Received: 11 November 2022 | Revised: 13 February 2023 | Accepted: 22 March 2023

DOI: 10.1111/roie.12673

ORIGINAL ARTICLE

WILEY

Identifying Chinese supply shocks: Effects of trade on labor markets

Andreas M. Fischer[1] | **Philipp Herkenhoff**[2] | **Philip Sauré**[3]

[1]LIUC and CEPR, Castellanza, Italy

[2]University of Mainz, Mainz, Germany

[3]University of Mainz and CEPR, Mainz, Germany

Correspondence
Philip Sauré, University of Mainz and CEPR, Mainz, Germany.
Email: philip.saure@uni-mainz.de

Abstract

An influential literature estimates the impact of trade on labor markets with shift-share instrumental variable designs under the assumption that common demand shocks in advanced economies are negligible. This article documents empirical patterns, which suggest that such common demand shocks are prevalent. It then proposes a strategy that directly identifies country-specific export supply shocks. Finally, it uses these supply shocks in reduced-form regression, which suggest contractions of manufacturing employment that are larger than those in the seminal contribution by Autor et al. (American Economic Review, 2013, 103, 2121–2168).

KEYWORDS

employment, instrumental variable, international trade

JEL CLASSIFICATION

F14, F16, J46

1 | INTRODUCTION

Early neoclassical trade theory shows already that international trade is bound to affect a nation's income distribution, possibly generating real losses for some individuals.[1] A fast-growing and highly influential literature uses shift-share regression designs to identify adverse effects of trade on manufacturing wages, employment and other labor market outcomes. Often focusing on the likely case of Chinese exports, a number of prominent contributions instrument (China's) sectoral exports to one specific destination with (China's) 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 three points to this literature. First, we provide robust evidence that common import demand shocks cannot be neglected. Second, we develop a strategy to directly identify country-specific supply shocks from readily available sectoral trade data. Third, we use the thus identified supply shocks in a shift-share instrumental variable approach to estimate the impact of China-specific supply shocks on U.S. labor markets, documenting systematic differences to Autor et al. (2013).

In the first step, we set off with 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 the sales of its competitors. 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 long-run export growth between 1991 and 2007 at the narrow product level against corresponding growth of comparable emerging market economies (EMEs).[4] Figure 1 exhibits a strong positive correlation, which suggests that China-specific supply shocks were not the dominant source of Chinese export growth and that, consequently, the assumption underlying the shift-share instrumental variable regression design applied in the recent literature may be violated.[5]

In our second step, we offer a new approach to identify the part 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

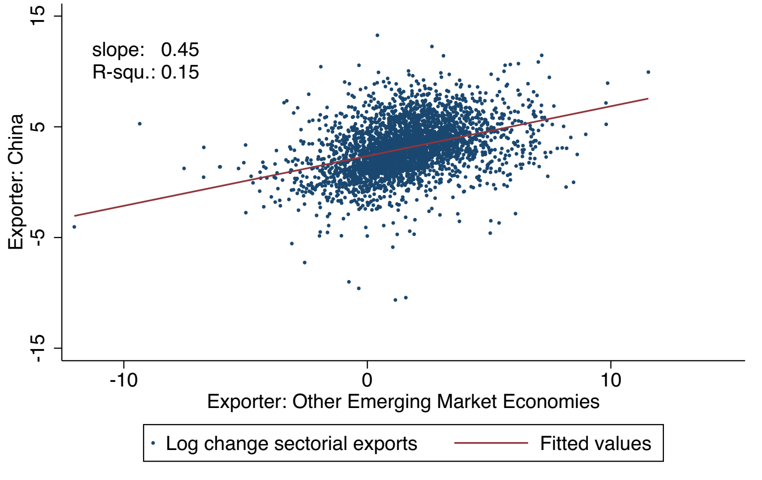

FIGURE 1 Sector export growth of China and other EMEs, 1991–2007. Log changes of exports between 1991 and 2007 by 6-digit HS class for China and other emerging market economies (India, Malaysia, Mexico, Philippines, Poland, Romania, Slovak Republic, Thailand, and Turkey). Exports are defined as trade 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. [Colour figure can be viewed at wileyonlinelibrary.com]

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. The 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, our decomposition offers a direct identification of the supply-induced components of export growth for any sector and any time period. In that way, we improve and advance the indirect approaches previously used. This direct identification is particularly useful for the new generation of general equilibrium models a la Caliendo and Parro (2015), which are recently calibrated to match supply shocks.[8]

In the third and final step, we use the supply shocks identified in the second step to 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] Reduced-form estimations identify important *differential* effects across commuting zones, but are inept to assess *aggregate* employment losses.[10] To assess such aggregate effects, we thus add an empirical exercise based on Caliendo et al. (2019) in the Online Appendix.

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; Autor et al., 2016), political voting patterns (Autor et al., 2017, 2020) 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).[11] 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).[12] 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.[13] 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.[14] By its very design, this literature is unaffected by our concerns.

Our paper also connects to the recent methodological advances in the shift-share literature that have advanced and refined the shift-share estimation strategy as employed in Autor et al. (2013). Borusyak et al. (2022) show under which conditions exogenous shocks allow for identification even in the presence of endogenous exposure shares. In the same setup, Adao et al. (2019) show how to correctly compute standard errors if exposure shares are endogenous but do not relax the assumption of exogenous shifters.[15] Both contributions, Borusyak et al. (2022) and Adao et al. (2019) highlight the importance of exogenous shifters (Chinese shocks in Autor et al., 2013), respectively. Our work directly complements these studies by defining an a priori exogenous shifter, which can be readily incorporated in the methodology proposed by Borusyak et al. (2022).[16] 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 conclude that the use of the shift-share instruments is valid under an exclusion restriction on the exposure shares.[17] 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. (2022). An additional contribution of our paper and an obvious advantage relative to all of the studies above is the direct decomposition of Chinese export growth into the supply-induced component and the rest. This decomposition does not only offer a valid instrument in Autor et al. (2013), it also provides suitable calibration targets for dynamic general equilibrium models (e.g. Caliendo et al., 2019 discussed at length in the Online Appendix).

