Export Expansion and Local Labor Market Outcomes in China*

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Abstract

We analyze the effect of China's export expansion between 2000 and 2015 on Chinese local labor markets. We exploit differential trade shocks to local labor markets arising from initial industry specialization patterns and instrument for China's exports to the world using China's predicted exports to the world based on China's predicted exports to each foreign country which captures the exports of all other countries exports to the foreign country and the import tariff reductions faced by Chinese exporters and their competitors selling in that country. According to our estimates, an increase in world export exposures increases the share of manufacturing employment, reduces the share of agricultural employment, and increases the share of unemployment in working-age population. In addition, local manufacturing TFP changes tend to be labor-saving in the manufacturing sector but job-creating in the service sector.

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1 Introduction

China is one of the fastest-growing exporting countries in the world. Between 2000 and 2015, the value of its exports has increased by 480%. China has also become the world's largest exporter of goods since 2009. In 2015, the value of its exports to the world reached 2.5 trillion U.S. dollars. The shift in the world manufacturing base towards China has retained significant attention from the world media and scholars alike. Recent papers in the literature have thoroughly examined the impact of import competition from China on the US labor market outcomes (e.g. Autor, Dorn and Hanson, 2013, Pierce and Schott, 2016, Shen and Silva, 2018, etc.). However, studies on the effects of a rise in exports from China on China's labor markets are limited. This paper fills the gap by examining the effects of China's regional exposures to trade on China's local labor market outcomes.

Specifically, in this paper we relate changes in China's local labor market outcomes from 2000 to 2015 to changes in exposure to China's export expansion to the world. Similar to Autor, Dorn and Hanson (2013), hereafter referred to as ADH, local labor markets are subject to differential trade shocks according to initial industry specialization patterns. The geographic unit for a local labor market used in this paper is a Chinese county. Counties are logical units in the analysis due to the Hukou system in China, which is at the county level and limits the amount of labor mobility across counties.[1] Initial impacts of trade will rapidly diffuse across local labor markets through reallocation of workers if labor mobility is large (ADH 2013). The counties used in this paper cover the entire mainland China and

[1]Resident with Hukou in one county who chooses to relocate to another county does not enjoy the same public benefits (such as healthcare, social security, etc.) as a resident with Hukou in that county.

[citation from ANY paper to back up this statement?]

include both metropolitan and rural areas.

The main difficulties in identifying the causal effect of China's export expansion to the world arise from the fact that export expansion in China is driven by both demand-side and supply-side shocks. While demand shocks to exports such as tariff reductions lead to increased access to foreign markets and drive up demand for manufacturing employment, the effect of China's supply shocks such as new technology or TFP growth on the manufacturing employment is ambiguous ex ante. On the one hand, a supply-side shock in China that is labor-saving will reduce China's employment but raises exports. On the other hand, a supply-side shock that expands product variety tends to increase both exports and employment. This causes difficulty in identification.

Our identification strategy ensures that the export expansion in China is driven by foreign demand shocks and *not* driven by supply-side shocks in China. To correct for supply shocks, we employ the following two strategies. First, we control for regional manufacturing productivity changes constructed based on the firm level TFPs estimated in Orr, Trefler and Yu (2018) for all manufacturing firms in China over the 2000-2006 period. Next, we follow the strategy in Feenstra and Ma (2017) and construct China's predicted exports to the world. Based on the CES framework in Feenstra and Ma (2017), China's exports to each foreign market is represented in an equation similar to the gravity equation. First, it captures the exports of *all* other countries to the foreign market that China exports to. This measure encompasses the main instrument used in ADH (2013), which is a select number of countries' exports to that foreign market. Second it also captures reductions in import tariffs faced by Chinese exporters and their competitors exporting to that foreign market. Once we obtain China's predicted exports to each foreign market, we can sum across all foreign markets to obtain China's predicted exports to the world. Next, we construct the predicted change in export exposure per person based on the change in China's predicted exports to the the world and use it to instrument a county's export exposure to the world per person.

