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Job creation and job destruction: The effect of trade shocks on U.S. manufacturing employment

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Abstract

This paper studies the effect of export expansion on the US labour market over the last two decades. Exploiting foreign emerging markets' unilateral liberalisation, this paper provides new empirical evidence for the importance of export expansion to the US labour market at the industry level. Using a novel instrumental variable strategy, the result confirms that US exports played a critical role in supporting manufacturing employment. Reduced-form estimates imply that US exports to different markets created more than 1.6 million manufacturing jobs between 1991 and 2007, which is comparable to the estimated job losses attributed to the import competition from China. Meanwhile, there is substantial heterogeneity in this positive employment effect across export destinations and industries. Industries not only respond differently to various export shocks, but could also experience differential employment growth facing the same export shock. I find that the job creation effect is larger for industries with a higher initial share of workers who are older, less-educated or non-white, and performing routine-based tasks. In addition, the effect is more pronounced for industries that had higher labour market concentration.

KEYWORDS

employment, export performance, import competition, liberalisation, trade

1 | INTRODUCTION

A fundamental idea in the theory of international economics is that all trading partners benefit from trade in general. Although winners and losers appear simultaneously, the standard theory posits that costs are outweighed by benefits generated by trade in general. This notion, however, has been challenged within developed economies during the rapid and deep globalisation of the last two decades. The backlash against globalisation we see today in those countries is partially due to the fact that people are losing faith in trade. And this lost faith is built upon strong intellectual ground.[1]

Import competition can cause job losses, but better export performance can lead to job gains. Previous studies suggest that trade with China on average accounts for the loss of nearly 1.5 million jobs in the US manufacturing sector during 1990–2007.[2] While US imports from China increased substantially from $26 billion to $330 billion,[3] US exports to China only rose from $10 to $57 billion. By looking at the bilateral relationship with China only, there seems to be no evidence of job gains from exports. However, in a multi-country world, the shock to exports may manifest as increased exports to countries other than China. Based on this logic, stating that exports did not increase to China does not prove that exports in general were not stimulated.[4]

This paper provides new empirical evidence on how export expansion affects US employment in the manufacturing sector. The domestic country in this paper is the United States, and I consider the rest of the world as the source that generates demand for individual U.S. products. Specifically, I examine the effect of US export expansions that are triggered by foreign countries' unilateral liberalisation, while accounting for the import competition from the world. I find that there is a substantial positive effect of growing exports on US manufacturing employment. Two-stage least-squares (2SLS) estimates suggest that the total US export expansion to major trading partners created more than 1.6 million jobs during 1990 to 2007.[5] The analysis in this paper also extends the previous literature in two important respects. First, I find substantial heterogeneity in the effect of exports on employment across destinations and markets. As export shocks stemming from multiple destinations could target different industries, the elasticity of employment with respect to exports may vary across trading partners depending on the initial labour market condition in each industry. Specifically, results suggest that industries exposed to rising exports to NAFTA and ASEAN countries see an even larger increase in manufacturing employment.[6] And the positive employment effect is smaller yet noticeable for the exports to countries in Latin America, East Asia and Europe.

[1]Many recent studies document the significant and adverse economic consequences for the US, especially job losses, due to import competition from China or other low-income countries (Acemoglu et al., 2016; Autor et al., 2013; Bernard et al., 2006; Pierce and Schott, 2016)

[2]Autor et al. (2013) find that import competition from China had cost the US nearly 1.5 million manufacturing jobs from 1990 to 2007 at the commuting zone level.

[3]Trade data are taken from the UN Comtrade Database. Imports and exports are deflated to 2007 US dollars using the Personal Consumption Expenditure deflator.

[4]Between 1991 and 2007, Figure 1 shows that US total exports increased from $513 to $1000 billion and shared a similar trend as imports from China.

[5]Feenstra et al. (2019) find qualitatively similar results using a different empirical strategy.

[6]NAFTA represents The North American Free Trade Agreement, which was an agreement signed by Canada, Mexico and the United States; ASEAN represents the Association of Southeast Asian Nations, which is a regional intergovernmental organisation comprising ten countries in Southeast Asia.

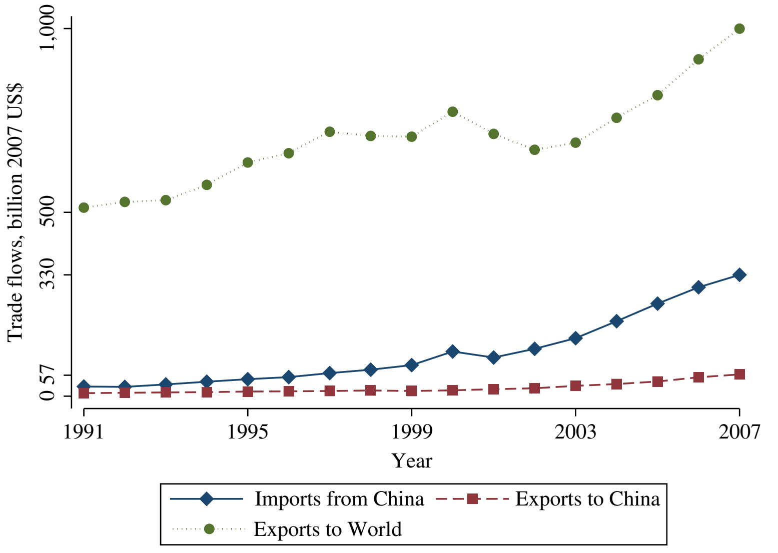

FIGURE 1 Trade with China and Total Exports to the World, 1991–2007 [Colour figure can be viewed at wileyonlinelibrary.com]

Because of this heterogeneity, the implied number of job gains due to export expansion in different destinations is actually far larger than the average impact on employment. Based on the reduced-form estimates, the total expansion of US exports to different destinations created more than 1.6 million jobs.

The other important feature of this analysis is the uncovering of heterogeneous effects of export expansion across industries. Given the observed heterogeneity of the employment effects of exports, it would be useful to identify to what extent observable industry or worker characteristics can explain these differences. I show that rises in employment are more pronounced in industries exposed to export opportunities and that had a higher share of workers performing routine tasks. In addition, this differential impact of exports on employment disproportionately benefits industries that hired more older, less-educated and non-white workers. Lastly, I find that industries that had higher labour market concentration, measured by the Herfindahl–Hirschman index, also experienced a larger employment increase due to the export expansion. This study also provides evidence on the influence of export shocks to other labour market outcomes such as the wage bill and establishment counts. Overall, I find that these outcomes, along with employment, are influenced by trade flows; when employment increases, so does the wage bill and the number of establishments. In contrast, I find no significant effects of either import or export shocks on wages.[7]

[7]This finding is in keeping with existing evidence on import competition in the recent literature: while some papers find that import competition has a negative impact on the wage rate, others find the opposite. Autor et al. (2013) find negative effect for the US facing Chinese import competition, Hakobyan and McLaren (2010) find negative effect for the US after signing NAFTA, and Costa et al. (2016) find negative effect for Brazil facing Chinese import competition. Acemoglu et al. (2016) find positive wage effect for industries facing import competition from China at the industry level.

This paper is most closely related to Feenstra et al. (2019), and the empirical literature exploring the relationship between exports and labour markets for different countries.[8] However, this paper differs in its methods from earlier papers and addresses the two major challenges in the literature in estimating the impact of exports on labour market outcomes. To correct biases caused by domestic technological or productivity shocks, previous work commonly uses other US-alike advanced countries' total exports to the world to isolate world's demand shocks. This approach, which delivers a highly informative instrument, relies on the key assumption that these high-income countries have not experienced supply shocks that are unique to the United States. Feenstra et al. (2019) then proposed an alternative instrument utilising the variation from import tariff changes in countries that imported US products.[9] Although this tariff-based instrument improves the instrument exogeneity by providing a clearer source of variation, the instrument itself is only weakly correlated with the US export growth. My identification strategy combines the strengths of each of these approaches.

To generate consistent estimates of the impact of export expansion on domestic employment, I exploit two separate sources of variation to identify the export-induced employment effect. To capture shocks to demand for US exports, I first use a cross-sectional product-by-country level variation, signifying the importance of each foreign market across individual US products. Then, I explore the change in total import growth in a set of recently liberalised countries for each product. As a country opens up, liberalisation may take many forms on tariffs, non-tariff barriers, exchange rate or other economic policies. All of these can contribute to a country's ability to import more from foreign countries around the liberalisation episode. Thus, my instrument for US export growth provides a strong first stage and captures exogenous shocks to foreign demand for US exports. Because of the use of different methods, as well as exploring heterogeneity in the employment effect of exports, results in this paper provide complementary evidence and reinforce past research on the impact of export expansion on labour markets.

The results also contribute to research on the labour market effects of imports from China, such as Acemoglu et al. (2016) and Pierce and Schott (2016) at the industry level, and build on Autor et al. (2013)'s seminal work at the local-labour market level.[10] According to Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2018), the Bartik "Shift-Share" instrument, which is formed by interacting local industry employment shares, acquires the instrument validity from either the orthogonality in the "shifts," in the "shares" or both. The identifying assumption for the local-labour market approach therefore requires these shares to be stable over time.[11] Workers in export-oriented sectors tend to be younger and to possess greater education attainment than workers in the import-competing sectors.

[8]Dauth et al. (2014) investigate the effect of both imports and exports on the local labor market in Germany. Another study by Costa et al. (2016) also considers how the Brazilian labor market adjusts to imports and exports between Brazil and China. Choi and Xu (2019) find that the increased exports to China raised the employment for Korean manufacturing firms. In general, most studies find that in labor markets experiencing growth in exports, employment or average hourly wages increased as well.

[9]I became aware of their work right after finishing the first draft of this paper. Their working paper version appeared around the same time my first draft was completed.

[10]A large literature explores geographic variation at the sub-national level and therefore illuminates the distributional effects of trade: Hakobyan and McLaren (2010) estimate effects of NAFTA on wages in the US. They find that NAFTA dramatically lowers wage growth for blue-collar workers in the most affected industries and localities. Using state and industry-level unemployment and trade protection data from India, Hasan et al. (2012) find no evidence unemployment increases the effect of trade reforms. Moreover, their industry-level analysis indicates that workers in industries experiencing greater reductions in trade protection were less likely to become unemployed, especially in net export industries. Lake and Millimet (2016) analyse the heterogeneous impact of rising trade exposure on employment growth of "good" and "bad" jobs.

[11]Autor et al. (2013) provide evidence that labor is immobile in the context of import competition from China.

Since adjustment frictions increase with age and decrease with skills, workers who respond to a local export shock are more likely to move and search for better job opportunities across sectors or regions. Monte et al. (2018) also provide evidence on finding substantial heterogeneity in local employment elasticities across locations, a pattern that commuting flows between and within large commuting zones can explain. Even though I found economically and statistically significant results at the local-labour market level, given the above reasons, the industry-level approach is more appropriate for the present study. The analysis, therefore, relies on industry-level changes, an approach consistent with labour mobility across regions. As this paper accounts for both import and export shocks simultaneously, it mainly aims to provide a more complete understanding of the direct impacts of trade on employment at the industry level.

The rest of the paper proceeds as follows. Section 2 presents a simple theoretical framework that is used to guide my empirical work. Section 3 describes the empirical strategy. Section 4 explains the data used in the paper. Section 5 provides the results and Section 6 concludes.

2 | THEORETICAL FRAMEWORK AND BACKGROUND

Expanding international trade is not painless, and policymakers are mainly concerned about the impact of trade on employment. Classical trade models, however, usually assume full employment and therefore only account for adjustments on factor's prices, not on employment in the countries involved. To address this limitation and shed some light on the impact of international exports on employment while considering imports at the same time, I choose a simple model which considers a two-sector, single-factor (labour), small-country Ricardian framework with standard search-matching frictions and imperfect intersectoral labour mobility.

The structure of the framework is mainly based on the work of Mitra and Ranjan (2010) and Hasan et al. (2012). The model considers an economy that produces a single, non-tradable final sector and two tradable intermediate sectors. The good in the final sector is chosen as the numeraire. The two intermediate sectors, namely an import-competing sector and an export sector, only use labour in their production. And the labour market equilibrium is described as a static version of Pissarides (2000) in a two-sector setting. The main feature of the model, imperfect sectoral labour mobility, allows the domestic country to remain incompletely specialised after opening to trade. As in the standard Ricardian model, the import-competing sector, where the value of the marginal product of labour would have been lower with trade, cannot survive trade liberalisation with perfect intersectoral labour mobility. In the more likely case of costly labour mobility (which could be due to loss of skills in moving from one sector to another or some other idiosyncratic costs due to heterogeneity of preferences), the home country may remain incompletely specialised and the no-arbitrage condition is satisfied for the marginal worker. These frictions generate sector-specific employment changes and job gains in one sector which may or may not offset losses in another. The full details of the model are provided in the Theory Appendix.[12]

[12]The work of Hasan et al. (2012) considers an economy that produces a single final good and two intermediate goods with two extreme cases: perfect labor mobility or no labor mobility between sectors. I borrow the idea of imperfect sectoral labor mobility from Mitra and Ranjan (2010), where they study the relationship between offshoring and unemployment. Following Mitra and Ranjan (2010) and Artuç et al. (2008), I model the cost of moving between sectors as workers' idiosyncratic preferences for working in a particular sector. I use a Gumbel cumulative distribution function to capture workers' idiosyncratic preferences for working in a particular sector.