Our paper further relates to the recent literature that studies the effect of trade shocks in general equilibrium with complex input–output structures, such as Caliendo et al. (2019), Adao et al. (2020), Galle et al. (2020), and Rodríguez-Clare et al. (2020). While all of these papers feature complex interdependencies through input–output likages, in none of them, the quantitative exercise identifies supply-induced (Chinese) export growth fully endogenously, that is, within the respective model framework.[18] Instead, exogenous trade shocks are identified by predicting from reduced-form regressions that mimic the first stage in Autor et al. (2013).[19] Model parameters such as underlying productivities are then calibrated to match these predicted values. Our work complements these contributions by offering an improved identification of precisely these exogenous Chinese supply shocks. At that stage we point out that one should be fully aware of the fact that our Armington-style model cannot capture the full complexities and interdependencies of the models developed in the studies above.[20] Clearly, a logical discrepancy emerges, when our identification procedure, which neglects trade in intermediate inputs, is used to feed a shock to models, in which intermediate inputs constitute a central feature. We do not apologize for the logical discrepancy, however. Instead, we point out that this conceptual gap does exist in all of the studies listed above that engage in the general equilibrium analysis. It surely is to be addressed in future work. In the meanwhile, we simply observe that our approach does not have the capacity to mend all possible problems, but simply aims at one particular one: the possible violation of the exclusion restriction in Autor et al. (2013). To that aim, we adopt the latter's approach.

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 and the according results, while Section 5 concludes.

2 | A CLOSE LOOK AT SECTORAL EXPORT GROWTH

This section scrutinizes the empirical 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 should not be read as conclusive evidence that other demand-type factors were present. 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 stemming from economic growth), second, factors related to global values chains (GVC), and third factors 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 inventions of new products 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.[21]

Motivated by these concerns, we refine our conjecture above as follows. Under Chinese supply shocks, the correlation of sectoral export growth from China and from another country should be smaller (more negative), the more intensely both countries compete on international markets—that is, the more similar their comparative advantage actually is.[22]

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. For the first metric of the similarity of the revealed comparative advantage between country c and China, we define $prox_c^{CN}$ 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.[23] The second metric relies on the relative GDP per capita, which we take as a measure of economic development. Specifically, we define the alternative $prox_c^{CN}$ 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, 2004; Hallak & Schott, 2011). 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 over the full period 1991 to 2007 (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

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

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 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.[24] 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

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

Note: 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 ***$p < .01$, **$p < .05$, *$p < .1$.

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.[25]

2.2 | Substitution effects and immiserizing growth

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).[26] 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.

A different but related concern may stem from effects of immiserizing growth, which potentially accounts for the observed positive correlation of bilateral sectorial export growth observed in Figure 1. In this case again, strong price effects may account for the observed positive correlation.[27]

We address these concerns by investigating the corresponding correlation between the volume of exports (measured in units or kilogram) instead of its values.[28] In fact, if the positive correlation in Figure 1 were generated by pure price effects induced, for example, by Chinese competitors substituting towards higher quality in other emerging economies, the correlation should turn negative when measuring exports by quantity (or weight), because changes in export values stemming from price changes are be removed. Figure C2 in the Appendix documents 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. This observation suggests that neither (quality) substitution not immiserizing growth seems to drive the observed patter in Figure 1.

Yet 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.[29] 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), that is, 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 organized exchanges, or reference priced, (unlikely to be affected by demand complementarities), and differentiated goods (possibly affected by demand complementarities).

Figure C3 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.[30]

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 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, that is, Columns II, III; V; and VI from Table 1, as well as in Figure 2, which plots the change of quantities. 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).[31] If the WIOD sectors capture a relevant dimension of the input–output relations and if, at the same time, GVCs 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 Figure 1.

Overall, we find little indication that GVC account for a substantial part of the positive correlation between Chinese exports and exports from other EMEs.

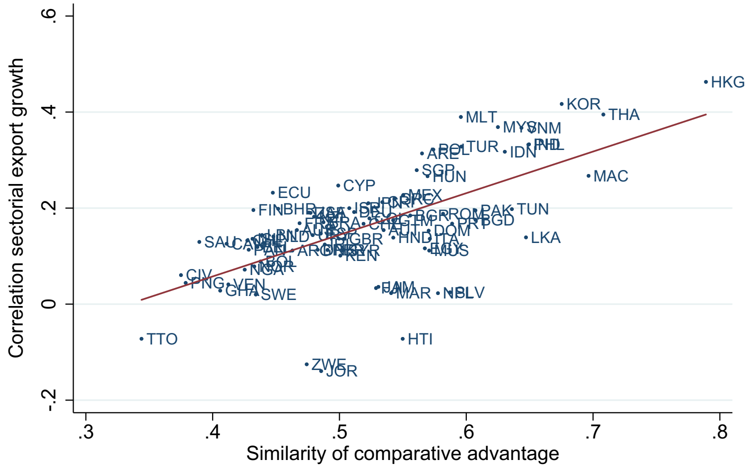

FIGURE 2 Synchronized export growth and similarity of comparative advantage, 1991 to 2007. The vertical axis shows the correlation of sectoral export growth between China and the indicated country. The reference period is 1991 to 2007, sectoral export growth is defined as log changes of a 6-digit HS 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 OA.B3 in the Appendix plots the parallel data, for the period 2000 to 2007 only. [Colour figure can be viewed at wileyonlinelibrary.com]

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.[32] 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 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.[33] 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. To the extent that these common components are driven by demand of the destination countries, the figure suggests that demand shocks in the United States and in OAEs exhibit a strong positive correlation.