Our empirical results find that world export exposures increase the share of manufacturing employment, reduce the share of agricultural employment, and increase the share of unemployment in working-age population. Regional manufacturing productivity changes tend to be labor-saving in the manufacturing sector but job-creating in the service sector. In addition, local manufacturing TFP changes tend to be labor-saving in the manufacturing sector but job-creating in the service sector. We also study the heterogeneous effects of export shocks on employment outcomes by gender, Hukou type (urban or rural), education (college, high school, or middle school) and age groups (16-34, 35-59, and 50-64). We find that following an export shock, men experience a larger increase in the share of manufacturing employment than women do. Rural-Hukou workers experience a rise in manufacturing employment while the share of manufacturing and service employment fall for urban-Hukou workers. This is driven by an increase in labor force non-participation rate for urban-Hukou workers. One possible explanation for this may be that urban-Hukou workers choose not to work due to better social security and welfare benefits for urban-Hukou people in China. Middle school educated workers experience a larger increase in manufacturing employment than high school and college educated workers do. The decline in agricultural employment is also greatest for workers with a middle school education. Workers in the youngest age group 16-34 experience a rise in manufacturing employment, whereas workers in the age group 50-64 experience a rise in service employment.

Our findings contribute to several literatures. First, they fill the gap on the effects of

"China shock" on the labor market outcomes in China. Our use of the instrument based on the predicted exports to the world follows a similar logic as Feenstra and Ma (2017) and is also similar to the gravity-type instrument used in ADH (2013). Our findings also contribute to the growing literature studying the effects of globalization in developed and developing countries.

For US labor market outcomes, ADH (2013) conclude that growing exposure of the U.S. economy to Chinese exports has had significant negative effect on manufacturing and non-manufacturing employment levels, as well as on wages, across US local labor markets measured by commuting zones. Shen, Silva and Wang (2018) find that occupational exposure to value-added imports from middle-income countries is associated with polarization in wages. Shen and Siliva (2018) find that the effects of U.S. exposure to Chinese exports depend on the position of the Chinese exporting industry in the global value chain. In particular, an increase in U.S. exposure to Chinese value-added exports in more downstream industries leads to negative effects on the share of manufacturing employment, while the same is not present in more upstream industries, leading to the result that the rising value-added exports from China to the U.S. do not have significant effects on the share of manufacturing employment, wages, and unemployment levels in U.S. local labor markets. These results are in line with other papers that consider the role of trade flows on U.S. labor market outcomes and how these outcomes depend on the position of the exporting industry in the global value chain. For instance, Pierce and Schott (2016) find that U.S. decision to grant normal trade relations to China on a permanent basis (grant most favored nation status to China) generated a more negative effect in more downstream industries in U.S. employment at industry level. Similarly, Acemoglu, Autor, Dorn, Hanson and Price. (2016) find that the effects of import competition on a particular industry's sellers from China is magnified. However, Wang, Wei, Yu and Zhu (2018) find that the effects of exposure to Chinese exports are positive on employment and wages after incorporating the supply chain perspective.

Among developed countries, Hummels, Jorgensen, Munch and Xiang (2014) find that import competition increases the wages of more skilled workers and decreases the wages of less skilled workers using Danish matched firm-worker level data (need to double check their results). Wolfgang and Utar (2017), on the other hand, find that import competition from China accounts for 17% decline in mid-wage employment but leads to increased employment in high- and low-wage jobs. Using French data, Harrigan, Reshef, and Toubal (2017) conclude that increased polarization in the French labor market is caused by technological change rather than imports from China. While previous papers thoroughly examine the effects of rising imports in goods, Liu and Trefler (forthcoming) study the effects of imports in services from China and India using the matched US worker data from the Current Population Survey (CPS). They find that a 10-year rise in imports from China and India in services increases downward occupation switching by 17% and upward occupation switching by 4%. In addition, under the assumption of working sorting, a rise in service imports have no significant impact on earnings. In another paper, Liu and Trefler (2008) find service offshoring to China and India has small net positive effect US labor markets.