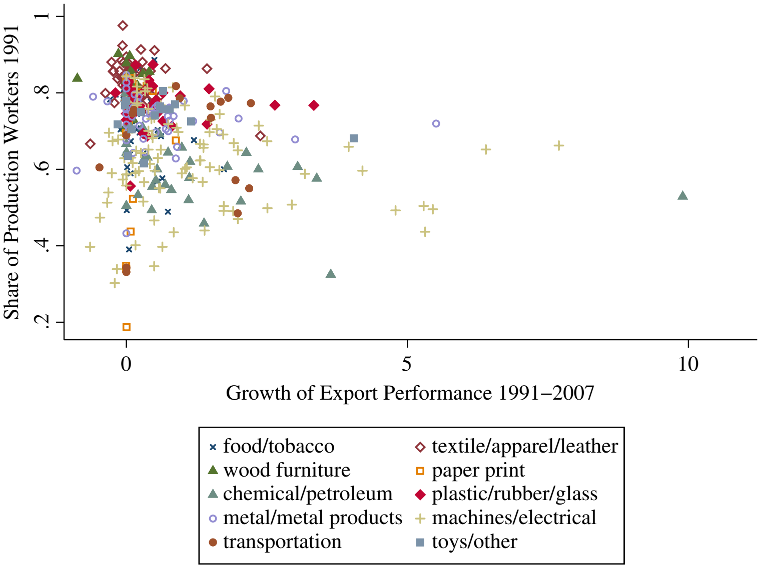

FIGURE 2 Export performance, 1991–2007 [Colour figure can be viewed at wileyonlinelibrary.com]

Extending standard trade models to this framework is helpful for understanding the empirical results as this framework captures both "push" and "pull" factors that were at play in shaping the impacts of trade on employment. Since the bulk of the literature on the impact of trade on employment studies the importance of imports, this framework addresses the issue of whether export creates job opportunities while considering the import competition simultaneously. Though this is largely viewed as an empirical question, the model provides some preliminary answers.

The implications of the framework are quite straightforward: an increase in foreign demand for US exports of a good raises employment in the same industry, and an increase in foreign supply to US imports of a good reduces employment in the same industry. These two direct effects of trade for a given industry could happen independently and simultaneously. Depending on the initial labour market conditions and where the shocks are coming from, affected industries could respond very differently to these trade shocks.

Similar implications can also be obtained from more sophisticated spatial models in studies that investigate the employment adjustment to import shocks at the regional level (Autor et al., 2013; Caliendo et al., 2019; Dix-Carneiro & Kovak, 2017). Although the presence of labour market frictions or worker mobility in spatial models is usually created at the geographical level, the link between intersectoral and interregional labour mobility is also intuitive. For example, it is an intuitive assumption that displaced workers would more likely be looking for similar jobs. And if a trade shock has hit a sector in a specialised region, the former employees would have to find another job either in a different sector (intersectoral labour mobility) or in a different region (interregional labour mobility). Since the aim of the model is to provide guidance to the empirical work at the industry level, I choose a simple two-sector model which can adequately portray the main mechanisms supporting the empirical work and avoid the analytical complexity.

Before turning to the empirical strategy, I present the difference in industries and jobs that are exposed to import and export shocks. Figures 2 and 3 show the growth in total export performance and import penetration from China for 392 manufacturing industries during 1991–2007 measured in percentage point changes, indicating that jobs supported by exports and destroyed by imports are quite

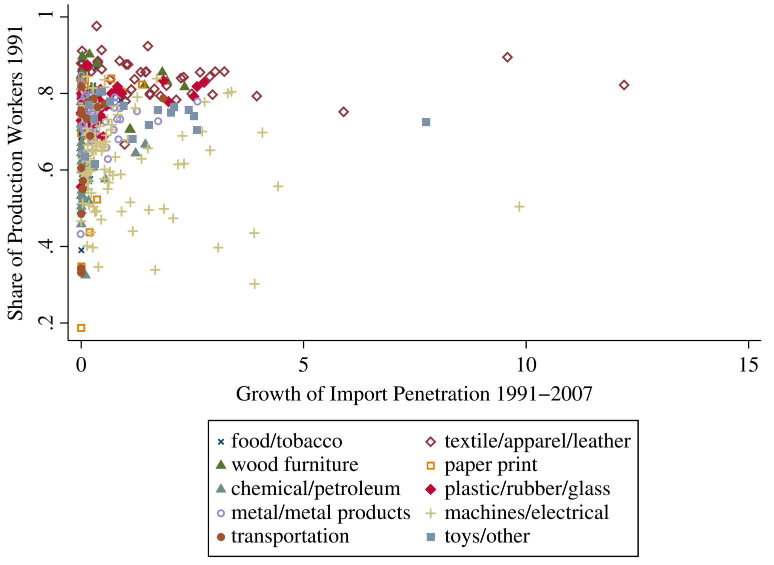

FIGURE 3 Import penetration, 1991–2007 [Colour figure can be viewed at wileyonlinelibrary.com]

different.[13] The most export-expanding industries are mainly gathered in machinery, electrical, chemical and transportation manufacturing. Even within each subsector, there is quite a lot of variation, which allows us to compare similar industries with different export performances. Most of the industries to the right have large import exposures to China.[14] They are mostly in textile, apparel, toys and luggage, etc. Those two graphs basically show the United States' comparative advantage over the rest of the world: industries facing foreign import competition that tend to be labour-intensive, such as textile and apparel; and industries that have strong export performances specialise in products such as semiconductors, medical/biological products and other optical instruments.

3 | METHODOLOGY

3.1 | Empirical specification

The empirical objective of this paper is to estimate the elasticity of employment with respect to shocks to exported manufacturing products. This analysis is based on employment in American industries by year, for which I have an industry-by-year panel.

To assess the fully adjusted labour market in the long run, I attempt to address the problem by using the "long difference technique," which is widely used in the literature examining the labour market impact of globalisation. The long-difference model serves two important roles here: first, it can eliminate serially correlated measurement errors that usually exist in employment and trade data. This is argued by Griliches and Hausman (1986). Long-difference estimators also increase the explanatory

[13]Export performance represents the total exports for each industry as a share of that industry's total production, showing how important the foreign market is for a certain industry's production capacity.

[14]Similarly, import penetration is defined as imports from China divided by initial industrial domestic absorption (industry's total production plus imports minus exports).

power of the instruments, thereby further reducing the finite sample bias and decreasing the mean squared error of the estimator.

I fit the estimation separately for stacked first differences covering the two subperiods 1991–1999 and 1999–2007. To show that this serendipitous choice of 1999 as a middle year is not the main cause that drives our results, I provide robustness checks using shorter differences with other choices of middle years. The analysis treats 1991 as the initial year because it is the earliest year for which the requisite disaggregated bilateral trade data are available for a large number of countries. To avoid other disturbances generated by the Great Recession, most regressions end before 2007, which is prior to the onset of the recession. I do not, however, find different results in robustness checks where I widen the second subperiod to 1999–2009.

Thus, the relationship is modelled by the following stacked long-difference specification:

$$\Delta \ln L_{jt} = \alpha_t + \beta_1 \Delta \mathrm{EP}_{jt} + \beta_2 \Delta \mathrm{IP}_{jt} + \mathbf{Z}_{j,0}\Gamma + e_{jt}, \tag{1}$$

where $\Delta \ln L_{jt}$ indicates the log change in employment of industry j between time period $t-1$ and t. $\Delta \mathrm{EP}_{jt}$ and $\Delta \mathrm{IP}_{jt}$ measure changes in US performance of exports to the world and in import penetration of industry j between time period $t-1$ and t under various of measures. $\mathbf{Z}_{j,0}$ includes a set of observed industry-specific characteristics to control for initial technological progress, production structure and pretrends for each industry.[15] α_t is time dummy which captures period-specific macro shocks, and e_{jt} is the error term.[16]

3.2 | Trade variables and instruments

To study the export-induced effects at the industry level, I create the baseline trade measures for the export performance of US manufacturing industries. The export performance variable measures each industry's overall export performance, defined as:

$$\Delta \mathrm{EP}_{jt} = \frac{\Delta X_{jt}^{\mathrm{US} \rightarrow \mathrm{World}}}{size_{j,0}}, \tag{2}$$

where for the US industry j, $\Delta X_{jt}^{\mathrm{US} \rightarrow \mathrm{World}}$ is the change in total exports in industry j over the period $t-1$ to t as a share of that industry's size, which is measured by that industry's initial domestic absorption. The size of the industry j is computed as $Y_{j,0} + M_{j,0} - X_{j,0}$, which is equal to industry's total production, $Y_{j,0}$, plus industry's imports, $M_{j,0}$, minus industry's exports, $X_{j,0}$). Alternative size measures are constructed by replacing the denominators with either total production or industry's initial employment. Overall, results

[15] The controls in vector Z, when included, are each normalised around the mean to facilitate interpretation of the time effects.

[16] All variables are measured at the level of 392 four-digit manufacturing industries. Later models also use NBER-CES employment data and are estimated with 384 four-digit manufacturing industries. All industry-level regression estimates are weighted by start-of-period industry employment, and standard errors are clustered at the three-digit industry level to allow for arbitrary error correlations within industries over time. There are 135 three-digit manufacturing industry clusters encompassing the 392 four-digit industries.

stay robust. Basically, we would like this measure to capture the export intensity for an industry, representing how important foreign market is to an industry.[17]

To compare and assess the export expansion effect, I follow Acemoglu et al. (2016) and create an import penetration variable measuring each industry's import penetration. Using a similar approach as with overall export performance, the import penetration is defined as:

$$\Delta \mathrm{IP}_{jt} = \frac{\Delta M_{jt}}{\mathrm{size}_{j,0}}, \tag{3}$$

where ΔM_{jt} is the change in imports from different origins (total imports the World, imports from China, or imports from rest of the world [ROW] except for China) to United States for industry j during the same period.

The concern about the two variables measuring trade shocks is that observed changes in the exports or imports may in part reflect domestic demand or supply shocks to US industries that affect US import or export decisions. Thus, the identification hurdle is the need for separate instruments for both potentially endogenous variables. As both US labour markets and trade flows underwent transformative changes, disruptive silicon chip-based technologies, such as artificial intelligence and robots, arguably related to waves of both. On the export side, labour-saving technological upgrading may cause fewer employment and more exports to the world. Acemoglu and Restrepo (2020) find that adoption of robots leads to reductions in both employment and wages. The work of Bustos (2011) shows that export-induced revenues can lead firms to upgrade their technologies. Nevertheless, labour-augmenting technological change may boost labour productivity and gives firms incentives to hire more workers. This productive shock may also let firms become more competitive and export more.

Thus, to establish a causal relationship between export performance and employment, an ideal instrument for industry exports captures changes in foreign demand for US goods that are orthogonal to changes in American demand and supply conditions. Dauth et al. (2014) propose such an instrument for exports using other advanced economies' exports. They argue that the demand for similar products purchased from advanced economies avoids endogeneity issues caused by German excess supply, such as those from technology or productivity shocks. Similarly, one could construct an instrument for US export performance to the world by using exports from other advanced economies to the world. However, a major concern about using this strategy is that those advanced economies might experience comparable technological shocks that correlate with exports at the industry level. For example, both Airbus and Boeing might increase their sales to the world mainly because of technological advances that both adopt simultaneously.

Hence, a good instrument would purge out the variation coming from the industry-level technological changes or productivity shocks across the United States and other high-income countries. Aghion et al. (2017) generate firm-level export shocks to study the effect of exports on innovation in France. The central idea of those measures is to exploit the variation generated by all trading partners' demand shock. Inspired by their work, I apply an instrumental variable that only captures foreign demand shocks on US exports by exploring the variation in the changes in imports of other foreign countries at the country–product level.

[17]To test the robustness of the estimation results to the choice of normalisation, I also create different denominators using initial employment and initial total production. When using industry's initial employment for standardisation, the unit of trade variables becomes dollars per worker, and the size of coefficient on the import variable is consistent with the findings in Autor et al. (2013) where their import penetration is also measured by dollars per worker.

Demand shock as the source of exogenous variation: my instrumental variable for US export performance is defined as follows:[18]

$$\Delta \mathrm{EPIV}_{jt} = \frac{1}{\mathrm{size}_{j,0}} \sum_{s \in j} \sum_{n=1}^{N} \frac{X_{s0}^{\mathrm{US} \to n}}{X_{s0}^{\mathrm{US} \to \mathrm{World}}} \Delta \boldsymbol{M}_{\boldsymbol{st}}^{\boldsymbol{n} \leftarrow \mathbf{World}}, \tag{4}$$

The summand in the above equation consists of two parts. $\frac{X_{s0}^{\mathrm{US} \to n}}{X_{s0}^{\mathrm{US} \to \mathrm{World}}}$ is the share of US exports sold to country n in total US exports of product s in 1991. This part captures the importance of market n to the United States for selling a specific product s. Since this structure may change due to trade, I use the share in the initial year. $\Delta M_{st}^{n \leftarrow \mathrm{World}}$ is the change in country n's imports from the world for product s over the same period. For each product, I sum across countries to get the product-level demand shocks on US exports. At the six-digit Harmonized Commodity Description and Coding Systems (HS) level, there are about 5300 manufacturing products, I then finalised the procedure by mapping each product into one of the four-digit Standard Industrial Classification (SIC) industries to get the industry-level demand shocks on US exports.

To better understand the source of the identifying variation, I then focus only on a set of countries (N) that implemented their liberalisations recently. The criterion used to designate a country's liberalisation is based on Wacziarg and Welch (2008), who update the set of countries originally designated by Sachs et al. (1995). I pick countries that unilaterally implemented liberalisation after late 1980s, which is just before the onset of my sample period. These countries are Bangladesh, Brazil, China, Colombia, Ecuador, Haiti, India, Mexico, New Zealand, Paraguay, Romania, Sri Lanka, Trinidad and Tobago, Tunisia, and Turkey. Selecting those countries as the source that generates shocks to demand for US exports is supported by Goldberg and Pavcnik (2016). They argue that many of these recent liberalisations are unilateral and plausibly exogenous to economic conditions of advanced countries. For example, India's trade liberalisation in 1991 occurred as a result of IMF interventions that dictated the pace and scope of the reforms; Columbia's liberalisations in the late 1980s and early 1990s were implemented to reduce dispersion of tariffs across industries to a more uniform level instead of requiring negotiations for individual tariffs. The variation generated by import changes in these newly liberalised countries must meet three criteria to be valid for our instrument purposes: First, it must be correlated with actual foreign demand (informative); second, it must be uncorrelated with any supply shocks to domestic industry employment (exclusion restriction); third, of particular importance for this paper, it must be uncorrelated with any omitted variables in the error term varying by industry and time (instrument exogeneity). The first-stage results are shown in Table A4.