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

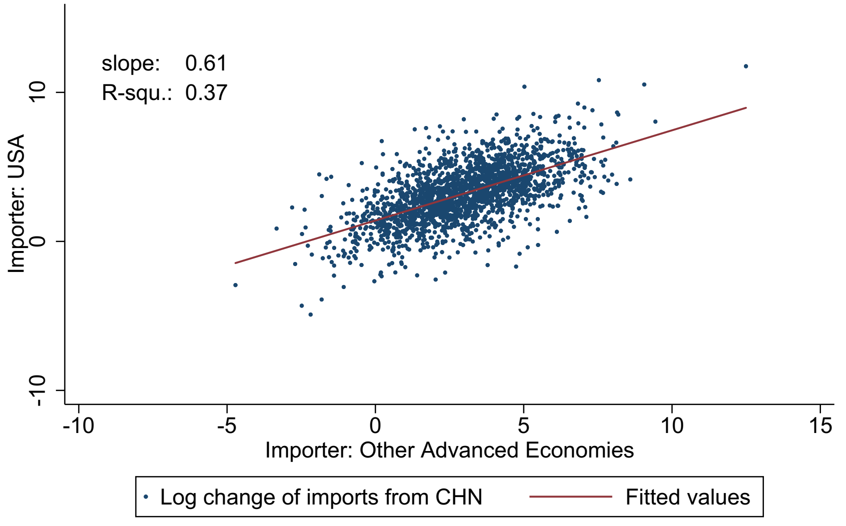

FIGURE 3 China's sector export growth—Common component with other EMEs (1991–2007). Common component of Chinese export growth and export growth of other advanced economies (OAEs) by destination market. The common component is defined separately for each destination market based on a principle component decomposition with a single common factor of the two series Chinese and OAEs export growth. [Colour figure can be viewed at wileyonlinelibrary.com]

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 in order to avoid potential 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 of magnitude.[34] 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 of the presence of demand shocks, 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.[35] 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.[36] The collection of all other shocks comprises, for example, 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.[37]

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

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

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), $c = OE$ (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, for example, driven by supply and demand of other goods that are imperfect substitutes.[38] 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:

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

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.[39]

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.[40] 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 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.[41]

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, that is, $DX = X_t - X_{t-1}$ but we drop the time subscript for simplicity. Denoting further country c's export value 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

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

While c denotes the exporter country, importer indices are dropped for simplicity and introduced later. We can now isolate the China-specific supply shock, the factor χ_j^{CN} in (3), by taking differences of (4) between China and other EMEs:

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

We point out 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

$$\frac{\partial \ln\left(E_j^{CN}\right)}{\partial \chi_j^{CN}} = \left[1 + \frac{p_j'(q_j)}{p_j(q_j)} q_{CNj,0}\right] \frac{\partial \ln(q_{CNj})}{\partial \chi_j^{CN}},$$

where p_j' is the partial derivative of p_j with respect to q_j. The fraction in the squared bracket can be expressed in terms of demand elasticities:

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

where we have used (1) to replace $p_j'(q_j)/p_j(q_j) = -1/(\sigma_j q_j)$ and (2) to write $q_{CNj}/q_j = E_j^{CN}/(E_j^{OE} + E_j^{CN})$. Equation (6) yields an expression for our object of interest—the response of Chinese exports to China-specific shocks—in marginal terms. We approximate the last term in (6), $\partial \ln(q_{CNj})/\partial \chi_j^{CN}$, with differences using (3):

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

Notice that the total response of exports to the China-specific supply shock equals the expression in (6), that is, the marginal response, multiplied with the magnitude of the shock, that is, the term $\chi_j^{CN} - 1$.

Finally, combining the last two equations, while using Equation (5) to replace the term $\ln(\chi_j^{CN})$ and replacing log differences with percentage changes, we can rewrite (6) as

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

where we have indicate absolute changes of export due to the China-specific shock with *hats*.

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," that is, 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.

We stress that the derivation of Equation (7) through (5) does not require demand- and export-supply shocks to be uncorrelated. A total derivative of E_j^{CN} with respect generalized demand factors (a_j from (1)) and both supply factors (χ in (2)) generates the same marginal effect of China-specific supply shocks. (Effects of such correlations become relevant through second order effects at best.)

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).[42] For the next step, the practical implementation in the following section, we also point out that the expression in (7) is undefined for those product classes for which $E_{j,0}^{CN} = 0$ or $E_{j,0}^{OE} = 0$ (or both). For these cases, we replace the respective export growth with the top percentile of export growth of the corresponding variable.

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 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.

TABLE 2 Summary statistics—Chinese exports, total and supply-induced.

	Imports from China (1)	Explained by Chinese supply (2)	Increase explained by Chinese supply (%) (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%

Note: Numbers in billion 2007 USD.
Source: UN Comtrade and own calculations.

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.[43] 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.[44] 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 GVC.

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 modeling 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 from EMEs are close substitutes among each other (see Equation (2)). This assumption, in turn, is consistent with evidence prominently presented in Schott (2003, 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 C3) 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. In the Online Appendix, we also provide an assessment of the full general equilibrium effects of the Chinese supply shock for the model by Caliendo et al. (2019).

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 $l_{ij,t} = L_{ij,t}/L_{i,t}$ denotes 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 United States to adapt the regression (8) by replacing export growth in the key regressor (9) with the supply-induced component.

