671***	-0.340***	-0.344***	-0.342**	-0.345***	-0.386***
	(0.068)	(0.116)	(0.129)	(0.133)	(0.114)	(0.120)
1st Stage F-Stat.	77.391	34.742	29.959	27.364	30.237	27.900
	(ii) Instrument: Supply-Induced exports to OAE					
$\Delta IPW^{CN,US}$	-0.572***	-0.353***	-0.396***	-0.564***	-0.414***	-0.450***
	(0.075)	(0.117)	(0.137)	(0.099)	(0.120)	(0.124)
1st Stage F-Stat	29.044	21.673	17.938	29.232	20.583	20.019

Columns (1) to (6) correspond to those in Autor et al. (2013) successively including the control variables. See also notes to Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Replication ADH – cross section 2000 to 2007

	Replication of ADH 2SLS (corresponds to Table D3, Panel (i))					
	(1) ΔL^m	(2) ΔL^m	(3) ΔL^m	(4) ΔL^m	(5) ΔL^m	(6) ΔL^m
$\Delta IPW^{CN,US}$	-0.671***	-0.340***	-0.344***	-0.342**	-0.345***	-0.386***
	(0.068)	(0.116)	(0.129)	(0.133)	(0.114)	(0.120)
Perc. of empl. in manufacturing		-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)
Perc. of college-educated population				-0.031		-0.002
				(0.024)		(0.020)
Perc. of foreign-born population				0.013		0.056***
				(0.010)		(0.013)
Perc. of empl. among women				0.014		0.069*
				(0.040)		(0.038)
Perc. of empl. in routine occupations					-0.104	-0.135
					(0.103)	(0.092)
Average offshorability index of occupations					-0.091	-0.798**
					(0.356)	(0.330)
fsf	77.391	34.742	29.959	27.364	30.237	27.900

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D5: 2SLS with Supply-induced exports – cross section 2000 to 2007

	Supply Induced 2SLS (corresponds to Table D3, Panel (iii))					
	(1) ΔL^m	(2) ΔL^m	(3) ΔL^m	(4) ΔL^m	(5) ΔL^m	(6) ΔL^m
$\widehat{\Delta IPW}^{CN,US}$	-0.740***	-0.461***	-0.519***	-0.497***	-0.595***	-0.622***
	(0.108)	(0.149)	(0.168)	(0.173)	(0.179)	(0.182)
$\Delta IPW^{\mathrm{L},\ CN,US,res}$	-0.073	-0.078	-0.087	-0.067	-0.112	-0.093
	(0.091)	(0.082)	(0.088)	(0.083)	(0.107)	(0.107)
Perc. of empl. in manufacturing		-0.119***	-0.111***	-0.116***	-0.108***	-0.092***
		(0.027)	(0.030)	(0.033)	(0.028)	(0.025)
Middle atlantic dummy			0.370	0.220	0.541*	0.628
			(0.254)	(0.297)	(0.320)	(0.419)
East north central dummy			0.184	0.167	0.403	0.658
			(0.466)	(0.441)	(0.564)	(0.519)
West north central dummy			1.413**	1.462**	1.361**	1.415***
			(0.611)	(0.615)	(0.608)	(0.517)
South atlantic dummy			-0.143	-0.232	-0.188	-0.028
			(0.337)	(0.355)	(0.346)	(0.329)
East south central dummy			0.905***	0.880**	0.977***	1.628***
			(0.316)	(0.358)	(0.342)	(0.399)
West south central dummy			1.369***	1.224***	1.247***	1.447***
			(0.263)	(0.322)	(0.302)	(0.325)
Mountain dummy			0.618*	0.624	0.456	0.648
			(0.358)	(0.402)	(0.383)	(0.422)
Pacific dummy			1.367***	1.145***	1.335***	1.066***
			(0.255)	(0.341)	(0.320)	(0.330)
Perc. of college-educated population				-0.022		0.005
				(0.025)		(0.021)
Perc. of foreign-born population				0.015		0.057***
				(0.010)		(0.014)
Perc. of empl. among women				0.011		0.062
				(0.041)		(0.042)
Perc. of empl. in routine occupations					-0.149	-0.179*
					(0.109)	(0.097)
Average offshorability index of occupations					0.240	-0.517
					(0.357)	(0.380)
fsf	25.903	21.237	19.977	21.806	19.974	19.485