Among developing countries, McCaig and Pavcnik (2018) find that reductions in US tariffs from the US-Vietnam bilateral trade agreement decreases employment in informal sectors and increases the share of manufacturing employment in the formal sector. Ural (2017) find that regional exposure to exports from OECD countries in India increases employment in the manufacturing sector and business services and reduces employment in the agricultural sector. Garred and Pessoa (2016) find slower wage growth for manufacturing workers across Brazilian local labor markets tht are more affected by Chinese import competition, while they find faster wage growth in those that specialize in raw materials demanded by China between the years 2000 and 2010. Focusing on the effects of import competition, instead of using change in trade flows, Dix-Canairo and Kovak (2017) find that Columbian regional exposure to reduction in tariffs lead to negative employment outcomes. On the firms side, Goldber et al. (2010) provide empirical evidence that firms from India have become more productive give greater access to imported inputs after the implementation of a trade liberalization in the early 1990s, and more importantly, they show that access to new imported inputs has increased the product scope of those firms. Halpern, Koren, and Szeidl (2015) estimate a structural model of imported imports using Hungarian microdata and attribute one-quarter of productivity growth between 1993 and 2002 to imported imports.

The rest of the paper proceeds as follows. Section 2 presents our econometric strategy. Section 3 describes the data in details. Section 4 presents the results, and Section 5 concludes the paper.

2 Empirical specification

Our econometric specification considers the effects of changes in China's local labor market exposure to trade in region i for the following periods, 2000-2005, 2005-2010, and 2010-2015. More specifically, our basic model builds on the strategy used by ADH (2013) and is represented by the following econometric specification:

$$\Delta y_{it} = \beta_1 \Delta EPW_{it} + \beta_2 \Delta MfgTFP_{it} + \mathbf{X}'_{it-1}\beta_3 + \alpha_p + \alpha_t + \varepsilon_{it} \tag{1}$$

where Δy_{it} is the five-year change in the manufacturing employment share of the working-age population in county i in period t.

Our main measure of local market exposure to exports, ΔEPW_{it}, is the change in China's exports exposure per worker in region i, where exports are proportioned to the region according to its share of national industry employment:

$$\Delta EPW_{it} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\Delta X^c_{jt}}{L_{it}}. \tag{2}$$

In this expression, L_{ijt} is the start of the period (year t) employment in region i in China in industry j. ΔX^c_{jt} is the change in China's exports to the world in industry j between the start and end of the period t.

As is clear from expression (1), we also include a set of local market controls described by the matrix $\mathbf{X}$. These controls include possibly relevant characteristics of local labor markets, such as the percentage of the employment in the manufacturing sector, the percentage of the college-educated population, the percentage of migrant population, the percentage of population with rural Hukou, the percentage of employment among women, the share of high-skilled employment, and a set of province dummies. The idea is that, controlling for these local market characteristics, we can capture the effects of changes in market exposure on the employment share in each sector. We describe the construction of these control variables in the Appendix section in details. Note that we use $\mathbf{X}_{it-1}$, or start-of-the-previous period controls, to mitigate possible simultaneity bias between Δy_{it} and $\mathbf{X}_{it}$. By construction, $\Delta y_{it} = y_{it+1} - y_{it}$, as a result, the controls used in $\mathbf{X}_{it}$ such as the percentage of employment in the manufacturing sector may be directly affected by the manufacturing employment share of the working population in time t. We include 2005-2010 and 2010-2015 period dummies α_t to control for aggregate changes over time. We also include provincial dummies α_p to absorb province-specific trends in the manufacturing employment share. In addition, all estimated versions of expression (1) weight observations by the county's share of the national employment at the start of the period and standard errors are clustered at the province level.

The key remaining problem is that there may be variables missing from expression (1) that are correlated with the measure of change in local market exposure to trade, possibly generating biases in the econometric results from the estimation of this expression. We need to ensure that the export expansion in China is driven by foreign demand shocks and *not* driven by supply-side shocks in China. A foreign demand shock will lead to a rise in exports and employment. However, export expansion may also reflect supply-side shocks in China, as shown in the structural model of exports in Feenstra and Ma (2017). On the one hand, a supply-side shock in China that is labor-saving will reduce China's employment but raises exports. On the other hand, a supply-side shock that expands product variety tends to increase both exports and employment. To correct for supply shocks, we employ the following two strategies. First, we control for regional manufacturing productivity changes, $\Delta MfgTFP_{it}$. $\Delta MfgTFP_{it}$ is constructed as follows:

$$\Delta MfgTFP_{it} = \sum_j \frac{L_{ijt}}{L_{it}} \Delta TFP_{ijt}, \tag{3}$$

where ΔTFP_{ijt} is the five-year change in manufacturing total factor productivity (TFP) for industry j in region i at time t. The region-industry TFPs is constructed from the weighted sum of the firm level TFPs estimated by Orr, Trefler and Yu (2018) for all manufacturing firms in China over the 2000-2006 period. While we can control for changes in manufacturing productivities for region i in the 2000-2005 period in our analysis, these measures are not available for other periods.[2] As a result, we follow the strategy in Feenstra and Ma (2017) and construct China's predicted exports to the world due to reductions in import tarriffs faced by Chinese exporters and their competitors selling in foreign countries.

Specifically, Feenstra and Ma (2017) show that based on a CES utility and the gravity model in Romalis (2007), we can predict China's exports of good j to country m as follows:

$$\ln X_{jt}^{c,m} = \gamma_{jt}^{c} + \gamma_1 \ln\left(\tau_{jt}^{c,m}\right) + \gamma_2 \ln\left(\sum_{k\neq c} X_{jt}^{k,m}\right) + \gamma_3 \ln\left(T_{jt}^{m}\right) + \beta_4\left(d_t^{c,m}\right) + \varepsilon_{jt}^{m}.$$

According to the model in Feenstra and Ma (2017), China's exports of good j to country m are determined by the following five items. The first is China's export variety and marginal costs of production captured by γ_{jt}^{c}. The second item is the import tariffs imposed by importer m on Chinese exporters $(\tau_{jt}^{c,m})$. The third item is the total imports by m from all other exporters $\left(\sum_{k\neq c} X_{jt}^{k,m}\right)$ or country m's import demand from the rest of the world excluding China. This term is intended to reflect common foreign demand shocks that drive China's exports and other countries' exports. The identification relies on the exogenous growth of China's exports that arises from the world's rising demands for goods in these sectors. This could be driven by increasingly fragmented production processes and falling trade costs which allow middle-income countries to become more involved in the global supply chains (Feenstra, 1998). Note that this term is similar to the instrument used in ADH (2013),

[2] In our regression analysis, to utilize the data for all three periods, we assume the change in regional manufacturing productivity after 2005 are the same as those in 2000-2005. After controlling for period dummies, this specification is equivalent to assuming that the changes in productivity in later periods are linearly correlated with the changes in productivity in the 2000-2005 period. In an alternative setting, we set $\Delta MfgTFP$ to zero for periods after 2005. The latter assumes that the changes in productivity across all regions are the same and these changes are captured by the period dummies. Results are qualitatively the same in both specifications.

where U.S. exports are instrumented using other similar high-income countries' exports. The fourth item is a measure of country m's average import tariffs for good j from the rest of the world, which is the deviation from the MFN tariffs if m has preferential tariffs due to free trade agreements. The last item $d_t^{c,j}$ is the distance and other trade cost measures that could change over time such as FTA between China and m.

We estimate a simplified version of the structural model in Feenstra and Ma (2017) as follows:

$$\ln X_{jt}^{c,m} = \gamma_{jt}^{c} + \gamma_1 \ln\left(\tau_{jt}^{c,m}\right) + \gamma_2 \ln\left(\sum_{k\neq c} X_{jt}^{k,m}\right) + \alpha_{jm} + \alpha_{mt} + \varepsilon_{jt}^{m}. \tag{4}$$

where the industry-importer fixed effects (α_{jm}) capture country m's time-invariant demand for good j from the rest of the world, which is equivalent to controlling for country m's average import tariffs for good j from the rest of the world across all years in the data.[3] The country-time fixed effects (α_{mt}) capture other trade costs such as distance and average preferential tariffs across all products for country m over time. Robust standard errors are clustered at the country level. We expect $\gamma_1 < 0$ and $\gamma_2 > 0$.