Concerned about potential attenuation bias due to measurement errors, however, we chose to adopt an instrumentation strategy. For example, it is well-known that demand elasticities are notoriously plagued by measurement errors, which is likely to translate into measurement errors of our definition of import penetration, $\widehat{\Delta IPW}$. We therefore proceed along the lines of Autor et al. (2013), taking $\widehat{\Delta IPW}^{CN,AE}$ as an instrument of the observed $\Delta IPW^{CN,US}$.[45] Specifically, 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 define the first stage of our IV strategy with (11) as

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

while the second stage is defined by (8).[46]

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 the coefficient of interest for the variable, $\Delta IPW_{i,t}^{CN,US}$.[47] 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.[48] 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 OA.C3 in the Online Appendix reports the results for the period 2000 to 2007 in the same format as Table 3.[49] In Autor et al. (2013), the cross-section estimates for the period 2000 to 2007 drop severely in absolute magnitudes relative to the one full staggered regression. 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. It is favorable and reassuring for our identification strategy that our estimates are relatively stable across both specifications.

TABLE 3 Baseline estimates, balanced panel 1991–2007.

Dep Var: 10× 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

Note: Columns 1–6 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.

$^{*}p < .1$.

$^{**}p < .05$.

$^{***}p < .01$.

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 we argue based on two observations. First, we observe substantial differences when focusing on specific labor market segments, such as those defined by gender and skill level.[50] Second, the quantitative implications between our approach and the one in Autor et al. (2013) are strong, as the following 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 1839 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 ($((-0.519/100) * 0.792 * 1.839 * (178.7 + 194.3)/2 = 1.411)$ 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 show substantial differences in our approach and the one from Autor et al. (2013). But we treat them with caution because the estimated coefficients presented in Table 3 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.[52] Instead, reliable information about total manufacturing employment losses must be based on a full general equilibrium model. The interested reader is referred to the Online Appendix, where we provide a full application of or supply-induced shock to the model developed in Caliendo et al. (2019).

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 United States, instead of those between China and other emerging markets. This has two undesirable implications. On the one hand, it picks 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.[53] The effect of these forces is then counted twice (once as 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 distinction to our approach, 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, 2004), goods within the same narrow product classification 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 Equation (7) shows. 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.[54]

5 | CONCLUSION

An influential literature based on the seminal paper by Autor et al. (2013) identifies the impact of Chinese exports on U.S. manufacturing employment and has enjoyed high popularity in recent years.[55] Their shift-share 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 this identification assumption. It thus uncovers a potential problem and calls for a mindful use of the identification strategy from Autor et al. (2013).

We propose a simple structural model to identify sector-specific Chinese supply shocks as a remedy to the identification problem. Our approach allows a direct decomposition of Chinese exports into a supply-driven component and a residual for any 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%. Our decomposition does not only offer a valid instrument in the procedure Autor et al. (2013), it also provides a suitable calibration target for general equilibrium models such as Caliendo et al. (2019).

We use the resulting supply-induced Chinese exports to assess its impact on the U.S. labor markets with reduced-form regressions. 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) but implies larger employment losses. In the Online Appendix, we also offer an exercise of how to use the decomposition in a general equilibrium model.

ACKNOWLEDGMENTS

The authors would like to thank Raphael Auer, David Autor, Stefan Bauernschuster, David Dorn, Peter Egger, Gordon Hanson, Philipp Harms, Sebastian Krautheim, Brian Kovak, Xenia Matschke, Claudio Michelacci, Dalia Marin, Richard Rogerson and Davide Sala for helpful comments, David Autor, David Dorn, and Gordon Hanson for their help with the data and Fernando Parro and Lorenzo Caliendo for kind guidance with the GE model. Andrea Duarte, Roman Elbel, and Lucca Zachmann provided excellent research assistance. Open Access funding enabled and organized by Projekt DEAL.

DATA AVAILABILITY STATEMENT

Data used in this study are available on request by the authors.

ORCID

Philip Sauré https://orcid.org/0000-0002-9923-2965

ENDNOTES

[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).

[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. (2022).

[3] Autor et al. (2013) recognize " … 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] Our choice of period follows Autor et al. (2013) and is mainly data-driven. Our restriction to other EMEs as *competitors* with which to compare Chinese sales is motivated by the fact that countries with similar stage of development tend to have a similar product mix within narrowly defined 6-digit HS product classes (see Schott, 2003, 2004). Therefore, products within each product class from such countries are close substitutes. Comparable EMEs, listed in the note to the figure, 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. See the appendix for more information on the data.

[5] Section 2 takes a much closer and rigorous 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. Notice also that Figure 1, by taking log differences, ignores those product classes that are not traded in either 1991 or 2007. Figure C1 in the appendix repeats the plot based on differences of the arcsine. While the scatter plot exhibits more outliers and presents less of a firm cloud, the strong positive correlation still emerges. In 2007, Chinese exports of products with zero exports in 1991 accounted for less than 1.1 percent of total exports.

[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, for example, 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—see footnote 31 in Autor et al. (2013) and our discussion 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.

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

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

[12] 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.

[13] 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.

[14] 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.

[15] 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.

[16] Borusyak et al. (2022) "... 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.

[17] 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.

[18] In a related paper, Caliendo et al. (2018) develop a static general equilibrium model to examine the impact of specific episodes of shocks (defined as deviations from long-run trends) within the United States, that is, shale oil boom, real-estate and finance and the hurricane Katrina. The model features intersectoral and interregional trade linkages that propagates sectoral productivity changes. With the help of U.S. regional and industry data they estimate aggregate, regional, and sectoral elasticities of total factor productivity, GDP, and employment to regional and sectoral productivity changes. Their main finding is that the elasticities vary considerably because of the U.S. economy's spatial structure.