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D6: Wage Effects by Gender - by Education Level, panel 1991-2007. (corresponds to Table 6 in Autor et al. (2013))

Dep Var: Ten-year equivalent changes in average log weekly wage

	All workers (1)	Male workers (2)	Female workers (3)
All Education Levels			
Panel (i): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	-0.680***	-0.799***	-0.547**
	(0.245)	(0.284)	(0.227)
Panel (ii) Supply-Induced 2SLS			
$\Delta IPW^{CN,US}$	-0.504**	-0.677**	-0.300
	(0.247)	(0.296)	(0.223)
College Education			
Panel (iii): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	-0.680**	-0.891**	-0.463*
	(0.300)	(0.362)	(0.267)
Panel (iv) Supply-Induced 2SLS			
$\Delta IPW^{CN,US}$	-0.542*	-0.781**	-0.300
	(0.307)	(0.382)	(0.273)
Non College Education			
Panel (v): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	-0.716***	-0.605**	-1.003***
	(0.227)	(0.243)	(0.258)
Panel (vi) Supply-Induced 2SLS			
$\Delta IPW^{CN,US}$	-0.395*	-0.356	-0.549**
	(0.234)	(0.257)	(0.265)

All regressions include the full vector of control variables from Column (6) of Table 3. Robust standard errors clustered on the state level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D7: Employment Effects on Manufacturing and Non-manufacturing by Education Level, Panel 1991-2007 (corresponds to Table 7 in Autor et al. (2013))

Dep Var: Ten-year equivalent changes in log workers, log wage

	Manufacturing Sector			Non-Manufacturing Sector		
	All workers	College	Non-College	All workers	College	Non-College
	(1)	(2)	(3)	(4)	(5)	(6)
			Employment			
			Panel (i): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	-3.853***	-3.714***	-4.042***	-0.165	0.370	-0.860
	(1.006)	(1.126)	(1.202)	(0.607)	(0.549)	(0.716)
			Panel (ii) Supply-Induced 2SLS			
$\Delta IPW^{CN,US}$	-3.794***	-3.758***	-3.874***	0.161	0.690	-0.393
	(1.255)	(1.299)	(1.476)	(0.765)	(0.686)	(0.877)
			Wage			
			Panel (iii): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	0.149	0.462	-0.067	-0.651***	-0.649**	-0.692***
	(0.463)	(0.330)	(0.345)	(0.243)	(0.284)	(0.227)
			Panel (iv) Supply-Induced 2SLS			
$\Delta IPW^{CN,US}$	0.399	0.606*	0.245	-0.365	-0.432	-0.256
	(0.464)	(0.323)	(0.387)	(0.250)	(0.290)	(0.246)

All regressions include the full vector of control variables from Column (6) of Table 3. Robust standard errors clustered on the state level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E: Adapting the model from Caliendo et al. (2019)

This appendix documents how we adapt the model from Caliendo et al. (2019) to our purpose and, in particular, our definition of the Chinese export supply shock. First, we provide an overview of the model proposed by Caliendo et al. (2019) and explain how the China shock is modeled in this framework. Second, we spell out a number of decisions we need to make concerning data adaptation and issues related to the code.

Equilibrium conditions in Caliendo et al. (2019). Caliendo et al. (2019) study the China shock in a dynamic general equilibrium model featuring trade between countries and U.S. states as well as labor mobility across U.S. states and sectors. Labor is immobile internationally. The production side of the model is based on a multi-sector version of Eaton and Kortum (2002), in which each market (a state-sector combination) produces a sectoral aggregate good that is used for final consumption and as an input in the production of other goods. In addition to labor and intermediate inputs from all sectors, production requires local structures (local fixed factors). While standard market clearing conditions apply for the labor and goods markets, the returns to local structures are redistributed to (immobile) rentiers through a global portfolio. For a given allocation of labor across sectors and states and economic fundamentals like productivity, this trade model is solved period-by-period.