Using these criteria to designate a country's liberalisation status based on Wacziarg and Welch (2008), I examine those newly liberalised countries case by case. The changes in imports among those countries are plausibly driven by the following reasons. According to Sachs–Warner criteria, a country was classified as closed if it displayed at least one of the following characteristics: (i) average tariff rates of 40% of more, (ii) non-tariff barriers covering 40% or more of trade, (iii) a black market exchange rate at least 20% lower than the official exchange rate, (iv) a state monopoly on major exports and (v) a socialist economic system (as defined by Kornai 1992). Tariff and non-tariff barriers restrict

[18]The ideal data for this paper are the firm (e.g. Longitudinal Business Dynamics) and custom (e.g. Longitudinal Firm Trade Transactions Database) linked data like the one used in Aghion et al. (2017), but such datasets are not publicly available in the US.

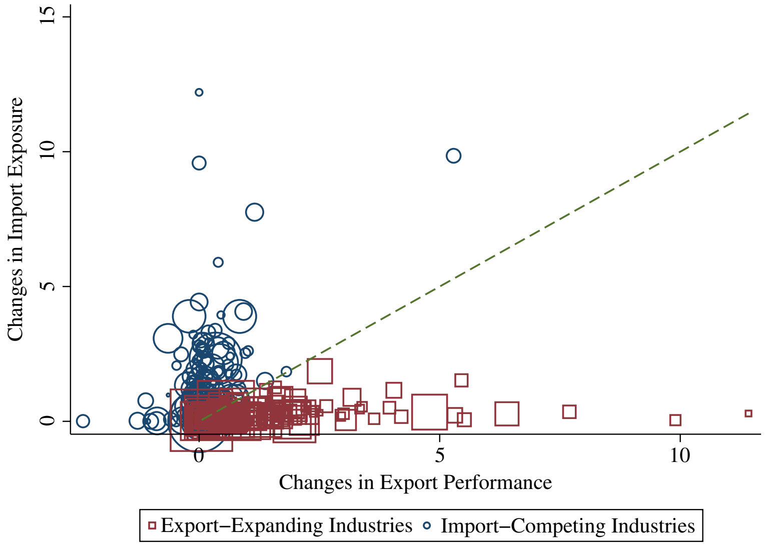

FIGURE 4 Export performance vs. import penetration, 1991–2007 [Colour figure can be viewed at wileyonlinelibrary.com]

trade directly. A black market premium on the exchange rate and other political or state monopoly could have effects equivalent to formal trade restrictions. Alleviation of any of those trade restrictions could increase imports flow into those economies, which also differentially strengthen US exports to those destinations given the size of each foreign market.

On the import side, I follow Autor et al. (2013) and Acemoglu et al. (2016) and use imports from different origins (World, China, ROW) to other advanced economies to instrument the imports from China to the United States. The validity of this instrumental variable is based on the fact that the origin's supply shock, which radiates to the US and other advanced economies, can purge out US domestic unobservable shocks. Thus, I instrument the import penetration with the following:

$$\Delta \mathrm{IPIV}_{jt} = \frac{\Delta M^{\mathrm{Other}}_{jt}}{\mathrm{size}_{j,0}}, \tag{5}$$

where $\Delta M^{\mathrm{Other}}_{jt}$ is the change in imports in industry j between $t-1$ and t in eight other high-income countries.[19] Figures A1 and A2 and Table A4 show the first-stage results of two instruments. Both instruments are informative and strongly correlated with variables of interests. Each dot in the graph represents a four-digit manufacturing industry ($N = 392$). Lines are fitted by OLS regressions, weighted by each industry's employment in 1991.[20] Figure 4 also graphically shows what these two sources of variation look like. This picture shows the spectrum of which US industries have advantages and disadvantages compared to the rest of the world.

On top of using instruments, I add additional industry-level covariates to control for technology or productivity shocks that may threaten the exclusion restriction for instrument of the import variable. I

[19]These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

[20]Details of first-stage results will be made available upon request.

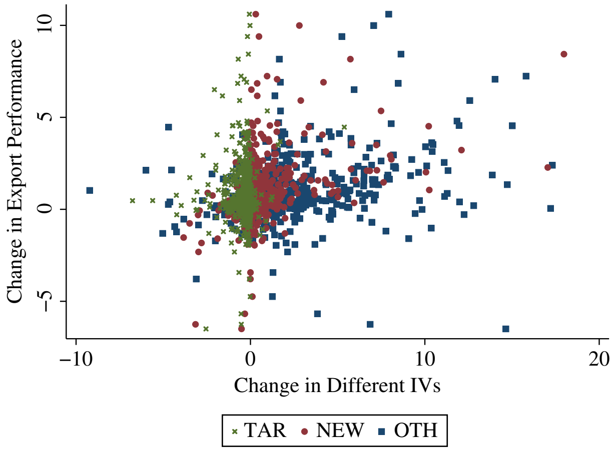

FIGURE 5 Comparison between instruments [Colour figure can be viewed at wileyonlinelibrary.com]

also add pretrends of the dependent variable as controls to tease out the beforehand overall declining trend that the specification may in part reflect.

3.3 | Discussion of IV strategies

Estimating the employment effect of exports is empirically challenging as finding a plausible exogenous variation that is orthogonal to other labour market shocks can be difficult. To deal with the endogeneity issues raised by domestic supply shocks such as the technological upgrading or other productivity shocks, previous researchers have most often depended on the variation from other US-alike high-income countries' exports to estimate the elasticity of employment with respect to exports (Choi & Xu, 2019; Costa et al., 2016; Dauth et al., 2014); Feenstra et al., 2019, hereafter FMX). This approach of creating a highly informative instrument for the US exports relies on the key assumption that these high-income countries have not experienced supply shocks that are unique to the United States. This assumption, however, might raise concerns because it is unclear what is driving the overall export growth for these advanced economies. For example, United States and these could have had similar technological upgrades in the production or systemic structural changes. Thus, there still may be a problem after the instrumentation. That is why FMX then also proposed an alternative instrument utilising the variation in import tariff changes in countries that imported US products. Although this tariff-based instrument improves the instrument exogeneity by providing a clearer source of variation, this instrument itself is weakly correlated with the US export growth and has to be used with the previously mentioned instrument simultaneously in the estimations.

The empirical strategy in this paper is, I would argue, an improvement over previous methods of identifying the export effects on employment. Before proceeding to the empirical strategy used in my paper, it is useful to be clear what liberalisation includes in emerging markets and why only relying on the tariff-based instrument is insufficient and leads to the weak IV problem. As a country opens up, its liberalisation may take many forms—liberalisation of tariffs, non-tariff barriers, exchange rate and other economic policies. All of these can contribute to changes in a country's demand for products from foreign countries around the liberalisation episode. Thus, only relying on the variation on tariff changes in the liberalised countries alone to predict US export growth may not capture all of the demand shocks on US exports and may lead to weak first-stage results. Therefore, I utilise the aggregate import flows into each liberalising country for each product to capture demand shocks on US exports. The underlying idea is that changes in liberalising destinations' imports of a product will be a good measure of the change in demand of that exported product in the United States.

Next, to graphically compare the sources of variation used in three different instruments, I plot Figure 5, which presents the change in export performance (along the y-axis) against the change in different demand shocks to US exports measured by the different instrumental variables (along the x-axis) for all US manufacturing industries at the four-digit level.[21] The three compared instruments are as follows: tariff-based instrument (TAR), represented by crosses; the instrument utilising the other advanced countries' export flows (OTH), represented by squares; and, the instrument used in this paper exploiting the demand shocks triggered by the import flows into newly liberalised economies (NEW), represented by dots.

There are two important observations in this graph. First, for the two instruments used by previous researchers, "TAR" is much less variable than "OTH," which provides the majority of the explanatory power for the endogenous variable. Thus, the variation provided by "OTH" mainly drives the results in FMX. Second, the comparison with the two instruments that FMX uses is salient and again useful. The identifying variation of the "NEW" instrument has some overlapping, yet, very different variation relative to previously used ones. The variation in "NEW" can be viewed as a weighted average of the variations in "TAR" and "OTH." This "NEW" instrument contains both the exogeneity portion provided by the "TAR" and the correlated portion provided by "OTH." Thus, the proposed instrument not only addresses the weak IV problem but also assists the analysis by providing a clear source of identifying variation which is from the recent liberalisation of emerging markets. In the subsection 5.1 of the results, I also compare the estimated coefficients using different IV strategies to test the sensitivity and the robustness of each method to various added controls.

4 | DATA SOURCES

The study requires information for an extended period of time on US manufacturing activity at the industry level as well as extensive trade data. The main source of annual data on manufacturing activity is the Country Business Pattern Data (CBP). CBP provides information on employment, establishment counts and payroll at the county–industry level.[22] The sample includes 392 four-digit SIC manufacturing industries that are surveyed annually from 1991 to 2007.[23] For the purpose of this analysis, county-level data are aggregated to the national level.[24]

The NBER-Center for Economic Studies Manufacturing Industry Database (NBER-CES) provides additional information for the years 1971–2007. The NBER-CES contains annual industry-level data on output, employment, payroll and other input costs, investment, capital stocks, total factor productivity and various industry-specific price indexes. These data allow the exploration of labour market

[21]This is equivalent to the first-stage regression.

[22]It covers all US employment except most government employees, self-employed individuals, employees of private households, railroad employees and agricultural production employees.

[23]This version of SIC is a slightly aggregated version of SIC-87 and combines those industries that experience zero trade shocks with their closest industries. The version is consistent with the one used by Autor et al. (2013) and Acemoglu et al. (2012).

[24]To preserve confidentiality, CBP information on employment by industry is sometimes reported as an interval instead of an exact count. We compute employment in these cells using the fixed-point imputation strategy developed by Author et al. (2013). Details on how to construct the CBP data can be found on David Dorn's website: http://www.ddorn.net/data.htm

outcomes not reported in CBP. They also provide information on industrial characteristics that are used as control variables, including the ratio of capital to value added, computer investment as a share of total investment, high-tech equipment as a share of total investment, production workers as a share of total employment and the log average wage. All variables are computed in the initial year at the industry level to avoid letting them be bad controls. Additionally, these data permit calculation of pretend controls from the period 1976–1991, including changes in industry log average wages and share of total US employment.

Trade data are needed to compute our main regressors of interest. The values of international trade flows for 1991–2007 are from the UN Comtrade Database, which provides bilateral import and export values at the six-digit HS product level.[25] To assign these product-level import flows to four-digit SIC industries, I use the crosswalk file created by Autor et al. (2013), which allows me to concord imports from HS six-digit products to SIC four-digit industries. To perform the assignment of exports, I first create a comparable export-weighted concordance table and then match each HS-level export value to a SIC four-digit industry. All trade data are expressed in 2007 US dollars using the Personal Consumption Expenditure deflator.

To explore heterogeneous effects across different industries, I use Integrated Public Use Microdata Series (IPUMS) Census Data (Ruggles et al., 2015) for 1990 and 2000 and the IPUMS American Community Survey (ACS) for 2006 through 2008. IPUMS data provide individual information that allows me to compute shares of individuals who (i) are above age 45, (ii) have no college degree, (iii) are Hispanic or Black (non-White) and (iv) are female in each census manufacturing industry. I then assign 74 census industries to 392 four-digit SIC using a concordance table provided by Lake and Millimet (2016). Next, I use detailed occupations at the individual level from the census to construct the routine task intensity (RTI) measure for each manufacturing industry. Following Autor et al. (2015), I assign to each occupation a routine manual and abstract index depending on the content of the tasks defining each occupation.[26] I then compute the RTI measure for occupation o, defined as $\mathrm{RTI}_o = \ln(\mathrm{Routine}_o) - \ln(\mathrm{Manual}_o) - \ln(\mathrm{Abstract}_o)$. I then compute the industry-specific RTI measure considering jobs and employment for each industry in the initial period. Finally, following Hou and Robinson (2006) and other papers on market competition, my main proxy for industry concentration is the Herfindahl–Hirschman index (HHI) at the three-digit SIC level. Based on the Compustat Database, the HHI is defined as $\mathrm{HHI}_{j,0} = \sum_{i=1}^{N_j} s_{ij,0}^2$, where $s_{ij,0}$ is the market share of firm i in industry j in the initial period. Since this measure is constructed by only using publicly listed firms from Compustat, I use both firms' employment and sales to compute market shares to reduce the noise of the measure in certain industries and test the robustness.

Tables A1–A3 provide summary statistics for labour-outcome variables, trade measures and control variables used in estimates of the industry-level equation (1). The employment-weighted mean industry faces a 0.39 percentage point increase in Chinese import penetration per year from 1991 to 1999 and 0.99 increase per year from 1999 to 2007. Meanwhile, the employment-weighted mean of industry export performance rises 0.26 percentage points during 1991–1999 and 0.74 percentage points during 1991–2007. The means of both trade measures grow substantially during 1999–2007. Correlation of the two measures for period 1991–1999 and 1999–2007 are −0.007 and −0.003. This

[25] http://comtrade.un.org.

[26] The value of each occupation varies between 0 and 10 for these three measures of task content. Those measures are obtained from the O*Net Database.