[19] 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-consistent way into supply-effects (see Online 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.

[20] We acknowledge that, in a period of intensifying global value chains (GVC) (see Johnson, 2018), our decision to abstract from GVC in our identification strategy may appear puzzling. Indeed, recent literature has highlighted the role of the international input–output network for the propagation of shocks. Thus, Lafrogne-Joussier et al. (2022) and Boehm et al. (2019). These studies show that temporary supply disruptions stemming from Chinese lockdowns or natural disasters result in negative cross-border effects along the GVC. Freund et al. (2022), studying the long-run effects of the 2011 Tohoku earthquake, however find that Japanese exports of intermediate goods were less affected by supply chain reconfiguration than final goods. For example, Boehm et al. (2019) and Lafrogne-Joussier et al. (2022) present evidence that temporary supply disruptions due to Chinese lockdown or natural disasters result in negative cross-border spillovers along GVC. Studying long-run effects of the 2011 Tohoku earthquake, Freund et al. (2022) find that Japanese exports of intermediate goods were less affected by supply chain reconfiguration than final goods (see also Auer et al. (2019) for inflation spillovers). Alfaro et al. (2019) presents a theory where organizational decisions shape the transmission of shocks along the value chain, as relationship-specific investments made by upstream suppliers affect the incentives in downstream stages.

[21] 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.

[22] 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.

[23] 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 5-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.

[24] 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.

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

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

[27] Immiserizing growth arises when adverse price effects are stronger than positive productivity shocks. Under such conditions, Chinese supply shocks would simultaneously decrease China's export value and that of its competitors (other EMEs). Such concerns may be addressed a priori by pointing out that the mechanics materialize if and only if the (residual) demand elasticity falls short of unity—a condition that is empirically not the relevant case (see Broda et al., 2008 or Soderbery, 2015). Also, the mentioned effects would imply that Chinese export growth reduced Chinese income per capital over the last decade, which appears to be a rather far proposition.

[28] Quality correlates with prices and prices correlate with unit values, see for example, 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).

[29] In the specific example above, exports would be classified in two separate HS classes: 950,651 for tennis rackets and 950,661 for tennis balls.

[30] Figure OA.B2 in the Online Appendix 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). Neither of the panels exhibits the negative correlation consistent with pure Chinese supply shocks.

[31] 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 5 and describe them in more detail in our Online Appendix.

[32] 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.

[33] 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).

[34] 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.

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

[36] 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.

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

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

[39] 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, 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.

[40] The literature on the China shock usually understand these factors as market-oriented reforms and trade liberalization. These factors are represented by such China-specific shocks.

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

[42] Export growth in Equation (7), $E^{CN}_{j,1}/E^{CN}_{j,0}$ and $E^{OE}_{j,1}/E^{OE}_{j,0}$, respectively, is defined for each HS class. The estimated elasticities in Broda and Weinstein (2004) are known to be very noisy, some actually being negative. To limit the influence of outliers, we restrict the elasticities to exceed unity. This restriction affects about one percent of all HS classes. A sensitivity analysis shows that our results do not depend heavily on the variation of elasticities. Specifically, an alternative definition of supply-induced shocks based on constant elasticities, set to the sample average of 4.51, generates alternative growth rates of Chinese exports to the United States by 6-digit HS class. These alternative log-growth rates exhibit correlations with our measure of 0.9964 for the period 1991 to 2000 and 0.9935 for the period 2000 to 2007 (the corresponding number for Chinese export growth to AE are, respectively, 0.9928 and 0.9928). Finally, as we work with generalized HS classes, we define the elasticities from Broda and Weinstein (2004) as weighted averages whenever 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.

[43] 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 than the demand elasticity.

[44] 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.

[45] Doing so, we note that mismeasured elasticities may affect the instrument but not the instrumented variable.

[46] 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 article.

[47] The complete estimation results with the full set of dependent variables are reported in Tables OA.C1–OA.C5 in the Appendix.

[48] 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.

[49] 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 2001.

[50] In Tables D1 and D2 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).

[51] 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—compare footnote 31 in Autor et al. (2013).

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

[53] See Vernon (1966), Krugman (1979), Flam and Helpman (1987), and Eriksson et al. (2021).

[54] The according coefficient is −0.29 in Panel E of Table 10 in Autor et al. (2013). Although the scaling of the regressor differs slightly from that in the baseline, Autor et al. (2013) interpret it in the same manner, writing that "… a one unit increase in the gravity measure corresponds to a 1000 per worker increase in a region's Chinese import exposure stemming from a rise in China's productivity or fall in China's trade costs." (p. 2154). In the subsequent paragraph, the authors reiterate their interpretation of the coefficient in exactly that manner.

[55] See, for example, Ashournia et al. (2014), Balsvik et al. (2015), Dauth et al. (2014), Autor et al. (2014, 2019, 2020), Malgouyres (2017), Bloom et al. (2019) and Albouy et al. (2019).

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

REFERENCES

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, *34*(S1), S141–S198.

Acemoglu, D., Dorn, D., Hanson, G. H., & Price, B. (2014). Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review*, *104*(5), 394–399.

Adao, R., Arkolakis, C., & Esposito, F. (2020). *General equilibrium effects in space: Theory and measurement* [Working paper].

Adao, R., Kolesar, M., & Morales, E. (2019). Shift-share designs: Theory and inference. *Quarterly Journal of Economics*, *134*, 1949–2010.

Albouy, D., Chernoff, A., Lutz, C., & Warman, C. (2019). Local labor markets in Canada and the United States. *Journal of Labor Economics*, *38*(S2), S533–S594.