Dynamics enter through the modeling of labor migration across states and sectors. Observing economic conditions in all markets and taking into account their idiosyncratic preference shocks as well as relocation costs, at time t households choose their preferred place of work and residence for the next period $t + 1$. Under their assumption of perfect foresight, Caliendo et al. (2019) study counterfactuals as changes in economic fundamentals over time (such as local productivity) that are unanticipated by economic agents. Once the shock occurs, agents learn about the entire future path of these fundamentals. In this setup, Caliendo et al. (2019) show how to solve for the counterfactual path of the economy in relative time differences, such that the *levels* of the economic fundamentals do not need to be estimated (a key feature of the dynamic hat algebra). Specifically, they define the ratio of time changes between the counterfactual equilibrium and the initial equilibrium in any variable as

$$\hat{y}_{t+1} \equiv \dot{y}'_{t+1} / \dot{y}_{t+1}, \tag{E.1}$$

where $\dot{y}'_{t+1} = y'_{t+1}/y'_t$ and $\dot{y}_{t+1} = y_{t+1}/y_t$. Thus, if $\hat{y}_{t+1} = 1$, then y is changing *in the same way* between two periods in the counterfactual and the baseline model.

Our aim in this section is to explain where and how the China shock is introduced in this model. To that end, we first introduce the notation from Caliendo et al. (2019) and then restate their Proposition 3, which shows how counterfactuals can be computed. Next, we explain where the China shock enters and how the counterfactual can be interpreted intuitively.

Introducing notation, let L_t denote a vector of labor forces in each labor market nj at time t (a combination of region n and sector j), $\pi_t = \left\{\pi_t^{ij,nj}\right\}_{i=1,k=1,n=1}^{N,J,N}$ denote a matrix of expenditure shares in market nj on sector j goods from market i at time t. $X_t = \left\{X_t^{nj}\right\}_{n=1,j=1}^{N,J}$ denotes total expenditure in a market, and $\mu_t = \left\{\mu_t^{nj,ik}\right\}_{n=1,j=0,i=1,k=0}^{N,J,N,J}$ indicates the share of the labor of market nj moving to market ik for the next period. Let further $u_t = \left\{u_t^{nj}\right\}_{n=1,j=0}^{N,J}$, where $u_t^{nj} = \exp(V_t^{nj})$ and V_t^{nj} denotes expected lifetime utility of a representative agent in labor market nj. P_t^{nj} denotes the price of the sectoral aggregate good j in region n at time t, x_t^{nj} denotes the unit price of an input bundle in market nj at time t, $w_t = \left\{w_t^{nj}\right\}_{n=1,j=1}^{N,J}$ denotes wages, and $\bar{\Theta} \equiv (\Upsilon, H, b)$ denotes a set of fundamentals of the model that are assumed to be constant over time, where $\Upsilon = \left\{\tau^{nj,ik}\right\}_{n=1,j=0,i=1,k=0}^{N,J,J,N}$ is a matrix of labor relocation costs, $H = \left\{H^{nj}\right\}_{n=1,j=1}^{N,J}$ denotes the stock of land and structures across markets, and $b = \{b^n\}_{n=1}^{N}$ denotes the value of home production in each region. The time-constant model parameters are given by final consumption expenditure shares α^j, the discount factor β, value added shares γ^{nj} and input-output coefficients $\gamma^{nk,nj}$, portfolio shares ι^n, the migration elasticity ν, the trade elasticities θ^j, as well as labor shares in value added $1-\xi^n$. Crucially, time-varying fundamentals are denoted by $\Theta_t \equiv (A_t, \kappa_t)$ with bilateral trade costs $\kappa_t = \left\{\kappa_t^{nj,ij}\right\}_{n=1,i=1,j=1}^{N,N,J}$ and sector-region-specific productivities $A_t = \left\{A_t^{nj}\right\}_{n=1,j=1}^{N,J}$.