TABLE 1 Baseline 2SLS estimates: effects of trade on manufacturing employment

	Depvar = log change in employment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ EP World	0.506***	0.525***	0.519***	0.544***	0.522***	0.513***	0.598***
	(0.163)	(0.180)	(0.165)	(0.171)	(0.188)	(0.158)	(0.202)
Δ IP World	−0.033						
	(0.040)						
Δ IP CHN		−1.286***	−0.834***	−1.158***	−1.291***	−0.826***	−0.687***
		(0.338)	(0.198)	(0.314)	(0.353)	(0.210)	(0.216)
Δ IP Non-CHN		0.145	0.080	0.125	0.165	0.084	0.002
		(0.090)	(0.050)	(0.078)	(0.106)	(0.062)	(0.079)
Sector controls	No	No	Yes	No	No	Yes	No
Production controls	No	No	No	Yes	No	Yes	No
Pretrend controls	No	No	No	No	Yes	Yes	No
Four-Digit SIC FE	No	No	No	No	No	No	Yes
First-Stage KP FStat	39.004	30.866	44.234	41.851	33.103	46.422	137.340

Note: The dependent variable is the annual log change in each industry's employment over the periods 1991–99 and 1999–2007. For independent variables, Δ EP is the annual change in US overall export performance to the world; Δ IP World is the annual change in US import penetration from the world; Δ IP CHN is the annual change in US import penetration from the China; Δ IP Non-CHN is the annual change in US import penetration from the world except China. Independent variables are instrumented as described in the text. For control variables, sector controls are dummies for 10 one-digit manufacturing sectors; production controls for each industry include initial period (in 1991) production workers as a share of total employment, the log average wage, and the ratio of capital to value added; Pretrend controls are changes in the log average wage and in the industry's share of total employment over 1976–1991. In the Final column, I include a full set of four-digit industry fixed effects. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. $N = 784$ (= 2 time period × 392 manufacturing industries).

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

orthogonal relationship suggests that the change in the export performance for an industry is unlikely to be driven by the change in direct import penetration from China.

5 | RESULTS

5.1 | Estimates of the effect of exports on US manufacturing employment

Table 1 presents the baseline 2SLS results of the stacked long-difference model for period 1991–2007 with various additional control variables. Utilising the identification strategy outlined previously, I first focus on estimating the average treatment effect of export performance on employment, as shown in the top row of results in Table 1. As the theory suggests, industries experiencing larger export expansion create jobs, and industries facing stronger import competition lose jobs. Therefore, one expects a coefficient for the export performance variable and a negative coefficient for the import penetration variable.

Columns 1–6 provide coefficient estimates for the 2SLS regression that includes the total US export performance and permutate among combinations of these three groups of industry controls. [27]To control for import shocks, I also include various import penetration measures (total imports, imports from China only and imports from ROW except for China) in the regressions to check how the coefficient responds. As shown in column 1, the coefficient on overall US export performance is positive and statistically significant. The estimate indicates that a one percentage point increase in industry export performance leads average US industry employment to grow by 0.506 percentage points. Yet, the coefficient on overall import penetration from the world is negative and insignificant, suggesting that the effects of import penetration can be diverse depending on the origin countries. Thus, to separate the salient China shock from total imports, I include both the import penetration from China and ROW simultaneously in the remaining regressions. The results show that the estimates are not statistically distinguishable from one another across columns and are robustly distinguishable from zero. Ideally, if the applied instrument is valid, we would not expect substantial changes on the estimated coefficients after including control variables. Comparing estimates across columns 1–7, while the export performance coefficient is largely unaffected, the coefficient magnitude on import penetration from China slightly drops from 1.253 to 0.811. First-stage F-statistics in all regressions are well above the Kleibergen–Paap weak IV threshold.

As a further check to tease out confounders at the industry level, column 8 includes a full set of fixed effects for the 392 four-digit SIC industries. These dummies can be viewed as industry-specific trends in a standard fixed-effect model, so the effect of trade shocks on industry employment in this specification is identified by changes in the growth rates of industry employment and trade shocks in 1999–2007 relative to 1991–1999. Including this exhaustive set of industry-specific trends reassuringly has limited impact on the significance of our coefficients of interest. Industry-specific trends also have a marginal effect on the size of our estimated coefficient for import penetration from China.[28]

5.2 | Comparing coefficients using different methods

Finally, I perform an important exercise to compare the estimated effect of exports on employment in this paper with estimates from the previous literature. I first graphically show the baseline estimates of Table 1 in the top panel of Figure 6. I then re-estimate the baseline table using instruments from FMX and summarise those estimates in the bottom panel of Figure 6. The estimated coefficients are positive

[27]A major threat to my identification strategy is that other economic shocks correlated with trade shocks may affect industries subject to trade shocks. Thus, I consider three groups of control variables to deal with confounding threats that may invalidate our instruments. Including one-digit manufacturing dummies as sector controls allows us to explore the variation within each one-digit sector. Regressions with these additional sector dummies identify the impacts of trade while purging common trends that influence average outcomes within each sector. A second concern stems from the observation that US manufacturing as a share of total employment was already declining prior to the 1990s. To rule out the possibility that pre-existing trends for some industries confound our analysis, I add controls for pretrends industry employment and earnings: the change in the industry's share of total US employment and the change in the log of an industry's average wage between 1976 and 1991.

[28]A possible explanation for why the import penetration coefficient shrinks could be that common technological shocks among advanced economies lead to an increase in labour-intensive imports from China. This result is in part consistent with findings by Acemoglu and Restrepo (2020) in which they find that the size of their coefficient on import penetration drops slightly after considering technological shocks from automation.

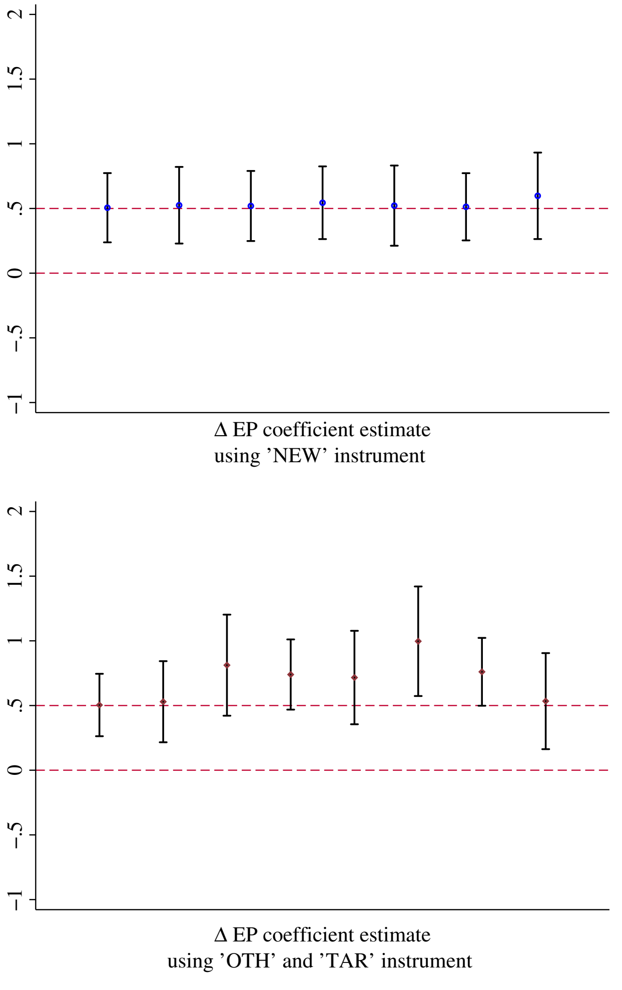

FIGURE 6 Coefficient comparison, Δ EP estimates. *Note:* The "Baseline" estimates (at the top), using the "NEW" instrument are results are from Table 1. The comparing estimates (at the bottom) are using the "TAR" and "OTH" instruments from FMX. All estimates are variations on the baseline model where the outcome is the annual is the annual log change in each industry's employment. Estimates 2–8 are based on the NBER-CES Manufacturing Database and vary the set of controls (fixed effects)

and significant using both methods. The estimates in the top panel, however, are more robust and less sensitive to added controls, suggesting the '`NEW'' method performs better in terms of eliminating potential biases caused by technological or labour supply shocks.

5.3 | Robustness analysis

This subsection provides a summary of a variety of robustness checks that examine the sensitivity of my estimates. Many of these robustness checks are summarised in Figure 7, which displays coefficient estimates and confidence intervals for a range of specifications using two alternative datasets. The results based on the CBP dataset are presented in Table A5, and the results estimated using the NBER-CES dataset are shown in Table A6.

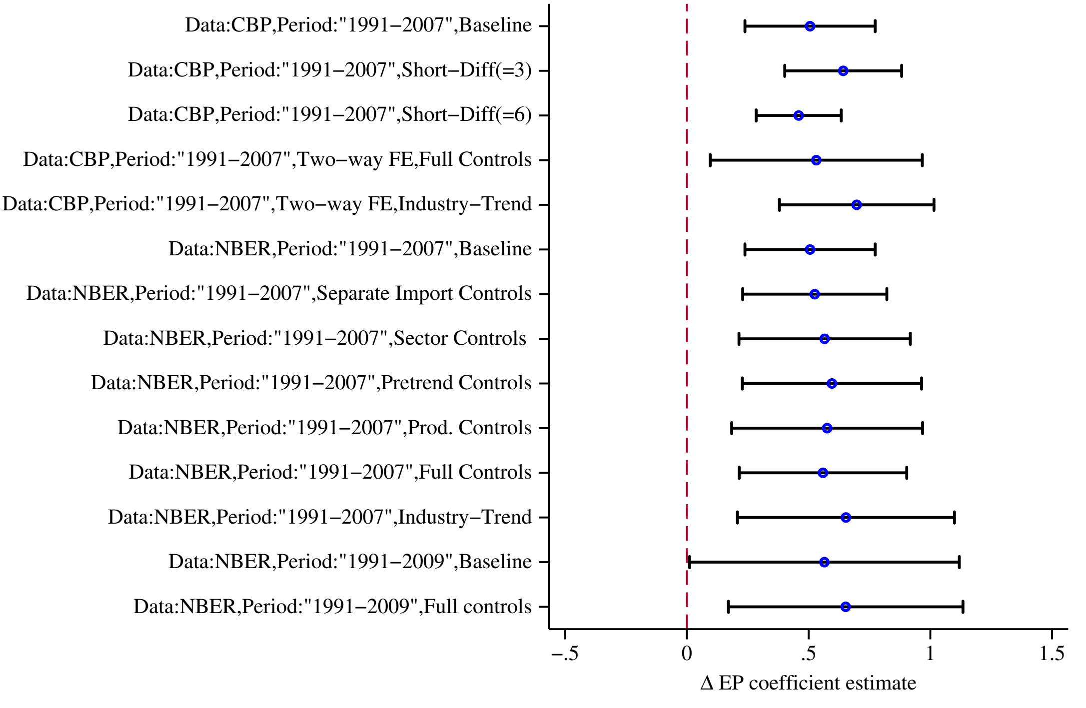

FIGURE 7 Robustness analysis, Δ EP estimates. *Note:* The "Baseline" estimate (at the top) uses the specification from Column 2 of Table 1. All estimates are variations on the baseline model where the outcome is the annual is the annual log change in each industry's employment. Estimates 2–5 are based on the CBP dataset and are estimated using various specifications. Short-Diff(=x) denotes shorter first-difference model with x lag years. Estimates 4 and 5 are based on the two-way fixed-effect model with and without the industry-specific trends. The remaining estimates 6–14 are estimated using the NBER-CES Manufacturing Database with varying set of controls

TABLE 2 Falsification test, trade shocks on beforehand employment (1963–1991)

	1963–1971		1971–1981		1981–1991	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EP_{t=(1991–2007)}$	0.219	−0.331	0.042	−0.888	−0.723	−0.527
	(0.445)	(0.528)	(0.433)	(0.581)	(0.515)	(0.510)
$\Delta IP_{t=(1991–2007)}$	−0.106	−0.241	0.231	0.189	−0.325	0.021
	(0.248)	(0.240)	(0.310)	(0.244)	(0.287)	(0.251)
One-Digit Sector FE	No	Yes	No	Yes	No	Yes
Observations	384	384	384	384	384	384

Note: The dependent variable is the annual log change in each industry's employment in each relevant period. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level.
*p <.10,**p <.05, ***p <.01.

Following the baseline estimate (i.e. the main specification) presented in Figure 7, the next four estimates demonstrate insensitivity to the choice of specifications. I consider first-difference (FD) moving averages from 3 to 6 years bandwidth, as well as the two-way fixed effects model (FE) including industry-specific linear time trend. The FD moving-average model with shorter lags may better capture national macroeconomic shocks occurring within the original 9-year intervals. The FE has enough variation to control for industry-specific trends rather than a common trend without dropping observations from the initial sample year. Those results based on the CBP dataset are presented in Table A5.

The outcome variable in the remaining estimates in Figure 7 are based on the NBER-CES dataset. To examine how the estimates react to an alternative dataset, I re-estimate the regressions in the baseline table using the NBER-CES data. Those results are reported in Table A6. The last two columns of the Table A6 extend the second subperiod to 1999–2009, which covers the financial crisis. Still, the coefficient stays statistically significant and the change in magnitude is mild. Overall, the coefficients for ΔEP is not sensitive to the chosen specification, a particular dataset, or a specific time period.

The last robustness check reports the falsification tests for pretrends. For my identification strategy, it is problematic if the instrumented endogenous variables can predict the previous employment in a significant way. Table 2 presents the 2SLS regression results of the key endogenous variables on employment beforehand. In this exercise, both predicted trade variables are statistically insignificant with the 1960s (1963–1971), 1970s (1971–1981), or 1980s (1981–1991) employment. Therefore, the results in this table are consistent with the hypothesis that the within-industry correlation between trade exposure and manufacturing employment in the 1990s and 2000s are from contemporaneous trade shocks rather than from long-term factors such as industry-level trend.

5.4 | Decomposing export shocks: heterogeneity across destinations

Having established a relationship between US manufacturing employment and exports in general, I now consider whether this increased export performance varies as the destination of exports changes. On the subject of examining how exports can affect employment, their effects can be mixed, depending on destination and/or type of affected industries. As different types of trade shocks could have very different effects on employment depending on the nature of the affected industries (e.g. labour-intensive vs. capital-intensive), it is important to understand how this important elasticity of employment with respect to exports varies across trading partners. Meanwhile, for the demand shocks that embody multiple regions and markets that have experienced trade liberalisation, the method also provides flexibility and enough variation in estimating the heterogeneous effect across destinations.