Alfaro, L., Chor, D., Antras, P., & Conconi, P. (2019). Internalizing global value chains: A firm-level analysis. *Journal of Political Economy*, *127*(2), 508–559.

Artuç, E., Chaudhuri, S., & McLaren, J. (2010). Trade shocks and labor adjustment: A structural empirical approach. *American Economic Review*, *100*(3), 1008–1045.

Ashournia, D., Munch, J. R., & Nguyen, D. (2014). *The impact of Chinese import penetration on Danish firms and workers* (Technical report, IZA Discussion papers 8166).

Auer, R., & Schoenle, R. (2016). Market structure and exchange rate pass-through. *Journal of International Economics*, *98*(C), 60–77.

Auer, R. A., Chaney, T., & Sauré, P. (2018). Quality pricing-to-market. *Journal of International Economics*, *110*, 87–102.

Auer, R. A., Degen, K., & Fischer, A. M. (2013). Low-wage import competition, inflationary pressure, and industry dynamics in Europe. *European Economic Review*, *59*, 141–166.

Auer, R. A., Levchenko, A. A., & Sauré, P. (2019). International inflation spillovers through input linkages. *Review of Economics and Statistics*, *101*(3), 507–521.

Autor, D., & Dorn, D. (2009). The skill content of jobs and the evolution of the wage structure. *American Economic Review*, *99*, 45–51.

Autor, D., Dorn, D., & Hanson, G. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, *103*(6), 2121–2168.

Autor, D., Dorn, D., & Hanson, G. (2015). Untangling trade and technology: Evidence from local labour markets. *Economic Journal*, *125*(584), 621–646.

Autor, D., Dorn, D., & Hanson, G. (2016). The China shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, *8*, 205–240.

Autor, D., Dorn, D., & Hanson, G. (2019). When work disappears: Manufacturing decline and the falling marriage market value of young men. *American Economic Review: Insights*, *1*(2), 161–178.

Autor, D., Dorn, D., Hanson, G., & Majlesi, K. (2017). *A note on the effect of rising trade exposure on the 2016 presidential election*. Appendix to "Importing Political Polarization".

Autor, D., Dorn, D., Hanson, G., & Majlesi, K. (2020). Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review*, *110*(10), 3139–3183.

Autor, D. H., Dorn, D., Hanson, G. H., & Song, J. (2014). Trade adjustment: Worker-level evidence. *Quarterly Journal of Economics*, *129*(4), 1799–1860.

Balsvik, R., Jensen, S., & Salvanes, K. G. (2015). Made in China, sold in Norway: Local labor market effects of an import shock. *Journal of Public Economics*, *127*, 137–144.

Berman, N., Martin, P., & Mayer, T. (2012). How do different exporters react to exchange rate changes? *Quarterly Journal of Economics*, *127*(1), 437–492.

Bernard, A. B., Jensen, J. B., & Schott, P. K. (2006). Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of US manufacturing plants. *Journal of International Economics*, *68*(1), 219–237.

Bernard, A. B., Smeets, V., & Warzynski, F. (2016). *Rethinking deindustrialization* (Technical report). National Bureau of Economic Research.

Bloom, N., Draca, M., & Van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *Review of Economic Studies*, *83*(1), 87–117.

Bloom, N., Handley, K., Kurmann, A., & Luck, P. (2019). The impact of Chinese trade on US employment: The good, the bad, and the apocryphal. *American Economic Association Annual Meetings*, 2019.

Boehm, C. E., Flaaen, A., & Pandalai-Nayar, N. (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics*, *101*(1), 60–75.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Review of Economic Studies*, *89*(1), 181–213.

Brandt, L., Van Biesebroeck, J., Wang, L., & Zhang, Y. (2017). WTO accession and performance of Chinese manufacturing firms. *American Economic Review*, *107*(9), 2784–2820.

Broda, C., Limao, N., & Weinstein, D. E. (2008). Optimal tariffs and market power: the evidence. *American Economic Review*, *98*(5), 2032–2065.

Broda, C., & Weinstein, D. E. (2004). *Globalization and the gains from variety* (Technical report). National Bureau of Economic Research.

Burstein, A., & Gopinath, G. (2014). *International prices and exchange rates*. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics* (Vol. *4*, pp. 391–451). Elsevier.

Caliendo, L., Dvorkin, M., & Parro, F. (2019). Trade and labor market dynamics: General equilibrium analysis of the China trade shock. *Econometrica*, *87*(3), 741–835.

Caliendo, L., & Parro, F. (2015). Estimates of the trade and welfare effects of NAFTA. *Review of Economic Studies*, *82*(1), 1–44.

Caliendo, L., & Parro, F. (2021). *The quantitative effects of trade policy on industrial and labor location* (Technical report, mimeo). Yale University.

Caliendo, L., Parro, F., Rossi-Hansberg, E., & Sarte, P.-D. (2018). The impact of regional and sectoral productivity changes on the us economy. *Review of Economic Studies*, *85*(4), 2042–2096.

Carluccio, J., Cuñat, A., Fadinger, H., & Fons-Rosen, C. (2019). Offshoring and skill-upgrading in French manufacturing. *Journal of International Economics*, *118*, 138–159.

Dauth, W., Findeisen, S., & Suedekum, J. (2014). The rise of the east and the far east: German labor markets and trade integration. *Journal of the European Economic Association*, *12*(6), 1643–1675.

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, *19*, 3104–3153.

Di Giovanni, J., Levchenko, A. A., & Zhang, J. (2014). The global welfare impact of China: Trade integration and technological change. *American Economic Journal: Macroeconomics*, *6*(3), 153–183.

Eaton, J., & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, *70*(5), 1741–1779.