We now restate

Proposition 3 ***from Caliendo et al. (2019)*** *Given a baseline economy, $\{L_t, \mu_{t-1}, \pi_t, X_t\}_{t=0}^{\infty}$, and a counterfactual convergent sequence of changes* *in fundamentals (relative to the baseline change),* $\left\{\hat{\Theta}_t\right\}_{t=1}^{\infty}$*, solving for the counterfactual sequential equilibrium* $\left\{L_t^{\prime}, \mu_{t-1}^{\prime}, \pi_t^{\prime}, X_t^{\prime}\right\}_{t=0}^{\infty}$ *does not require information on the baseline fundamentals* $(\{\Theta_t\}_{t=0}^{\infty}, \bar{\Theta})$ *and solves the following system of non-linear equations:*

$$\mu_t^{\prime nj,ik} = \frac{\mu_{t-1}^{\prime nj,ik} \dot{\mu}_t^{nj,ik} \left(\hat{u}_{t+1}^{ik}\right)^{\beta/\nu}}{\sum_{m=1}^{N} \sum_{h=0}^{J} \mu_{t-1}^{\prime nj,mh} \dot{\mu}_t^{nj,mh} \left(\hat{u}_{t+1}^{mh}\right)^{\beta/\nu}}, \tag{E.2}$$

$$\hat{u}_t^{nj} = \hat{\omega}^{nj}\left(\hat{L}_t, \hat{\Theta}_t\right) \left(\sum_{i=1}^{N} \sum_{k=0}^{J} \mu_{t-1}^{\prime nj,ik} \dot{\mu}_t^{nj,ik} \left(\hat{u}_{t+1}^{ik}\right)^{\beta/\nu}\right)^{\nu}, \tag{E.3}$$

$$L_{t+1}^{\prime nj} = \sum_{i=1}^{N} \sum_{k=0}^{J} \mu_t^{\prime ik,nj} L_t^{\prime ik}, \tag{E.4}$$

for all j*,*n*,*i*, and* k *at each* t*, where* $\left\{\hat{\omega}^{nj}\left(\hat{L}_t, \hat{\Theta}_t\right)\right\}_{n=1,j=0,t=1}^{N,J,\infty}$ *is the solution to the temporary equilibrium given* $\left\{\hat{L}_t, \hat{\Theta}_t\right\}_{t=1}^{\infty}$*; namely, at each* t*, given* $\left(\hat{L}_t, \hat{\Theta}_t\right)$*,* $\hat{\omega}^{nj}\left(\hat{L}_t, \hat{\Omega}_t\right) = \hat{w}_t^{nj}/\hat{P}_t^n$ *solves*

$$\hat{x}_{t+1}^{nj} = \left(\hat{L}_{t+1}^{nj}\right)^{\gamma^{nj}\xi^n} \left(\hat{w}_{t+1}^{nj}\right)^{\gamma^{nj}} \prod_{k=1}^{J} \left(\hat{P}_{t+1}^{nk}\right)^{\gamma^{nj,nk}}, \tag{E.5}$$

$$\hat{P}_{t+1}^{nj} = \left(\sum_{i=1}^{N} \pi_t^{\prime nj,ij} \dot{\pi}_{t+1}^{nj,ij} \left(\hat{x}_{t+1}^{ij} \hat{\kappa}_{t+1}^{nj,ij}\right)^{-\theta^j} \left(\hat{A}_{t+1}^{ij}\right)^{\theta^j \gamma^{ij}}\right)^{-1/\theta^j} \tag{E.6}$$