Our instrument for China's exports to the world is constructed as the sum of China's predicted exports to country m over all countries:

$$\widehat{X\_PRE}_{jt}^{c} = \sum_{m} \exp\left(\ln \widehat{X}_{jt}^{c,m}\right), \tag{5}$$

where $\ln \widehat{X}_{jt}^{c,m}$ is the predicted value from estimating the equation (4). It is important to note that the predicted value of China's exports to country m from equation (4) does not include the fixed effects γ_{jt}^{c}, so the predicted value of China's exports is not driven by supply shocks

[3] One can think of the α_{jm} as controlling for the average deviations from the MFN tariffs over the years.

in China, such as changes in technology or TFP. We then use China's predicted exports to the world to construct the instrument for region i's export exposure per worker as follows:

$$\Delta IV\_EPW_{it} = \sum_j \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta \widehat{X\_PRE}^c_{jt}}{L_{it-1}}, \tag{6}$$

where $\Delta \widehat{X\_PRE}^c_{jt}$ is the five-year change in China's predicted exports to the world in period t ($\Delta \widehat{X\_PRE}^c_{jt} = \widehat{X\_PRE}^c_{jt+1} - \widehat{X\_PRE}^c_{jt}$). The variable ΔIV_EPW_{it} represents the change in exports in region i for industry j between the start and the end of the period t in China based on the change in China's predicted exports to the world. The instrumental variable described by expression (6) uses employment-based variables measured in the start-of-the-previous period, $t-1$. In this case, the objective is to mitigate possible simultaneity bias generated by the employment-based variables used to calculate the instrumental variable, as is done in ADH (2013). Our strategy is to estimate expression (1) using a two-stage least square approach where expression (6) instruments our measure of change in labor market exposure described by expression (2). Our strategy also provides information about the quality of the instrumental variables, including a statistical test for under-identification and weak instruments.

Note that we choose to use the instrument in expression (6) instead of using other middle-income countries' exports to the world to instrument for China's exports to the world which is directly comparable to the main instrument used in ADH (2013),[4] for the following reasons. Since China's is a middle-income country (a lower-middle income before and later China becomes a upper middle-income country), among 86 middle-income countries based

[4]ADH (2013) used eight high-income countries' imports from (and exports to) China as the instrument. Note that ADH (2013) also constructed an instrument based on the gravity approach as well. The instrument is constructed using the change in residuals from a gravity equation, controlling for industry FE and country FE, multiplied by the initial US imports from China.

on the World Bank's classification of income in 1990 (including both lower- and upper-middle income countries), it is hard to assess which middle-income countries' exports to the world we should use to construct the instrument. In addition, it is also hard to assess the exact number of middle-income countries we should use to construct the instrument. Out of these 86 middle-income countries, we tried to pick the set of countries whose exports to (imports from) the world have the highest correlation with China's exports to (imports from) the world, respectively. However, the highest correlation is 0.48 and it drops quickly to 0.08 for the top 8th correlation. This problem becomes worse when we try to find the set of countries whose exports to (imports from) U.S. have the highest correlation with China's exports to (imports from) U.S. The constructed IV based on those countries for exports to U.S. has a negative correlation with China's export exposure to U.S. in the first stage estimates of the 2SLS. We show and discuss this results later in Appendix Table A3. One potential explanation for this may be that China's export expansion is subject to supply-side shocks in China, as shown the model in Feenstra and Ma (2017), and therefore tend to substitute other middle-income countries' exports to U.S. As a result, we adopt the instrument that is similar to the one used in Feenstra and Ma (2017) throughout this paper.

We also consider the role played by China's import exposures in determining China's labor market outcomes. On the one hand, firms that face import competition may shrink and therefore displace workers (Autor Dorn and Hanson (2013) and Pierce and Schott (2016)). On the other hand, access to imported inputs raise firms productivity (Halpern, Koren, and Szeidl (2015)) which allows firms to expand and therefore hire more workers. We augment equation (1) and estimate the following specification with 2SLS:

$$\Delta y_{it} = \beta_1 \Delta EPW_{it} + \beta_2 \Delta IPW_{it} + \beta_3 \Delta MfgTFP_{it} + \mathbf{X}'_{it-1}\beta_4 + \alpha_p + \alpha_t + \varepsilon_{it}, \qquad (7)$$

where ΔIPW_{it} is region i's import exposures from the world per worker and is constructed as:

$$\Delta IPW_{it} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\Delta M^c_{jt}}{L_{it}}, \qquad (8)$$

where ΔM^c_{jt} is China's five-year change in imports from the world. Notice that we follow a similar approach to instrument the change in China's exposure to the imports. Based on the model from Feenstra and Ma (2017), China's imports from country m is country m's exports to China and can be expressed as the following:

$$\ln X^{m,c}_{jt} = \gamma^m_{jt} + \gamma_1 \ln\left(\tau^{m,c}_{jt}\right) + \gamma_2 \ln\left(\sum_{k \neq m} X^{k,c}_{jt}\right) + \gamma_3 \ln\left(T^c_{jt}\right) + \beta_4\left(d^{m,c}_t\right) + \varepsilon^m_{jt}.$$

We estimate the following equation to construct China's predicted imports from country m:

$$\ln X^{m,c}_{jt} = \gamma_1 \ln\left(\tau^{m,c}_{jt}\right) + \alpha_{jt} + \alpha_{mt} + \varepsilon^m_{jt}, \qquad (9)$$

where α_{jt} absorbs China's deviation from the MFN tariffs due to FTAs for good j ($\ln\left(T^c_{jt}\right)$) and c's imports from all other countries in the world in good j ($\ln\left(\sum_{k\neq m} X^{k,c}_{jt}\right)$) at time t. α_{mt} absorbs distance and other time-varying trade costs between China and country m. Note that in this specification, we cannot include country m's supply shocks in industry j at time t, γ^m_{jt}, which is the same number of dummies as the number of observations in the data used for this regression. However, since the predicted value in equation (9) should not include

γ_{jt}^{m}, we construct China's predicted imports from m without them. Alternatively, replacing the superscript c with l in equation (4), we could estimate equation (4) for each country l and construct the predicted exports from l to China, or the predicted China's imports from l. Results are qualitatively similar using this approach and are available upon request. We expect $\gamma_1 < 0$. Our instrument for China's imports from the world is constructed as the sum of China's predicted imports from country m over all countries:

$$\widehat{M\_PRE}_{jt}^{c} = \sum_{m} \exp\left(\ln \widehat{X}_{jt}^{m,c}\right). \tag{10}$$

We then use China's predicted exports to the world to construct the instrument for region i's export exposure per worker as follows:

$$\Delta IV\_IPW_{it} = \sum_{j} \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta \widehat{M\_PRE}_{jt}^{c}}{L_{it-1}}, \tag{11}$$

where $\Delta \widehat{M\_PRE}_{jt}^{c}$ is the five-year change in China's predicted imports from the world in period t. ΔIV_IPW_{it} represents the exogenous component of region i's per person change in the import exposure from the world.

For comparison purposes, we also use measures of exposures based on China's export to (imports from) the U.S. and study the effect of "China shock to U.S." on China. This strategy also allows us to consider whether the effects of changes in exports from China to the world differ from the effects of changes in exports from China to the US.

Finally, we explore the effects of trade exposures other other labor market outcomes, such as the effects of changes to trade exposures on the shares of non-manufacturing (service), agriculture, unemployment and those not in labor force (NILF) relative to the the working-age population in region i, those outcomes by education, gender and age groups, and labor mobility. In the next section, we explain the data used in this study and illustrate the relationship between the change in regional exposures to exports and the change in share of manufacturing employment.

3 Data

The previous section made it evident that our main objective is to investigate the relationship between China's regional exposure to trade and China's local labor market outcomes. This section provides a summary of data construction and variables used, with further details provided in the Appendix Data section.

The key variable for estimating equation (1) is the measure of change in China's local market exposure to exports to and imports from the world. We utilize China's census data for the following years, 1990, 2000, 2005, 2010, and 2015[5][6] and obtain trade flow data from UN Comtrade Database to construct China's local market exposure to exports described by equations (2) and (8). The Chinese Census data is at the 2-digit CIC industry level. We end up with 30 2-digit consistent CIC industries in the sample period. We utilize the crosswalk between Harmonized System (HS) 6-digit products and CIC industries from Lu and Liu (2015) to generate trade flows at 2-digit consistent CIC industries. See the Appendix Data section for details on the data construction and crosswalks used.