Eriksson, K., Russ, K. N., Shambaugh, J. C., & Xu, M. (2021). Trade shocks and the shifting landscape of us manufacturing. *Journal of International Money and Finance*, *111*, 102254.

Feenstra, R. C., Ma, H., & Xu, Y. (2017). *The China syndrome: Local labor market effects of import competition in the United States* [Unpublished manuscript].

Feenstra, R. C., & Sasahara, A. (2018). The 'China shock', exports and US employment: A global input–output analysis. *Review of International Economics*, *26*(5), 1053–1083.

Flam, H., & Helpman, E. (1987). Vertical product differentiation and north-south trade. *American Economic Review*, *77*, 810–822.

Freund, C., Mattoo, A., Mulabdic, A., & Ruta, M. (2022). Natural disasters and the reshaping of global value chains. *IMF Economic Review*, *70*(3), 590–623.

Galle, S., Rodríguez-Clare, A., & Yi, M. (2020). *Slicing the pie: Quantifying the aggregate and distributional effects of trade* (NBER working paper 23737).

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *100*(8), 2586–2624.

Hallak, J. C., & Schott, P. K. (2011). Estimating cross-country differences in product quality. *Quarterly Journal of Economics*, *126*(1), 417–474.

Handley, K., & Limão, N. (2017). Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States. *American Economic Review*, *107*(9), 2731–2783.

Hummels, D., Jørgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from Danish matched worker-firm data. *American Economic Review*, *104*(6), 1597–1629.

Johnson, R. C. (2018). Measuring global value chains. *Annual Review of Economics*, *10*, 207–236.

Keller, W., & Utar, H. (2016). *International trade and job polarization: Evidence at the worker-level* (Technical report). National Bureau of Economic Research.

Khandelwal, A. (2010). The long and short (of) quality ladders. *Review of Economic Studies*, *77*(4), 1450–1476.

Khandelwal, A. K., Schott, P. K., & Wei, S.-J. (2013). Trade liberalization and embedded institutional reform: Evidence from Chinese exporters. *American Economic Review*, *103*(6), 2169–2195.

Krugman, P. (1979). A model of innovation, technology transfer, and the world distribution of income. *Journal of Political Economy*, *87*(2), 253–266.

Lafrogne-Joussier, R., Martin, J., & Mejean, I. (2022). Supply shocks in supply chains: Evidence from the early lockdown in china. *IMF Economic Review*, *71*, 170–215.

Magyari, I. (2017). *Firm reorganization, Chinese imports, and US manufacturing employment* (CES working paper 17-58).

Malgouyres, C. (2017). *Trade shocks and far-right voting: Evidence from French presidential elections* (EUI working paper RSCAS 2017/21).

McLaren, J. (2017). Globalization and labor market dynamics. *Annual Review of Economics*, *9*, 177–200.

Ohlin, B. (1933). *Interregional and international trade*. Harvard University Press.

Pierce, J. R., & Schott, P. K. (2012). A concordance between ten-digit U.S. harmonized system codes and SIC/NAICS product classes and industries. *Journal of Economic and Social Measurement*, *37*(1-2), 61–96.

Pierce, J. R., & Schott, P. K. (2016). The surprisingly swift decline of US manufacturing employment. *American Economic Review*, *106*(7), 1632–1662.
Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of International Economics*, *48*(1), 7–35.
Rodríguez-Clare, A., Ulate, M., & Vásquez, J. P. (2020). *New-Keynesian trade: Understanding the employment and welfare effects of trade shocks* (NBER working paper 27905).
Samuelson, P. A. (1948). International trade and the equalisation of factor prices. *The Economic Journal*, *58*(230), 163–184.
Schott, P. K. (2003). One size fits all? Heckscher-Ohlin specialization in global production. *American Economic Review*, *93*(3), 686–708.
Schott, P. K. (2004). Across-product versus within-product specialization in international trade. *Quarterly Journal of Economics*, *119*(2), 647–678.
Soderbery, A. (2015). Estimating import supply and demand elasticities: Analysis and implications. *Journal of International Economics*, *96*(1), 1–17.
Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., & de Vries, G. J. (2015). An illustrated used guide to the world input-output database: the case of global automotive production. *Review of International Economics*, *23*, 575–605.
Utar, H. (2018). Workers beneath the floodgates: Low-wage import competition and workers' adjustment. *Review of Economics and Statistics*, *100*(4), 631–647.
Vernon, R. (1966). International investment and international trade in the product cycle. *Quarterly Journal of Economics*, *80*, 190–207.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Fischer, A. M., Herkenhoff, P., & Sauré, P. (2023). Identifying Chinese supply shocks: Effects of trade on labor markets. *Review of International Economics*, *31*(4), 1476–1507. https://doi.org/10.1111/roie.12673

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

$$X = \left[\sum_{g=1}^{G} \gamma_g \left(\sum_{k \in S_g} x_{gk}^{1-1/\eta_g} \right)^{\frac{\eta_g}{\eta_g - 1} \frac{\sigma-1}{\sigma}} \right]^{\sigma/(\sigma-1)} \tag{A1}$$

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

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

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

$$\alpha_g x_g^{-1/\sigma} \left[\sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)} \right]^{\sigma/(\sigma-1)-1} = \lambda p_g, \tag{A2}$$

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 (A2) therefore becomes

$$\alpha_g x_g^{-1/\sigma} = \frac{p_g}{E} \sum_{g'} \alpha_{g'} x_{g'}^{(1-1/\sigma)}. \tag{A3}$$

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[56]

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

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

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

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 $\{\alpha_g\}_{g=1,\ldots G}$, $\{x_g\}_{g=2,\ldots,G}$ and $\{p_g\}_{g=2,\ldots,G}$.