To provide some sense of how the US export has differed in each market, I start with disaggregating the total US exports by geographical region. From 1991 to 2007, Canada and Mexico, the US's two largest export destinations, accounted for 20% of the total growth of US exports. US manufactured exports to NAFTA in 2007 were $173 billion, which is 138.7% more than 1993 levels (pre-NAFTA), and the top export categories were mainly machinery and vehicles. The two decades of US exports to Latin American and the Caribbean countries have also been successful. Not only did Latin America's industry grow and open up to the world, but the United States has also engaged with Latin American countries on trade and investment matters through a number of initiatives.[29] As a result, manufacturing exports to Latin America totalled $199 billion in 2007, up 141.2% from the initial sample period level. Meanwhile, the US exports to Asian economies have also increased rapidly. Fast income growth and liberalised trading environment have transformed many developing countries in East Asia and Southeast Asia into an important market for US exports. Before the 2009 financial crisis, the annual

[29]For example, the US-Chile Free Trade Agreement came into force after January 2004.

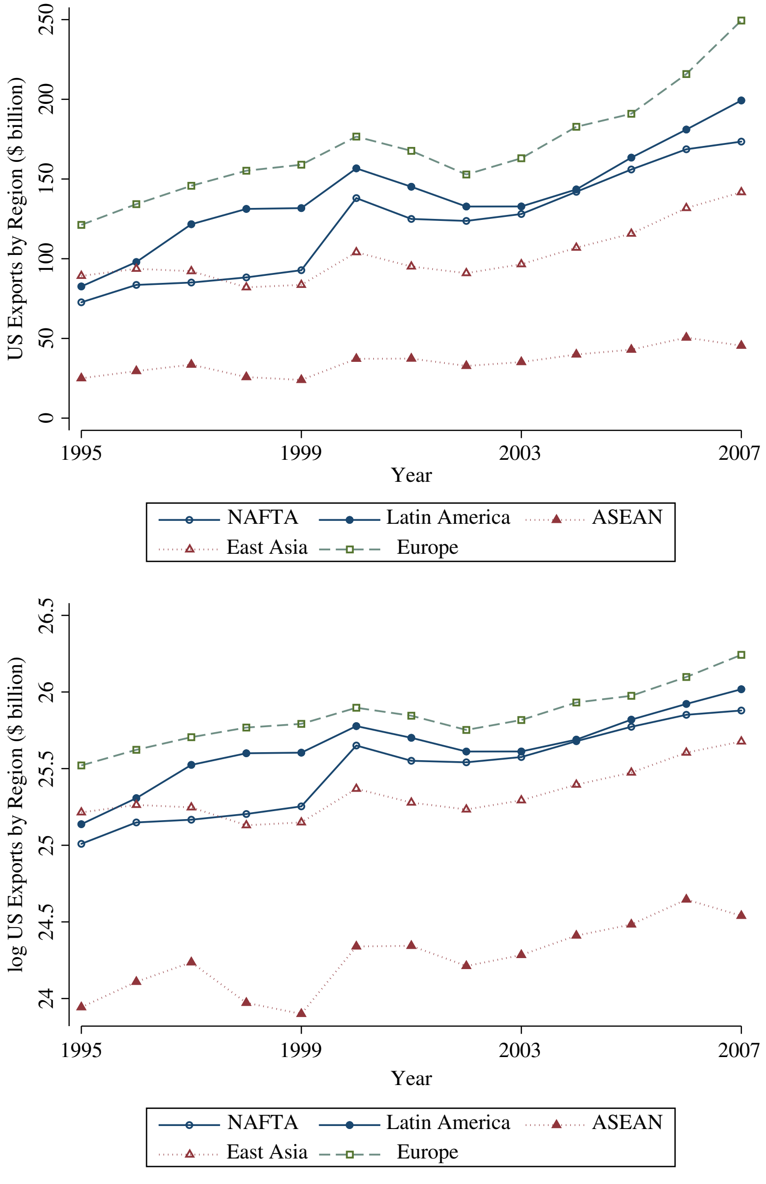

FIGURE 8 Export growth by region

total US manufacturing exports to East Asian and ASEAN countries were $148 billion and $58 billion, respectively (in year 2008), each up by 65.7% and 131.39% compared with their initial levels in 1995.[30] Lastly, US exports to the European Union have been sizable and steadily growing since 1995. The EU countries, together, ranked first as an export market for the United States in 2007. US exports to the EU increased during this period by 105%, totalling $249 billion in year 2007. The growth of US export performances to major trading regions is summarised in Figure 8.

In attempting to understand the extent to which US export expansions across different markets have various effects on the US manufacturing employment, I create the main variable of interest and the

[30]Trade data cross for many ASEAN countries before 1995 is not available.

TABLE 3 Heterogeneous employment effect by region

	Region						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	World	NAFTA	Latin America	ASEAN	East Asia	EU	NLC
Δ EP	0.498***	2.383**	0.346**	2.545***	0.306	0.249	1.090**
	(0.145)	(0.977)	(0.165)	(0.966)	(0.251)	(0.200)	(0.448)
Δ IP	−0.020	−0.132	−0.124*	−0.346**	−0.175**	0.061	−0.972***
	(0.031)	(0.155)	(0.071)	(0.169)	(0.072)	(0.149)	(0.197)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-Stage KP Stat	58.596	9.277	43.860	19.983	7.579	1.478	147.016

Note: The dependent variable is the annual log change in each industry's employment over the periods 1991–1999 and 1999–2007. For independent variables, Δ EP to each set of countries is the annual change in US export performance to the indicated destinations. Δ IP from each set of countries is the annual change in US import penetration from the indicated origins. Independent variables are instrumented as described in the text. Sector, production and pretrend controls are always included; see text for details. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. $N = 784$ (= 2 time period × 392 manufacturing industries).

*p <.10,**p <.05, ***p <.01.

corresponding instrument for each region. Each export instrument is constructed using the variation stemming from countries that recently experienced trade liberalisation in each region. To offer a symmetric analysis of the impact of trade shocks on employment, I control for the import competition for each regression from each region as well. I then repeatedly estimate the baseline equation using US export performance to different regions:

$$\Delta \ln L_{jt} = \alpha_t + \beta_1^r \Delta \mathrm{EP}_{jt}^r + \beta_2^r \Delta \mathrm{IP}_{jt}^r + \mathbf{Z}_{j,0}\Gamma + e_{jt}, \tag{6}$$

where the outcome is still the change in log manufacturing employment for each industry; r of the independent variable represents different US export destination regions: NAFTA, Latin America, East Asia, ASEAN and EU. To control for the import shocks from those regions, I have also included the change in import penetration variable which is constructed symmetrically using change in imports from each region. The logic of creating the instrument for each import penetration variable is the same as before.

Table 3 presents the 2SLS results for US exports to major destination regional markets. Column 1 shows the overall effect of the US export performance on employment controlling for the import penetration from the world as well as a full set of control variables. Much like the findings in the previous subsections, the estimated coefficient on ΔEP stays positive and robustly significant with magnitude in the interval of 0.5. Results in columns 2–6 display the employment effect of the raised export performance to NAFTA, Latin America, East Asia, ASEAN and EU, respectively. In general, I still find strong evidence that a better export performance leads to larger employment after decomposing the total exports into different regions. Furthermore, as expected, there is substantial heterogeneity in the estimated elasticity across destinations. Comparing the coefficients of ΔEP^r among different markets, a key point to focus on is that the estimates are statistically distinguishable from one another across columns 2–6. The results suggest that industries exposed to rising export opportunities

TABLE 4 Implied employment changes induced by various export shocks

	Implied employment changes (000s)		
Description & specification	**1991–1999**	**1999–2007**	**1991–2007**
Aggregate: total exports to world			
Baseline, no controls, Exports to world (Col. 2, Table 1)	534	405	939
Exports to different regions			
Exports to NAFTA (Col. 2, Table 3)	245	862	1107
Exports to Latin America (Col. 3, Table 3)	123	80	203
Exports to ASEAN (Col. 4, Table 3)	−5	235	230
Exports to East Asia (Col. 5, Table 3)	−2	92	90
Subtotal	361	1268	1629
Import penetration from China (Col. 2, Table 1)	−500	−1183	−1683
Exports to Newly Liberalised Countries (Col. 7, Table 3)	243	194	437

Note: Reported quantities represent the change in employment attributed to instrumented changes in export performance to each region in the specifications. The values indicate that export performance is estimated to have created employment. In my industry-level analysis, I first use the estimated coefficients to predict the changes in each industry's log employment induced by changes in export performance in each region over the periods 1991–1999 and 1999–2007.

in NAFTA and ASEAN countries see an relatively large increase in the manufacturing employment (columns 2 and 4), and the export expansion in newly liberalised economies such as Mexico, Malaysia and Vietnam seems to be mainly driving these effects. Meanwhile, the positive employment effect is smaller, though still substantial, for the exports to Latin America, East Asia and EU, with estimates of around 0.3. But the coefficients are statistically insignificant for East Asia and EU (columns 4 and 5). Finally, in the last column, I present the result of estimating the effect of job creation only due to exports to all newly liberalised economies that are used to construct the instrument. As expected, the estimated coefficient on ΔEP is a weighted average of the coefficients in columns 2–5, which is around 1.09. The estimates imply that balanced trade with those newly liberalised countries would cause balanced employment effect. Rising of global demand for better products and services, particularly from emerging markets, might be expected to trigger increased spending on US manufacturing products and to drive job growth.

5.5 | Quantifying estimated magnitudes

To evaluate the impacts of export on US manufacturing employment, I calculate the estimated aggregate change in employment due to each export-induced shock at the national level based on the above estimation results. Counterfactual changes in employment are defined as changes in employment that would have occurred in the absence of changes in trade volumes. Following Acemoglu et al. (2016), these counterfactual changes in manufacturing during period $t-1$ to t are written as:

$$\Delta L^{export} = \sum_j L_{jt}\left(1 - e^{-\hat{\beta}_1^r \Delta EP_{jt}^r}\right) \tag{7}$$

Equation (7) represents the estimated change in employment due to the change in export performance to different region r. I compute these estimated employment changes for both subperiods. ΔEP^r_{jt} represents the change in export performance to each region r. $\widehat{\beta}^r_1$ is the estimated coefficient on export performance to region r in 2SLS results. Numbers of estimated employment changes using different point estimates are shown in Table 4.

According to the estimation based on the aggregate export measure using overall US exports to the world, the result suggests that US total export expansion created around 0.9 million manufacturing jobs during the period 1991–2007 on average. However, as the evidence in the Table 3 shows that these average increases mask substantial heterogeneity across export destinations, I also calculate job gains due to the export expansion to each single market. Depending on the regions that deliver significant coefficients, the number of estimated job gains from exporting to NAFTA, Latin America, ASEAN and East Asia was nearly 1.63 million, which is roughly equivalent with the number of job losses due to the import penetration from China. Therefore, a consequence of this heterogeneity is that the actual implied number of job gains due to export expansion across destinations is far larger than its impact on the average employment effect. Next, based on these calculations, an important exercise can then be implemented. Holding the current deficit constant, if we assume a surge of imports from China leads to the same increase in US exports, the estimated job losses due to trade with China then becomes very small. In addition, using the same method to calculate implied employment changes due to trading with emerging markets, column 7 of Table 3 implies that exporting to emerging markets created more than 0.4 million jobs.

The above exercise serves several important purposes. First, emerging markets such as China, India, Vietnam, Mexico and Brazil are fast becoming the drivers of global growth and soon will catch the wave of growth that has washed through the developed world. With an ever-larger and increasingly educated middle class, particularly in Asia and Latin America, strong growth in higher-end products in these regions offers best prospects for US export expansion, which provides great opportunities for jobs in the manufacturing sector. Second, using trade flows between the US and emerging markets to construct the right-hand-side endogenous trade exposures would allow us to better examine the local average treatment effect (LATE) in this instrumental variable framework. We would expect the estimated coefficients to be bigger as more compilers, which are the captured trade flows that are affected by the instruments, are now included in the construction of the endogenous variables.

5.6 | Heterogeneous effects across industries: labour composition, occupation and labour market concentration

How do the effects of export expansion vary across industries with different initial industry characteristics? Given the evidence on the heterogeneity of the employment effect of exports, exploring the unveiled heterogeneity in the treatment effect across industries can help us better understand the channels through which the export expansion affects employment. As the above results suggest, there might be a number of channels embedded in the affected industries that could explain the difference among the estimated coefficients. Rising jobs for industrial machinery including computer equipment, transportation, and electronics benefited much of exports to NAFTA, ASEAN, which require very different labour and skills in jobs. Also, the same may not be true for jobs that are bundled with exporting industries to Latin America or Europe. Hence, to explore how industries respond differently to export shocks, I investigate the heterogeneous effects across various industry characteristics in the next subsection.

TABLE 5 Baseline 2SLS estimates: effects of trade on manufacturing employment

	Depvar = log change in employment			
	(1)	(2)	(3)	(4)
ΔEP	0.454**	0.836***	0.763***	0.295
	(0.189)	(0.241)	(0.209)	(0.218)
Δ EP × share of workers above age 45	1.035***			
	(0.340)			
Δ EP × share of non-college workers		0.762*		
		(0.402)		
Δ EP × share of non-white workers			0.838*	
			(0.458)	
Δ EP × share of female workers				0.550
				(0.396)

Note: The dependent variable is the annual log change in each industry's employment over the periods 1991–1999 and 1999–2007. For independent variables, Δ EP is the annual change in US overall export performance to the world. Independent variables are instrumented as described in the text. A full set of control variables are included. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. $N = 784$ (= 2 time period × 392 manufacturing industries).

*p <.10,**p <.05, ***p <.01.