$$\pi_{t+1}^{\prime nj,ij} = \pi_t^{\prime nj,ij} \dot{\pi}_{t+1}^{nj,ij} \left(\frac{\hat{x}_{t+1}^{ij} \hat{\kappa}_{t+1}^{nj,ij}}{\hat{P}_{t+1}^{nj}}\right)^{-\theta^j} \left(\hat{A}_{t+1}^{ij}\right)^{\theta^j \gamma^{ij}}, \tag{E.7}$$

$$X_{t+1}^{\prime nj} = \sum_{k=1}^{J} \gamma^{nk,nj} \sum_{i=1}^{N} \pi_{t+1}^{\prime ik,nk} X_{t+1}^{\prime ik} + \alpha^j \left(\sum_{k=1}^{J} \hat{w}_{t+1}^{nk} \hat{L}_{t+1}^{nk} w_t^{\prime nk} L_t^{\prime nk} \dot{w}_{t+1}^{nk} \dot{L}_{t+1}^{nk} + \iota^n \chi_{t+1}^{\prime}\right), \tag{E.8}$$

$$\hat{w}_{t+1}^{nk} \hat{L}_{t+1}^{nk} = \frac{\gamma^{nj}\left(1+\xi^n\right)}{w_t^{\prime nk} L_t^{\prime nk} \dot{w}_{t+1}^{nk} \dot{L}_{t+1}^{nk}} \sum_{i=1}^{N} \pi_{t+1}^{\prime ij,nj} X_{t+1}^{\prime ij}, \tag{E.9}$$

where $\chi_{t+1}^{\prime} = \sum_{i=1}^{N} \sum_{k=1}^{J} \frac{\xi^i}{1-\xi^i} \hat{w}_{t+1}^{ik} \hat{L}_{t+1}^{ik} w_t^{\prime ik} L_t^{\prime ik} \dot{w}_{t+1}^{ik} \dot{L}_{t+1}^{ik}$.

We follow Caliendo et al. (2019) and model the China shock as a sequence of counterfactual changes in Chinese sectoral productivities, i.e.,

$\left\{\hat{A}_t^{China\ j}\right\}_{j=1,t=1}^{J,\infty}$. The intuition works as follows. Through the lens of the model, the observed data on Chinese production and trade with all countries over the observed time horizon imply an unobserved and potentially time-varying sequence of economic fundamentals in the model. As this baseline economy is based on observed data, it includes by construction all the demand-side and supply-side effects that drive the increase in Chinese exports to the United States between 2000 and 2007. Given a correct identification of the China shock, the dynamic hat algebra methodology allows for the construction of a counterfactual sequence of trade equilibria and labor movements across sectors and states *in the absence* of the China shock without the need to estimate the unobserved levels of economic fundamentals. In other words, the model can be used to calculate the economic outcomes had Chinese productivity not increased at all.

We follow Caliendo et al. (2019) and use reduced-form estimates of exogenous Chinese export growth to find those productivity changes the model needs to generate exactly these Chinese sectoral export changes. While Caliendo et al. (2019) use the first stage from Autor et al. (2013), we use our new IV to generate these exogenous sectoral export growth values. We describe the calibration procedure in the following section.

Calibration of sectoral Chinese productivity changes to sectoral export growth. We calibrate sectoral productivity changes to match the sectoral supply-induced Chinese export growth stemming from two different approaches – the one based on Autor et al. (2013) and the other our own. Doing so, we closely follow the procedure advanced by Caliendo et al. (2019), who iterate over two broad steps. In the first step, a guess is made for the Chinese sectoral productivity changes under which a restricted version of the model from Caliendo et al. (2019) with time-varying fundamentals generates the supply-induced sectoral changes of U.S. imports from China between 2000 and 2007 – i.e., the *target vector*. The restricted version of the model forces labor shares to match the data throughout, i.e., it shuts down endogenous labor adjustments across U.S. states and industries.[74]

In the second step, the model is used to compute the U.S. imports from

[74] This step reduces the computational burden and implies that the code calculates the counterfactual scenario in a quarterly series of static trade models, where the distribution of labor forces changes exogenously along with the data from one period to another. As we report below, we later compare the matching precision of the calibration using the restricted model with the full model and find that allowing for endogenous labor movements does not deteriorate the precision of the calibration.