Column 1 in Panel A of Table 1 reports China's exports to the world for the years 2000, 2005, 2010, and 2015 in billions of U.S. dollars (in nominal terms). This export value has

[5]Note that we do not have access to China's census data in 1980, and therefore we use the employment shares in this year to construct the instrument for the changes in trade between 1990-2000. Therefore, our analysis focuses on the years between 2000 and 2015.

[6]Note that the census data 1990, 2010, and 2015 did not have information on wages, therefore we cannot study the effects of export shocks on wages.

increased by a factor of 4.9, from $438 billion to $2,563 billion. By comparison, column 2 reports China's imports from the world and this value has increased by a factor of 6.2. During this period, the change in China's exports to the world is in fact slightly smaller than the change in China's imports from the world. Columns 3 and 4 report China's exports to and imports from the U.S. The growth in China's exports to and imports from the U.S. between 2000 and 2015 reveals a similar pattern to that of China's trade to the world: the growth in exports to the U.S. is slightly less than the growth in imports from the U.S. (by a factor 3.9 and 5.0 for exports and imports, respectively). To assess the validity of the trade flows in our data, it is useful to compare the numbers to those available in other studies. In the data provided by ADH (2013), China's exports to and imports from U.S. in year 2000 are 121.6 and 23 billions in 2007 U.S. dollars.

The key variable of interest, China's regional exposure to change in exports to the world, on average, weighted by each region's population size, is $1,434 per worker between 2000 and 2005, $1,082 between 2005 and 2010, and $637 between 2010 and 2015. To assess the validity of our measure of China's regional exposure in trade with the world, we construct China's regional exposure in trade with the US and compare the magnitudes to those in ADH (2013). In their data, the weighted average US regional exposure to change in imports from China is $263 per worker per year between 2000 and 2007.[7] In our data, China's average regional exposure to change in exports to the US is $45 per worker per year between 2000 and 2005, $44 between 2005-2010, and $32 between 2010-2015[8]. To make the comparison, we focus

[7] The weighted average of the US regional exposure to change in imports from China (d_tradeusch_pw) in the data provided Autor, Dorn and Hanson (2013) is $1,839 per worker for the period 2000-2007. The 10 year equivalent is $2,627 per worker. Therefore, between 2000 and 2007, the US exposure to change in imports from China is $263 per worker per year.

[8] Note that we use the numbers reported in column (3) in Panel B and divide them by 5 to obtain the per person *per year* exposures.

on the years between 2000 and 2005. We expect that China's average regional exposure to change in exports to the US from our data is close to the US average regional exposure to imports from China in ADH (2013). In the census year 2000, China's employed workers is 5.8 times that of the US.[9] If we reduced the number of employed workers in each Chinese region by 5.8 times, then China's average regional exposure to change in exports to the US would be $261, which is very close to the number obtained from Autor, Dorn and Hanson (2013).[10]

To assess the effect of China's exports to the world on local labor markets, we need to define regional economies in China. A local labor market in our analysis is a county in China. We utilize GB Codes of China, the codings for China's administrative units at the county level, to construct consistent counties over time by aggregating counties that change boundaries or codes over time. We end up with 315 consistent counties between 2000 and 2015 that cover the entire mainland of China including both metropolitan and rural areas. The effects of trade shocks on local labor markets are mitigated if labor mobility is large since the initial impacts will rapidly diffuse across regions through reallocation of workers (ADH 2013). One benefit for using a county as a local labor market in our analysis is that the Hukou system in China, which is at the county level, limits the amount of labor mobility across counties. This is because a resident with Hukou in county A who chooses to relocate to county B does not enjoy the public health benefits to the same extent as a resident with Hukou in county B. Therefore, county level seems to be a natural unit of analysis.

[9] The number of employed workers obtained from China's census for year 2000 is 656 millions. The number of employed workers in the US in year 2000 is 113 millions (l_no_workers_totcbp in ADH dataset).