First, I assess whether the heterogeneity in labour composition within each industry drives the heterogeneity across industries in the employment effects of exports. Using the 1990 IPUMS Census data, I construct and estimate for a number of characteristics. In particular, I explore differences in the effects of the export expansion by industry characteristics on hired workers' demographics, namely age, education, race and gender. From individual-level data, for each Census manufacturing industry, I construct industry-level employment shares of workers that (i) are above age 45, (ii) have no college degree, (iii) are Hispanic or Black (non-White) and (iv) are female.[31] I then extend the baseline estimating equation to include interactions of ΔEP and the computed share in each case. The results are presented in columns 1–4 of Table 5. Overall, the coefficients on ΔEP are still consistent with previous results, and not surprisingly, only estimating the average treatment effect masks a significant amount of heterogeneity. In column 1, the statistically significant estimated coefficient on the interaction term between export performance and share of workers above the age of 45 implies that export expansion generates relatively more jobs for industries that initially employed a more senior, potentially more experienced workforce. The estimate in column 2 indicates that industries hiring more non-college educated workers experienced a larger increase in employment relative to those with more college educated workers in response to export shocks. The findings are consistent with the literature showing that import penetration and automation disproportionately affect unskilled workers (Autor et al., 2014), and industries that hire more unskilled labour might directly benefit more from the rising foreign demands on US exports. The result in column 3 suggests the effect is more pronounced for industries that initially hired relatively more non-White workers. Lastly, in column 4, I do not find

[31]Relative to other data sources, the finest level of industry information in the Census and the ACS are 74 manufacturing industry codes. I map each SIC industry code to a unique Census industry to align with our previous dataset. To better interpret the result, both indexes are demeaned and divided by their own standard deviation.

TABLE 6 Baseline 2SLS estimates: effects of trade on manufacturing employment

	Depvar = log change in employment				
	Job & Task			Market concentration	
	(1)	(2)	(3)	(4)	(5)
ΔEP	0.785***	0.382**	1.214***	0.921***	0.949***
	(0.184)	(0.165)	(0.434)	(0.255)	(0.253)
Δ EP × Routine Task Index	1.365**				
	(0.561)				
Δ EP × Offshorability Index		0.617*			
		(0.329)			
Δ EP × share of high-tech investment			−0.607*		
			(0.314)		
Δ EP × HHI (based on empl.)				0.504**	
				(0.235)	
Δ EP × HHI (based on sales)					0.602**
					(0.258)

Note: The dependent variable is the annual log change in each industry's employment over the periods 1991–1999 and 1999–2007. For independent variables, Δ EP is the annual change in US overall export performance to the world. Independent variables are instrumented as described in the text. A full set of control variables are included. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. $N = 784$ (= 2 time period × 392 manufacturing industries).

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

significant differences in the employment elasticity with respect to exports between industries that hired more female workers and those that hired more males.

As worker characteristics are usually associated with the job for which the worker was employed, I explore two possible explanations that may address the observed heterogeneity. First, I investigate whether occupations, required skills and tasks performed can explain the differences across industries. Previous literature shows that the labour supply elasticity for low-income workers, especially those with low levels of education and non-whites performing routine-based tasks, is high. Therefore, we expect those production workers' employment levels to be affected more by demand shocks (a larger response in employment). Based on the RTI index constructed for each industry, I re-estimate the previous equation allowing for the heterogeneous effects of the export shocks across the US industry by including the interaction term between ΔEP and the RTI index. The result in column 1 indicates that the positive impact of the export shock on industrial employment is most pronounced in the industries where workers perform high RTI tasks. However, the impact of the shock remains significant even for industries with relatively low RTI tasks. I also construct an alternative measure, Offshorability Index (OFF), to check the robustness of the previous finding. Lastly, column 3 shows the effect is smaller for industries that have a larger share of investment in high-tech technologies, such as robot arms, PCs and others that may save labour. Overall, the results in column 2 and 3 confirm the idea that the positive employment effect of exports is more salient for industries with a high proportion of routine-based jobs that automation and offshoring is more likely to replace.

Another potential explanation why an export shock disproportionately affects disadvantaged workers is the through labour market concentration. Following the literature, I construct measures of market power in each manufacturing industry and examine the extent to which the relationship between

TABLE 7 2SLS estimates on additional labour market outcomes

	Depvar = log change in indicated quantity									
	County Business Patterns				NBER-CES					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Num Estabs.	Emp Per Estab.	Real Wage Bill	Real Wage	Prod. Emp.	Non-Prod. Emp.	Real Wage Bill	Real Wage	Real Prod. Wage	Real Non-Prod. Wage
Panel A: with full controls										
ΔEP	0.374**	0.182***	0.550***	−0.006	0.642***	0.479**	0.582***	−0.003	−0.028	0.041
	(0.180)	(0.065)	(0.186)	(0.028)	(0.215)	(0.241)	(0.219)	(0.020)	(0.030)	(0.062)
ΔIP	−0.246***	−0.564***	−0.742***	0.069	−0.813***	−0.668***	−0.753***	−0.017	0.070	−0.108
	(0.080)	(0.183)	(0.198)	(0.059)	(0.225)	(0.210)	(0.198)	(0.054)	(0.090)	(0.088)
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: with industry-specific year trends										
Change in export	0.355**	0.243***	0.587***	−0.012	0.737***	0.485*	0.649**	−0.006	−0.047*	0.123*
performance to World	(0.158)	(0.049)	(0.196)	(0.020)	(0.280)	(0.246)	(0.271)	(0.018)	(0.026)	(0.066)
Change in import	−0.403*	−0.283	−0.658***	0.029	−0.835**	−0.553**	−0.671***	−0.023	0.013	−0.067
exposure to China	(0.215)	(0.174)	(0.206)	(0.084)	(0.321)	(0.254)	(0.239)	(0.089)	(0.086)	(0.092)
Industry-Specific Year Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column stacks changes in the indicated outcome and changes in relevant trade variables over the periods 1991–1999 and 1999–2007. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. In cols. 1–5, N = 784 = 392 four-digit manufacturing industries × two periods. In cols. 6–9, we exclude eight industries for which post-1996 data are unavailable in the NBER-CES, yielding $N = 768 = 384$ industries × two periods.

*p <.10,**p <.05, ***p <.01.

employment and exports is stronger in more or less concentrated industries. To measure the labour market concentration, I construct a Herfindahl–Hirschman Index (HHI) for each industry, defined as the sum of squared employment shares of firms in the Compustat Database. An alternative HHI is computed based on the sales shares of firms. In the last two columns of Tables 6, I examine whether the response of employment is stronger among industries with greater values of these concentration measures. The important point to notice is that the coefficients on the concentration terms are all positive and significant, for both measures. One way to think about this heterogeneity is found in Melitz (2003). If the industry is concentrated in several big firms, we would expect the effect is stronger for bigger firms employing more workers and having more plants that can utilise the opening foreign markets. As a result, the export-induced labour demand raises the employment of industries with more concentration to a great degree than that of more dispersed industries.

5.7 | Estimates of trade effects on other labour market outcomes

The primary focus of this analysis is the effect of exports on industry employment. Next, I investigate the effects of trade on other important labour market outcomes. I explore the effect of trade on the number of establishments, and average employment per establishment and average wage bill for production and non-production workers.[32] Table 7 provides findings on how export shocks affect these additional labour market outcomes. Panel A presents results of regressions including a full set of controls, and Panel B provides estimated coefficients with 392 four-digit industry-specific time trends.

Not surprisingly, as export expansion generates jobs, it also raises the count of establishments (col.1), average employment per establishment (col.2) and the industry wage bill (cols.3 and 7). A one percentage point increase in overall export performance increases the establishment count by 0.36 percentage points, increases average employment per establishment by almost 0.2 percentage points and increases the average industry total wage bill by around 0.6 percentage points. Conversely, stronger import penetration from China similarly decreases all three labour market outcomes. A one percentage point increase in import penetration from China reduces the establishment count by 0.32 percentage points, reduces average employment per establishment by 0.4 percentage points and reduces the total average industry wage bill by around 0.7 percentage points. Production employment is more sensitive than non-production employment to trade shocks (cols.9 and 10). A one percentage point increase in export performance increases the number of production jobs and non-production jobs by nearly 0.7 and 0.48 percentage points, respectively. On the contrary, a one percentage point increase in import penetration decreases production jobs and non-production jobs by nearly 0.8 and 0.6 percentage points.

Previous findings do not reach a consensus on the wage effect of import penetration. This analysis suggests some of the underlying costs of variation. Based on results in columns 4 and 8, the impact of import penetration on the industry average wage rate is small and not statistically significant. However, the coefficients on export performance for average production wage and average non-production wage are significant in Panel B. Industries with a one percentage point increase in export performance reduce their average wage rate for production workers by 0.05 percentage points and raise their average wage rate for non-production workers by 0.12 percentage points. Combining these two effects suggests

[32]CBP provides information on the count of establishments and total industry wage bills. I then calculate the average employment per establishment and the wage rate. NBER-CES provides information on production employment, non-production employment, production wage bills and non-production wage bills. Similarly, I then calculate the average wage rate for production workers and non-production workers.

that skilled workers (non-production workers) benefit more in export industries relative to non-skilled workers (production workers). This interpretation is consistent with the finding in Lichter et al. (2014) that skilled workers are highly concentrated and demanded among exporting firms.

6 | CONCLUSION

Jobs are destroyed through import competition, and jobs are also generated by United States exporting to other trading partners. This paper contributes to the trade and labour literature by providing new estimates of the impact of exports on employment for US manufacturing industries. By taking the data to various specifications, I find robust estimates suggesting that US exports to multiple emerging markets created more than 1.6 million manufacturing jobs between 1991 and 2007, which is about the same as the estimated job losses attributed to the import competition from China.

Given the substantial heterogeneity observed in this positive employment effect, the paper makes a valuable contribution by exploring the heterogeneous effects across several important dimensions. Specifically, rising exports to NAFTA and ASEAN countries have created more jobs than exports to other destinations. To better understand the mechanisms through which the export expansion creates the differential impact, this study also examines the heterogeneous effects across an array of industry and worker characteristics. And the impact of exports on employment is larger for industries that hired more older, less-educated and non-White workers. Results also show that the impact is larger for industries where routine tasks are more prevalent and for industries with a more concentrated labour market.

Furthermore, this paper contributes to the debate on how to better empirically identify the impact of exports. This is empirically challenging because finding a plausible exogenous source of variation for exports that is also orthogonal to import shocks can be difficult. Exploiting foreign markets' unilateral liberalisation which is exogenous to US domestic supply and demand shocks, I construct an informative and flexible instrument to identify the impact of US export performance to different trading partners.

Although most economists emphasise that trade is a win-win for all countries that participate, the perception among the public, media and policymakers remains that trade is a major cause of job losses in the manufacturing sector. The consequence may be extreme trade policies, and escalated trade disputes between the United States and China have already led to tariffs on hundreds of billions of dollars in goods and generated a tremendous amount of uncertainty for businesses. Therefore, the results in this paper are important for at least two reasons. First, since the literature has largely overlooked assessment of job creation from trade until recently, this study tries to bridge this gap by providing evidence that trade could create a large number of jobs targeting certain workers and industries. Second, within the manufacturing sector, what industries and types of workers that could potentially benefit vastly from foreign countries' expansion remains unknown. This paper shows that promoting exports seems to be a direct and effective solution for workers whose jobs are threatened by the increasing foreign competition and automation. The implications of this study may be useful for policymakers that are rethinking trade and employment dynamics and reassess the direct job losses due to retaliatory tariffs on US manufacturing products in recent trade disputes, recognising the potential for job gains owing to better market access and stronger export growth in the future.

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REFERENCES

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2000s). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, *34*(S1, Part 2), S141–S198.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, *80*(5), 1977–2016.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, *128*(6), 2188–2244.

Aghion, P., Bergeaud, A., Lequien, M., & Melitz, M. (2017). The impact of exports on innovation: Theory and evidence. Technical report, Working Paper.

Artuç, E., Chaudhuri, S., & McLaren, J.(2008). Delay and dynamics in labor market adjustment: Simulation results. *Journal of International Economics*, *75*(1), 1–13.

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

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

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

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.

Borusyak, K., Hull, P., & Jaravel, X. (2018). Quasi-experimental shift-share research designs. Technical Report, National Bureau of Economic Research

Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms. *The American Economic Review*, *101*(1), 304–340.

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.

Choi, J., & Xu, M. (2020). The labor market effects of the China syndrome: Evidence from South Korean manufacturing. *The World Economy*, *43*, 3039–3087.

Costa, F., Garred, J., & Pessoa, J. P. (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics*, *102*, 50–69.

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.

Dix-Carneiro, R., & Kovak, B. K. (2017). Trade liberalization and regional dynamics. *American Economic Review*, *107*(10), 2908–2946.

Feenstra, R. C., Ma, H., & Xu, Y. (2019). Us exports and employment. *Journal of International Economics*, *120*, 46–58.

Goldberg, P. K., & Pavcnik, N. (2016). The effects of trade policy. *Handbook of Commercial Policy*, *1*, 161–206.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624.

Griliches, Z., & Hausman, J. A. (1986). Errors in variables in panel data. *Journal of Econometrics*, *31*(1), 93–118.

Hakobyan, S., & McLaren, J. (2016). Looking for local labor-market effects of nafta. *Review of Economics and Statistics*, *98*(4), 728–741.

Hasan, R., Mitra, D., Ranjan, P., & Ahsan, R. N. (2012). Trade liberalization and unemployment: Theory and evidence from India. *Journal of Development Economics*, *97*(2), 269–280.

Hou, K., & Robinson, D. T. (2006). Industry concentration and average stock returns. *The Journal of Finance*, *61*(4), 1927–1956.

Kornai, J. (1992). *The socialist system: The political economy of communism*. Oxford University Press.
Lake, J., & Millimet, D. L. (2016). Good jobs, bad jobs: What's trade got to do with it?
Lichter, A., Peichl, A., & Siegloch, S. (2017). Exporting and labor demand: micro-level evidence from Germany. *Canadian Journal of Economics/Revue canadienne d'économique*, *50*(4), 1161-1189.
Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725.
Mitra, D., & Ranjan, P. (2010). Offshoring and unemployment: The role of search frictions labor mobility. *Journal of International Economics*, *81*(2), 219–229.
Monte, F., Redding, S. J., & Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, *108*(12), 3855–3890.
Pierce, J. R., & Schott, P. K. (2016). The surprisingly swift decline of US manufacturing employment. *American Economic Review*, *106*(7), 1632–1662.
Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT Press.
Ruggles, S., Genadek, K., Goeken, R., Grover, J., & Sobek, M. (2015). *Integrated public use microdata series: Version 6.0 [Machine-readable database]*. University of Minnesota.
Sachs, J. D., Warner, A., Åslund, A., & Fischer, S.(1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity*, *1995*(1), 1–118.
Wacziarg, R., & Welch, K. H. (2008). Trade liberalization and growth: New evidence. *The World Bank Economic Review*, *22*(2), 187–231.