China between 2000 and 2007 that arise *in the absence of the guessed productivity changes*. The difference between these *counterfactual* imports and the observed U.S. imports is defined as the change in U.S. imports from China implied by the guessed productivity changes.

The steps 1 and 2 are iterated over until the difference between the data and the counterfactual U.S. imports from China matches the supply-induced changes in U.S. imports (i.e., the *target vector*). The precision of the match is defined as the sum of squared distances (SSQ) between the elements of our target vector and the elements of the model-implied change in imports.[75]

As pointed out above, we follow this procedure and apply it once for the supply-induced shock as defined by Autor et al. (2013) and once for our own supply-induced shock. We find that after the final iteration, the inclusion of endogenous labor adjustment increases the SSQ value by the factor 1.2 (19.3%) when supply-induced imports are defined following Autor et al. (2013), and by 1.1 (8.5%) when we use our own definition.[76] In both cases, the correlation between the model-implied growth of sectoral imports by the United States from China and the target is unaffected.

We generate all of our reported results and graphs by using the published replication code from Caliendo et al. (2019). Specifically, we plug our imputed vectors of productivity changes in the file "Counterfactual_economy.m." The change amounts to replacing the vector "china" in line 129 of the file with the imputed sectoral productivity changes.

The estimation of supply-induced import changes in Caliendo et al. (2019) and the relation to Autor et al. (2013). Caliendo et al. (2013) define the supply-driven import change as the prediction of the first stage from Autor et al. (2013) (i.e., by regressing the change in U.S. imports from China on the change in imports from China by other advanced economies using data from WIOD). Through this approach, Caliendo et al. (2019)

[75]We make two changes to the code provided by Fernando Parro. First, we remove the weighting from the sum of squares calculation. Second, we replace Matlab's *fsolve* command with *lsqnonlin*. The former is a solver for systems of nonlinear equations, while the latter is designed to solve non-linear least-squares problems, of which our matching problem is an example.

[76]These figures may seem large. They should be assessed also with regard to the absolute level of the sum of squares they refer to. In the former calibration, the SSQ increase by about 28000 from 145578 to 173780 with a correlation of 0.99997 between the model-implied sectoral U.S. import growth from China and the target. In the case of our estimates, the SSQ increases by about 3200 from about 37459 to 40652 at a correlation exceeding 0.99999. In the original Caliendo et al. (2019) calibration, the correlation is 0.96353, the absolute increase in SSQ is about 197500 from 604.1 million to 604.3 million.

attribute the entire increase in U.S. imports from China to supply-side factors. Moreover, the procedure implies that for some sectors, U.S. imports are over-predicted in the first stage, and that for some of these sectors, the 'supply-induced import change' turns out to be even larger than the import *level* in 2007 observed in the data. For these latter sectors, the model is implicitly asked to match negative trade flows in the counterfactual. The model's obvious inability to match negative trade flows prevents a perfect match of the *target vector*. Accordingly, Caliendo et al. (2019) report a correlation of 0.96353 between the model-implied import growth and import growth of the target vector and a precision of convergence measured by SSQ that is more that 3000 times worse than ours (604.3 million instead of 173780).

Finally, the definition of the supply-induced shock based on the first stage of Autor et al. (2013) is not entirely consistent with Autor et al. (2013) itself (as discussed in Section 4.2.1). The latter authors infer from the relation between the IV and the OLS estimates that only 44% of the U.S. imports from China are supply-driven. We deal with this issue by realigning the target vector with Autor et al. (2013). Specifically, we re-scale the original Caliendo et al. (2019) target vector such that the sum of the sectoral U.S. import changes equals the 44% of the total change in U.S. imports between 2000 and 2007 reported in the raw WIOD data. We thus ensure that the *aggregate* supply-induced change in U.S. imports is equal to 44% of the observed change in the data, while the sectoral variation generated by the instrument from Autor et al. (2013) is preserved. For the target vector according to our own definition of supply-induced U.S. imports from China, we use the methodology explained in Section 3.1.