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

$$\sum_k x_{1k} = \Lambda p_1^{-\bar{\varepsilon}_1}, \tag{A4}$$

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 $\left(\{\alpha_g\}_{g=1,\ldots,G}\right)$, other country's supply $\left(\{x_g\}_{g=2,\ldots,G}\right)$ and prices $\left(\{p_g\}_{g=2,\ldots,G}\right)$ 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

999,999), 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, that is, manufacturing employment at the level of the commuting zone as well as all control variables are as reported in Auer 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

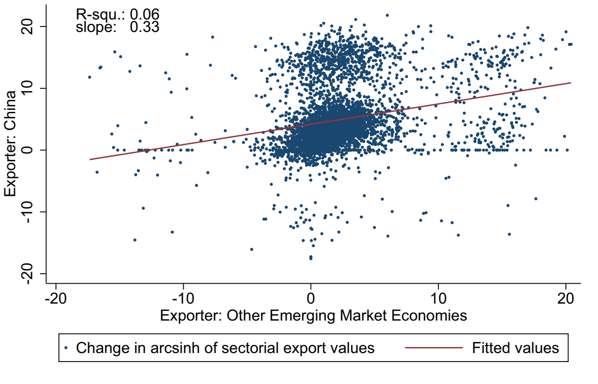

FIGURE C1 Sector export growth (arcsine): China and other EMEs, 1991–2007. See note to Figure 1. [Colour figure can be viewed at wileyonlinelibrary.com]

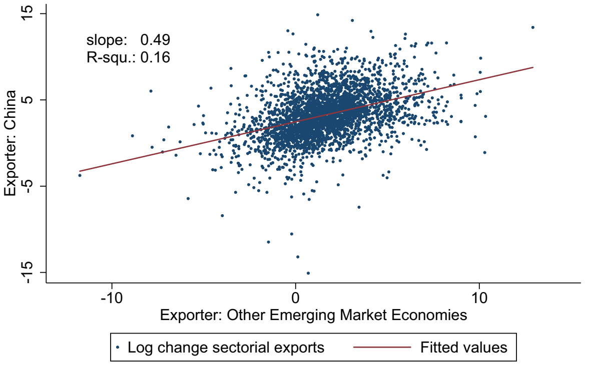

FIGURE C2 Export weight: Sectoral export growth of China and other EMEs, 1991–2007. Figure parallel to Figure 1 but for export weights (instead of value), 1991 to 2007. The estimated coefficient and the R-square of an OLS regression are reported in the figure. Figure OA.B1 in the Online Appendix plots the figure for the period 2000–2007. Data source UN Comtrade. [Colour figure can be viewed at wileyonlinelibrary.com]

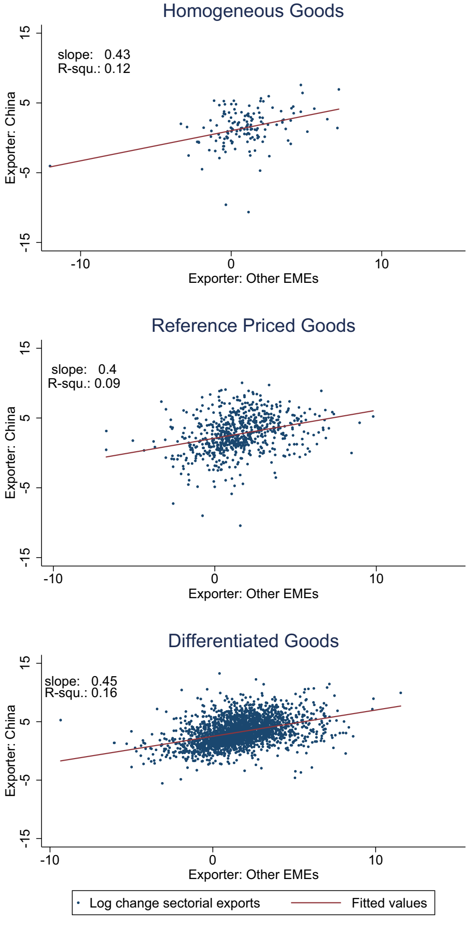

FIGURE C3 Homogeneous and differentiated goods: China's sectoral export growth, 1991–2007. Figure parallel to Figure 1 by product classification according to Rauch (1999). Figure OA.B2 in the Online Appendix plots the figure for the period 2000–2007. [Colour figure can be viewed at wileyonlinelibrary.com]

APPENDIX D. TABLES

TABLE D1 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 education levels		
	All workers	**Male workers**	**Female workers**
	(1)	**(2)**	**(3)**
Panel (i): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	−0.680*** (0.245)	−0.799*** (0.284)	−0.547** (0.227)
Panel (ii) Supply-induced 2SLS			
$\Delta IPW^{CN,US}$	−0.504** (0.247)	−0.677** (0.296)	−0.300 (0.223)
College education			
Panel (iii): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	−0.680** (0.300)	−0.891** (0.362)	−0.463* (0.267)
Panel (iv) Supply-induced 2SLS			
$\Delta IPW^{CN,US}$	−0.542* (0.307)	−0.781** (0.382)	−0.300 (0.273)
Non college education			
Panel (v): Replication ADH, 2SLS			
$\Delta IPW^{CN,US}$	−0.716*** (0.227)	−0.605** (0.243)	−1.003*** (0.258)
Panel (vi) Supply-induced 2SLS			
$\Delta IPW^{CN,US}$	−0.395* (0.234)	−0.356 (0.257)	−0.549** (0.265)

Note: 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.

$^{*}p < .1$.

$^{**}p < .05$.

$^{***}p < .01$.

TABLE D2 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)

Note: 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.

[*] $p < .1$.

[**] $p < .05$.

[***] $p < .01$.