APPENDIX 1

PART I—THEORY APPENDIX

Production structure

The setup of the model is as follows: The final good is non-tradable, while the intermediate goods are tradable. The final good is denoted by Z and the two intermediate goods are denoted by Y and X. Further, denote the prices of Y and X are p_y and p_x, respectively. The relative price becomes $p = \frac{p_y}{p_x}$. The production function of the final numeraire good is as follows:

$$Z = A\frac{Y^{\alpha}X^{1-\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}, \quad 0 < \alpha < 1. \tag{A1}$$

Given the prices p_x and p_y of two intermediate inputs, the unit cost of producing Z is:

$$c(p_x, p_y) = \frac{(p_x)^{1-\alpha}(p_y)^{\alpha}}{A} = 1. \tag{A2}$$

According to the Cobb-Douglas production function of Z, we can derive the following relative demand for the two intermediate goods:

$$\frac{Y^d}{X^d} = \frac{\alpha p_x}{(1-\alpha)p_y}. \tag{A3}$$

The aggregate production functions for X and Y are:

$$\begin{aligned} M &= h_y(1-u_y)L_Y \\ X &= h_x(1-u_x)L_X \end{aligned}, \tag{A4}$$

where L_i is the total number of workers affiliated with sector i. Therefore, the relative supply of the two intermediate goods is:

$$\frac{Y^s}{X^s} = \frac{h_y(1-u_y)L_y}{h_x(1-u_x)L_x}. \tag{A5}$$

Labour market clearing condition is:

$$L_Y + L_X = L.$$

Matching function has Cobb-Douglas form:

$$M_i(v_iL_i, u_iL_i) = m_i v_i^{\gamma} u_i^{1-\gamma} L_i = m_i\theta^{\gamma} u_iL_i = m_i\theta^{\gamma-1} v_iL_i.$$

Then, the probability for an unemployed searcher in sector i to find a job is:

$$p(\theta_i) = \frac{M_i}{U_i} = \frac{m_i\theta^{\gamma} u_iL_i}{u_iL_i} = m_i\theta_i^{\gamma}, \tag{A6}$$

and the probability for a vacancy to be filled is:

$$q(\theta_i) = \frac{M_i}{V_i} = \frac{m_i\theta^{\gamma-1} v_iL_i}{v_iL_i} = m_i\theta_i^{\gamma-1}. \tag{A7}$$

Assume that the job destruction rate for matched jobs in each sector is: δ_i, the change in unemployment in sector i can be written as:

$$du/dt = \dot{u} = \delta_i(1-u_i) - m_i\theta_i^{\gamma} u_i,$$

in steady state, the unemployment rate is constant ($du/dt = 0$), so we can derive the Beveridge curve as follows:

$$u_i = \frac{\delta_i}{\delta_i + m_i\theta_i^{\gamma}} \tag{A8}$$

Firm side

Two Bellman equations each represent the asset value of a vacant job V_i and a occupied job J_i:

$$rV_i = -c_i + m_i\theta^{\gamma-1}(J_i - V_i) + \dot{V},$$
$$rJ_i = p_ih_i - w_i - \delta_i(J_i - V_i) + \dot{J},$$

where c_i denotes the recruitment cost in sector i, r is the discount factor.

Since we focus on steady state equilibrium we can impose $\dot{V} = \dot{J} = 0$. Moreover, we assume free entry of firms and as a result $V = 0$. Thus, the above two equations imply the following condition (JC curve):

$$p_ih_i - w_i = \frac{(r+\delta_i)c_i}{m_i\theta_i^{\gamma-1}}, \tag{A9}$$

also j_i can be expressed as:

$$J_i = \frac{c_i}{m_i\theta_i^{\gamma-1}} \tag{A10}$$

Wage determination

Let E_i denote the present discounted value of employment in sector i and U_i the presented discounted value of unemployment for each worker. Each unemployed worker receives a reservation wage b (in unites of the final good), which includes the value of leisure as well as unemployment insurance payments. As mentioned above, workers also have idiosyncratic preferences for working in a particular sector. I borrow the modelling of imperfect labour mobility in the work of Mitra and Ranjan (2010). For individual j who works in sector i, the idiosyncratic utility is captured by ε_i^J. Define $\varphi^j = \varepsilon_y^j - \varepsilon_x^j$. If $\varphi^j < 0$, it is costly for worker j to move from sector Y to sector X. $\varphi^j = 0, \forall j$, will capture perfect mobility. Following Mitra and Ranjan (2010), I also assume that ε_y and ε_x are independent of each other and each follows the same Gumbel extreme value distribution, which has the following cumulative distribution function:

$$F(\varepsilon_i, i = X, Y) = \exp\left(-\exp\left(-\frac{\varepsilon_i}{\kappa}\right) - \gamma^*\right), \varepsilon_i \in (-\infty, \infty)$$

where $\gamma^* = 0.5772$ is the Euler's constant and κ is the scale parameter. The mean of ε_i is 0 and variance is $\frac{\pi^2\kappa^2}{6}$. Thus, by variable transformation, we can know for variable φ, it follows a symmetric distribution with zero mean and $\frac{\pi^2\alpha^2}{3}$ variance, and cumulative distribution:

$$G(\varphi) = \frac{\exp(\varphi/\kappa)}{1 + \exp(\varphi/\kappa)}, \varphi \in (-\infty, \infty).$$

Thus, the two Bellman equations governing E_i and U_i are given by:

$$\begin{aligned} rE_i^j &= \varepsilon_i^j + w_i + \delta_i(U_i^j - E_i^j) \\ rU_i^j &= \varepsilon_i^j + b + m_i\theta_i^\gamma(E_i^j - U_i^j), \end{aligned}$$

then can then derive:

$$E_i - U_i = \frac{w_i - b}{r + \delta_i + m_i\theta_i^\gamma}. \tag{A11}$$

For sector i, the total surplus, which is captured by the difference between value of match and value of vacancy, is:

$$\left(J_i + E_i\right) - \left(V_i + U_i\right) = \left(J_i - V_i\right) + \left(E_i - U_i\right).$$

The maximisation problem is:

$$\max_{w_i = E_i - U_i} (J_i - V_i)^{1-\beta}(E_i - U_i)^\beta, \quad 0 \le \beta \le 1$$

Through Nash Bargaining, the first-order condition of the maximisation problem is:

$$E_i - U_i = \frac{\beta}{1-\beta}(J_i - V_i),$$

where β is the bargaining power of the worker relative to the employer. Recall $J_i = \frac{c_i}{m_i\theta^{\gamma-1}}$ (Equation A10) and $V_i \equiv 0$ and Equation (A11). We can solve Nash-Bargained wage as (WC curve):

$$w_i = b + \frac{\beta c_i}{1-\beta}\left(\theta_i + \frac{r+\delta_i}{m_i\theta_i^{\gamma-1}}\right). \tag{A12}$$

For sector i, the key three Equations (A8), (A9) and (A12) can determine w_i, θ_i and u_i.

Sectoral choice of workers

Since unemployed workers can search in either sector, they search in the sector where their expected utility is higher. As shown above, the asset value of unemployed worker j searching in sector i is given by $rU_i^j = \varepsilon_i^j + b + m_i\theta_i^\gamma\left(E_i - U_i\right) = \varepsilon_i^j + b + \frac{\beta}{1-\beta}c_i\theta_i$. Then, worker j will search in sector Y if $rU_y^j > rU_x^j$ and will search in sector X if $rU_y^j < rU_x^j$. Since $\varphi^j = \varepsilon_y^j - \varepsilon_x^j$, the sectoral choice of workers is given as follows:

$$\begin{aligned}&\text{If } \varphi^j \geq \frac{\beta}{1-\beta}(c_x\theta_x - c_y\theta_y), &&\text{then search in sector } Y\\ &\text{If } \varphi^j < \frac{\beta}{1-\beta}(c_x\theta_x - c_y\theta_y), &&\text{then search in sector } X.\end{aligned}$$

Given the above relationship, the cut-off value of φ denoted by $\hat{\varphi}$ is:

$$\hat{\varphi}(\theta_x, \theta_y) = \frac{\beta}{1-\beta}(c_x\theta_x - c_y\theta_y), \tag{A13}$$

such that a fraction of $1 - G(\hat{\varphi})$ of workers are affiliated with sector Y, the rest of workers are affiliated with sector X. We have:

$$L_y = (1 - G(\hat{\varphi}))L;\ L_x = G(\hat{\varphi})L. \tag{A14}$$

In the case of perfect labour mobility ($\varphi^j = 0, \forall j$), all workers must be indifferent between the two sectors, which would imply the following no-arbitrage condition.

$$c_x\theta_x = c_y\theta_y. \tag{A15}$$

Equilibrium under autarky

For each pair of p_x/p_y, the prices of p_x and p_y can be obtained from the unit cost function of the numeraire Equation (A2). Then, by Equations (A8), (A9) and (A12), we can determine w_i, θ_i and u_i. From Equation (A2), we can represent p_x and p_y in terms of the relative price p:

$$p_x = Ap^{-\alpha}; p_y = Ap^{1-\alpha}.$$

By equations (A9) and (A12), we can substitute out w_i and get the relationship between p and θ_i:

$$\begin{aligned}h_xAp^{-\alpha} &= b + \frac{\beta}{1-\beta}c_x\theta_x + \frac{c_x\left(r+\delta_x\right)}{m_x\theta_x^{\gamma-1}}\\ h_yAp^{1-\alpha} &= b + \frac{\beta}{1-\beta}c_y\theta_y + \frac{c_y\left(r+\delta_y\right)}{m_y\theta_y^{\gamma-1}}.\end{aligned}$$

Therefore,

$$\begin{aligned}\frac{\partial\theta_x}{\partial p} &= -\frac{\alpha h_x A p^{-\alpha-1}}{\frac{\beta}{1-\beta}c_x + \frac{c_x(r+\delta_x)}{m_x}(1-\gamma)\theta_x^{-\gamma}} < 0,\\ \frac{\partial\theta_y}{\partial p} &= \frac{(1-\alpha)h_y A p^{-\alpha}}{\frac{\beta}{1-\beta}c_y + \frac{c_y(r+\delta_y)}{m_y}(1-\gamma)\theta_y^{-\gamma}} > 0.\end{aligned} \tag{A16}$$

So $\widehat{\varphi} = \frac{\beta}{1-\beta}(c_x\theta_x - c_y\theta_y)$ is decreasing in p. We also know that u_i is decreasing in θ_i from the Beveridge curve. Thus, the relative supply $\frac{Y^s}{X^s} = \frac{h_y(1-u_y)}{h_x(1-u_x)\exp(\widehat{\varphi}(p)/\kappa)}$ is increasing in p. To facilitate comparison of the autarky equilibrium with the open-economy equilibrium in the presence of various degrees of labour mobility, I follow the literature and assume that the relative demand passes through the common point of intersection of the autarky relative supply curves with varying degree of intersectoral labour mobility. Thus, the relative supply curve will intersect with the relative demand at a fixed point where $p = p^*$. The equilibrium price ratio can be determined with the perfect labour mobility case ($\kappa = 0$). In this case, the relative supply is zero for any $p < p^*$ since all workers are indifferent between working in the two sectors. The relative supply curve becomes horizontal. Once the price ratio is set, p_i can be determined with Equation (A2). w_i, θ_i, u_i, and L_i can be solved.

Impact of international trade

When the country opens up to trade, there is a change in the relative price. Assuming home country has the comparative advantage on sector X relative to the rest of the world, p_x will rise, and p_y will fall after trade liberalisation. Recall Equation (A16), without loss of generality, if p_x rises, then there will be an increase in θ_x, which leads to a decrease in u_x. The labour affiliated with sector X will also be affected, because $L_x = G\left(\widehat{\varphi}\right)L$, where $\widehat{\varphi}$ rises when p_x rises. If we treat sector X as the export sector and sector Y as the import-competing sector, we can have the following testable proposition:

Proposition 1 and 2 *Trade liberalisation will have positive impacts on the employment of the export-expanding sector and a negative impact on the employment of the import-competing sector.*

Basically, there will be two channels causing this effect. First, a rise (fall) in the sector price drives firms to open (close) more vacancies for the unemployed to search. Second, the rise (fall) in the sector price will pull (push) the labour force in (out) to search in affected sectors. The trade liberalisation also affects other labour market outcomes for different sectors.

Corollary 1 *The trade liberalisation leads to an increase in the vacancies (wage bill) of workers in the export sector and a decrease in the vacancies (wage bill) of workers in the import-competing sector.*

The idea behind is very simple. Without loss of generality, since sector price rises for export-expanding sector, the job creation curve will be pushed out, which intersects with the wage curve at a higher wage level. This shift causes the marginal value of product to rise and leads firms to create more vacancies, which can be approximated new entrants of establishments or firms.

APPENDIX 2

PART II: TABLES AND FIGURES

TABLE A1 Summary statistics: Dep.Var. change in labour market outcomes, 1991–2007.