Difference between Comtrade and WIOD. There are some differences in aggregate U.S. import values between the data from WIOD used by Caliendo et al. (2019) and our data from Comtrade. Aggregating the data for 2007 across the twelve manufacturing industries used by Caliendo et al. (2019) (i.e., over all manufacturing industries available in WIOD), the raw data sum to a total of USD 274744 million for U.S. imports from China. By contrast, when we convert our Comtrade data to nominal values and map all manufacturing industries into the twelve Caliendo et al. (2019) industries with the HS-NAICS concordance from Pierce and Schott (2012), we find a total of USD 332632 million. This discrepancy of the aggregate data is mostly driven by a large difference (USD 39300 million) in industry

12, "Furniture and Related Products, and Miscellaneous Manufacturing".[77] It is not possible to track down the origin of this discrepancy, but when we eliminate the components belonging to "Other Manufacturing" according to the industry concordance, the difference between the WIOD values and the aggregated Comtrade value for industry 12 reduces to about USD 1500 million. A likely explanation is thus that the WIOD industry "Furniture and Related Products, and Miscellaneous Manufacturing" does not include "Other Manufacturing" and we chose to exclude "Other Manufacturing" when we calculate the supply-induced changes in U.S. imports from China using our new instrument.

Further, in some sectors, the supply-induced changes in U.S. imports from China obtained from our own definition exceed the *level* of U.S. imports from China in the final period of the Caliendo et al. (2019) baseline economy.[78] We deal with this issue by capping the change in imports at 95% of the model-consistent *level* of imports of the Caliendo et al. (2019) baseline model in 2007. For the re-scaled Caliendo et al. (2019) target made consistent with Autor et al. (2013), we have to apply this cap to the two sectors with the Caliendo et al. (2019) numbers 4 and 5, referring to "Petroleum and Coal Products" and "Chemical". In the case of the estimates based on our new instrument, we apply the cap to the sectors with Caliendo et al. (2019) numbers 3 and 8, referring to "Wood Products, Paper, and Printing" and "Primary Metal and Fabricated Metal Products".

Caliendo et al. (2019) use nominal data for the baseline economy, but the China shock is calculated in real terms Caliendo et al. (2019) take their raw trade data from WIOD, which reports values in nominal terms. Therefore, the model generates counterfactual changes in U.S. imports from China also in nominal terms. However, the target vector in Caliendo et al. (2019) is calculated in real terms. As we aim to stay as close as possible to the Caliendo et al. (2019) setup, we use our supply-induced import changes also in real terms and use them in the *nominal* model.

[77]Note that "China" in WIOD is the aggregation of mainland China with Hong Kong and Macao, while the three are reported separately in Comtrade. If this were the only difference between the two datasets, the WIOD data used in Caliendo et al. (2019) would be *larger* than the values we get from Comtrade.

[78]This inconsistency does not arise within our Comtrade data. But as discussed in the preceding paragraph, the trade values of the Caliendo et al. (2019) baseline economy differ from the raw WIOD data, as the baseline economy contains a sequence of trade values based on the raw data but made consistent with the balanced trade conditions of the trade model.

Data – Skill Intensity In Figure 9, the unit of the vertical axis, 'Normalized Sectoral Employment Losses', are constructed by dividing the percent contribution of each sector's employment loss to the total manufacturing employment losses due to the China shock (i.e., the numbers from Figure 5) by the share of total manufacturing employment accounted for by each sector in 2000. Low Skill Intensity is the share of sectoral labor compensation paid to low-skill workers in the United States in the year 2000 from the 2013 release of the WIOD Socio-Economic Accounts. In these data, skill levels are defined based on educational attainment, where low-skill workers do not have more than lower-level secondary education.