	1991–1999	1999–2007	1991–2007
CBP			
100 × annual log Δ in Emp.	−0.30	−3.62	−1.96
	(3.49)	(4.15)	(3.25)
100 × annual log Δ in Num Estabs.	0.41	−1.20	−0.39
	(2.67)	(2.73)	(1.99)
100 × annual log Δ in Emp Per Estab.	−0.71	−2.42	−1.56
	(3.14)	(3.14)	(2.56)
100 × annual log Δ in Real Wage Bill	1.35	−3.09	−0.87
	(3.55)	(4.20)	(3.25)
100 × annual log Δ in Real Wage	1.65	0.53	1.09
	(0.96)	(1.06)	(0.77)
100 × annual log Δ in Emp.	−0.08	−3.72	−1.90
	(3.66)	(4.44)	(3.34)
NBER-CES			
100 × annual log Δ in Prod. Emp.	0.06	−3.98	−1.96
	(3.95)	(4.66)	(3.50)
100 × annual log Δ in Non-Prod. Emp.	−0.38	−2.81	−1.59
	(3.45)	(4.32)	(3.04)
100 × annual log Δ in Real Prod. Wage	1.19	0.55	0.87
	(0.81)	(1.21)	(0.69)
100 × annual log Δ in Real Non-Prod. Wage	1.79	0.12	0.96
	(1.35)	(1.68)	(0.89)
100 × annual log Δ in Real Wage Bill	1.34	−3.13	−0.90
	(3.56)	(4.62)	(3.34)
100 × annual log Δ in Real Wage	1.42	0.59	1.00
	(0.78)	(0.97)	(0.60)
Observations	392	392	392

Note: Mean coefficients; *SD* parentheses. $N = 392$ four-digit manufacturing industries. Observations are weighted by industry employment in 1991, as measured in the CBP.

TABLE A2 Summary statistics: trade variables, 1991–2007

	1991–1999	1999–2007	1991–2007
100 × annual Δ in US Export Performance to WLD	0.67	0.54	0.61
	(1.51)	(1.71)	(1.10)
IV for Δ in US Export Performance to WLD	0.73	0.13	0.43
	(3.25)	(2.86)	(0.86)
100 × annual Δ in US Import Penetration from CHN	0.27	0.84	0.55
	(0.75)	(1.61)	(1.03)
IV for Δ in US Import Penetration from CHN	0.18	0.60	0.39
	(0.44)	(1.07)	(0.69)
Other regional trade measures			
100 × annual Δ in US Import Penetration from WLD	1.27	1.44	1.35
	(1.89)	(4.98)	(2.95)
100 × annual Δ in US Import Penetration from ROW	1.04	0.71	0.88
	(1.70)	(4.16)	(2.42)
100 × annual Δ in US Import Penetration from NAFTA	0.41	0.25	0.33
	(1.13)	(0.61)	(0.59)
100 × annual Δ in US Export Performance to NAFTA	0.35	0.31	0.33
	(0.49)	(0.60)	(0.47)
100 × annual Δ in US Import Penetration from Latin America	0.56	0.31	0.43
	(1.38)	(1.27)	(1.01)
100 × annual Δ in US Export Performance to Latin America	0.64	0.15	0.40
	(0.99)	(0.83)	(0.48)
100 × annual Δ in US Import Penetration from ASEAN	0.29	0.26	0.28
	(1.36)	(0.95)	(0.85)
100 × annual Δ in US Export Performance to ASEAN	0.10	0.09	0.10
	(0.22)	(0.31)	(0.20)
100 × annual Δ in US Import Penetration from NLC	0.45	0.82	0.63
	(0.78)	(1.55)	(1.05)
100 × annual Δ in US Export Performance to NLC	0.18	0.16	0.18
	(0.46)	(0.51)	(0.26)
Observations	392	392	392

Note: Mean coefficients; *SD* parentheses. $N = 392$ four-digit manufacturing industries. Observations are weighted by industry employment in 1991, as measured in the CBP. NLC stands for newly liberalised countries. For countries whose trade data are not available at the HS6 level in 1991, I the use these countries' earliest available data at the HS6 level to compute the long-difference measures.

TABLE A3 Summary statistics, industry-level control variables

	Mean	*SD*	Min	Max
Production workers share of employment (1991)	68.43	15.50	18.72	97.62
Capital/value added (1991)	0.92	0.55	0.19	3.52
Log real wage (2007 USD) in 1991	10.54	0.29	9.78	11.09
Computer investment as share of total (1990)	6.56	6.07	0.00	43.48
High-tech investment as share of total (1990)	8.24	4.84	1.20	18.25
Change in industry share of total employment (1976–1991)	−0.03	0.07	−0.42	0.07
Change in log real wage (1976–1991)	3.57	9.94	−32.01	48.06
Share of workers above age of 45	57.59	4.61	42.17	72.02
Share of non-college workers	85.59	7.77	53.57	95.38
Share of non-whites	9.44	3.89	4.26	25.98
Share of females	33.83	15.64	6.56	76.66
Equipment per worker (thousand USD per worker)	50.65	56.62	2.14	428.40
Routine task intensity (RTI) index	2.60	0.83	0.11	4.74
Herfindahl–Hirschman index	0.27	0.22	0.00	1.00

Note: Mean coefficients; *SD* parentheses. $N = 392$ four-digit manufacturing industries. Observations are weighted by industry employment in 1991, as measured in the CBP.

TABLE A4 First-stage results****

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Endogenous variable = Δ *EP*							
ΔEPIV	1.668***	1.670***	1.618***	1.640***	1.676***	1.623***	1.515***
	(0.180)	(0.177)	(0.143)	(0.151)	(0.176)	(0.139)	(0.050)
ΔIPIV from World	0.041						
	(0.037)						
ΔIPIV from CHN		−0.013	−0.042	0.041	−0.039	−0.039	−0.307
		(0.166)	(0.201)	(0.175)	(0.176)	(0.212)	(0.432)
ΔIPIV from ROW		0.046	0.036	0.037	0.043	0.036	0.070**
		(0.042)	(0.036)	(0.036)	(0.040)	(0.035)	(0.030)
Cragg-Donald Wald Weak IV *F*-Stat	39.004	30.866	44.234	41.851	33.103	46.422	137.340
Anderson–Rubin chi-sq	6.864	20.281	22.617	21.735	20.422	23.592	25.048
Angrist-Pischke *F*-Stat	35.805	37.602	27.040	38.448	34.129	33.420	52.100
Sector controls	No	No	Yes	No	No	Yes	No
Production controls	No	No	No	Yes	No	Yes	No
Pretrend controls	No	No	No	No	Yes	Yes	No
Four-Digit SIC FE	No	No	No	No	No	No	Yes
N	784	784	784	784	784	784	784

Note: Δ EPIV is the instrument for US export performance using newly liberalising countries' demand changes. Δ IPIV represents the instrument for import penetration from different origins. Sector controls are dummies for 10 one-digit manufacturing sectors. Production controls for each industry include production workers as a share of total investment (in 1990). Pretrend controls are changes in the log average wage and in the industry's share of total employment over 1976–1991. In the final column, I include a full set of four-digit industry fixed effects. Covariates are demeaned to facilitate interpretation of the time effects. Observations are weighted by 1991 employment. Standard errors in parentheses are clustered at 135 three-digit industry level.

*p <.10,**p <.05, ***p <.01.

TABLE A5 Robustness analysis: effects of exports on employment with various specifications

	(1) Baseline	(2) Δ = 3	(3) Δ = 6	(4) Two-way FE	(5) Two-way FE
ΔEP	0.506***	0.642***	0.459***	0.531**	0.697***
	(0.163)	(0.145)	(0.105)	(0.263)	(0.192)
Four-Digit SIC FE	No	No	No	Yes	Yes
Four-Digit SIC Trend	No	No	No	No	Yes
First-Stage KP FStat	39.004	66.237	23.054	17.533	222.466

Note: The dependent variable is the annual log change in each industry's employment over the periods 1991–1999 and 1999–2007. For independent variables, Δ EP is the annual change in US overall export performance to the world (Δ EP represents EP in two-way fixed-effect models). It is instrumented as described in the text. Column 1 shows the baseline estimate using the long-difference model. Columns 2 and 3 are estimated over shorter stacked periods. Columns 4 and 5 show provide results based on two-way fixed-effect model where four-digit SIC fixed effects are included. Column 5 also adds a linear time trend for each specific SIC industry. Included control variables: sector controls are dummies for 10 one-digit manufacturing sectors; production controls for each industry include initial period (in 1991) production workers as a share of total employment, the log average wage, and the ratio of capital to value added; Pretrend controls are changes in the log average wage and in the industry's share of total employment over 1976–1991. In the Final column, I include a full set of four-digit industry fixed effects. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. $N = 784$ (= 2 time period × 392 manufacturing industries).

$^*p < .10$, $^{**}p < .05$, $^{***}p < .01$.

TABLE A6 Robustness analysis: effects of exports on manufacturing employment using NBER-CES Data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ EP World	0.556***	0.577**	0.566***	0.596***	0.576**	0.559***	0.653**	0.565*	0.652**
	(0.212)	(0.229)	(0.214)	(0.224)	(0.238)	(0.209)	(0.269)	(0.337)	(0.293)
Δ IP World	−0.028								
	(0.044)								
Δ IP CHN		−1.362***	−0.908***	−1.232***	−1.374***	−0.896***	−0.748**	−1.800***	−0.959***
		(0.363)	(0.206)	(0.327)	(0.378)	(0.217)	(0.300)	(0.206)	(0.199)
Δ IP Non-CHN		0.161*	0.087*	0.134*	0.182*	0.090	−0.037	0.368**	0.169
		(0.094)	(0.049)	(0.076)	(0.110)	(0.060)	(0.094)	(0.166)	(0.137)
Sector controls	No	No	Yes	No	No	Yes	No	No	Yes
Production controls	No	No	No	Yes	No	Yes	No	No	Yes
Pretrend controls	No	No	No	No	Yes	Yes	No	No	Yes
Four-Digit SIC FE	No	No	No	No	No	No	Yes	No	No
Period	1991–2007	1991–2007	1991–2007	1991–2007	1991–2007	1991–2007	1991–2007	1991–2009	1991–2009
First-Stage KP FStat	39.004	30.866	44.234	41.851	33.103	46.422	137.340	21.183	19.787

Note: The sample consists of 384 manufacturing industries for which data are consistently available in the NBER-CES Database. The dependent variable is the annual log change in each industry's employment over the periods 1991–1999 and 1999–2007. For independent variables, Δ EP is the annual change in US overall export performance to the world, Δ IP World is the annual change in US import penetration from the world; Δ IP CHN is the annual change in US import penetration from the China; Δ IP Non-CHN is the annual change in US import penetration from the world except China. Independent variables are instrumented as described in the text. For control variables, sector controls are dummies for 10 one-digit manufacturing sectors; production controls for each industry include initial period (in 1991) production workers as a share of total employment, the log average wage and the ratio of capital to value added; Pretrend controls are changes in the log average wage and in the industry's share of total employment over 1976–1991. In the Final column, I include a full set of four-digit industry fixed effects. Observations are weighted by 1991 employment. Robust standard errors in parentheses are clustered at 135 three-digit industry level. $N = 768$ (= 2 time period × 384 manufacturing industries).

$^*p < .10$, $^{**}p < .05$, $^{***}p < .01$.

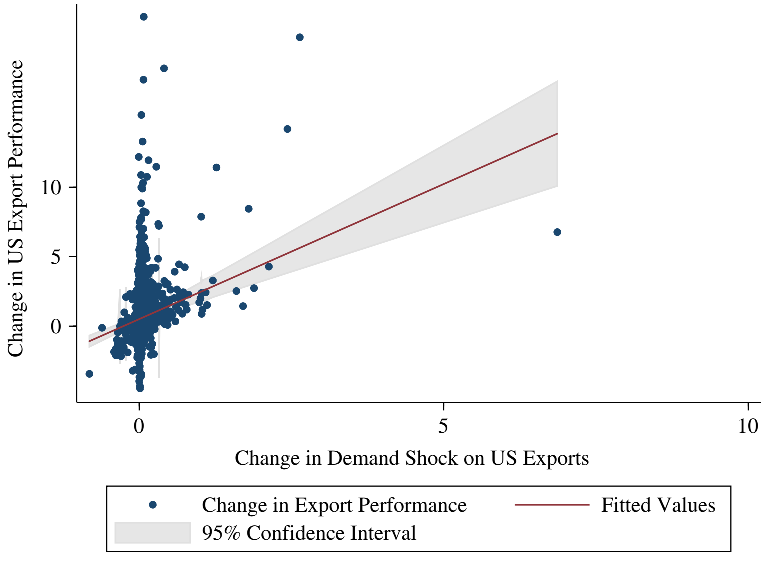

FIGURE A1 Industry-level first stage, export performance, 1991–2007 [Colour figure can be viewed at wileyonlinelibrary.com]

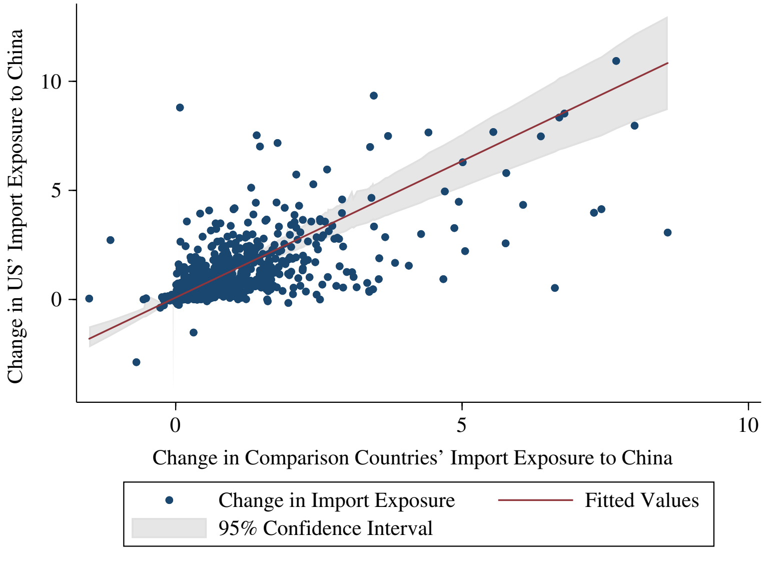

FIGURE A2 Industry-level first stage, import penetration, 1991–2007 [Colour figure can be viewed at wileyonlinelibrary.com]