[10] China's average regional exposure to exports to the U.S. calculated in Zhang (2015) for 2000-2005 is 2,926 Yuan per person between 2000 and 2005. Using the exchange rate in year 2005 (8.2 Yuan = 1 USD), it is equivalent to $71 per person *per year* (2926/5/8.2=71). Given China's employed workers is 5.8 times that of the US in year 2000, this would translate to $412 per person per year in the US average regional exposure to change in imports from China. As a result, we believe our construction of regional exposures to be more accurate.

The effects of China's local market exposure to exports to the world will likely vary across counties due to geographic variation in industry specialization. Counties that are more specialized in exporting industries should react more strongly to the growth in exports. Therefore, we control for local labor market characteristics as described in equation (1). Our measures of local labor market characteristics are derived from the Census data (see the Data Appendix for details).

Figure 1 presents the change in share of manufacturing employment in working-age population and China's regional exposure to change in exports to the world between 2000 and 2015. Figure 1 shows that the largest changes in export exposure to the world are concentrated along the East coastal region in China during the sample period. Figure 1 shows that between 2000 and 2010, the coastal regions in the East also experience large increases in the share of manufacturing employment in working-age population. In the 2010-2015 period, the increase in the share of manufacturing employment seems to be shifting inland. Figure 2 plots the correlation between the change in share of manufacturing employment in working-age population and the change in export exposure to the world per person in a county, while controlling for the county's start-of-the-period percentage of employment in the manufacturing sector and the change in TFP in the manufacturing sector.[11] The size of the circle represents the county's population at the start of the period.

Our identification strategy, outlined in Section 2, ensures that the export expansion in China is driven by foreign demand shocks and is not contaminated by supply-side shocks in China. We construct the instrument for China's change in export exposure to the world per person by first estimating equation (4). Table A1 in the Appendix reports the estimates in equations (4) and (9) to construct the predicted China's exports to and imports from

[11]The correlation looks similar if we do not control for the change in TFP in the manufacturing sector.

the world. China's predicted exports to the world in columns 1 and 2 do not include the fixed effects α_{jt} so the predicted value constructed from the estimates for equation (4) is not contaminated by China's supply shocks. In column 3, we report the predicted value if we include the supply shocks. As predicted by the theory, the coefficient for tariff is negative, indicating that higher tariff in the destination country m lowers China's exports to country m. As expected, the coefficient for country m's imports from all other countries is positive. We use China's predicted exports to the world in column 2 to construct the instrument for the change in export exposure to the world described in equation (6). Note that a census was not conducted in 1995, therefore we use the employment-based variables in the 1990 census to construct the instrument for the 2000-2005 period.

Figure 3 sketches our 2SLS estimation strategy. Panel A shows a strong and positive relationship between the instrument and changes in China's export exposure per worker after controlling for the full set of controls described in equation (1). The first stage estimate for Figure 3 is also reported in Table 2 column 6. A \$1000 increase in the predicted export exposure to the world per worker is associated with \$586 increase in the measured export exposure to the world per worker. Panel B plots a reduced form OLS regression of the change in share of manufacturing employment in working-age population on the instrument. This figure shows a substantial increase in the manufacturing employment in the counties facing large increases in the predicted export exposure to the world. For the import exposure instrument, columns 4 to 7 in Table A1 in the Appendix report the estimates for equation (9). We use China's predicted imports from the world in column 3 to construct the instrument for the change in import exposure from the world described in equation (11).

4 Results

4.1 Baseline results

We can now proceed to the description of our econometric results. The first two columns of Table 2 report the OLS estimates for equation (1) using the stacked first differences for the periods 2000-2005, 2005-2010 and 2010-2015. Both columns use the start-of-the-period local labor market controls. Column 2 includes the additional control for the change in manufacturing TFP in a local labor market. The coefficient of 0.83 in column 2 indicates that a rise in a county's export exposure to the world per worker is positively correlated with the share of manufacturing employment in working-age population. This is in line with the findings in Zhang (2015) using OLS for the 2000-2005. Instead, columns 3 and 4 report the OLS estimates for our preferred specification, where we use start-of-the-previous period controls to mitigate possible simultaneity bias between the dependent variable and the control variables. It is clear from columns 3 and 4 that the OLS estimates of a county's change in export exposure to the world are no longer significant. OLS estimates are subject to measurement errors in employment levels when we apply the Bartik formula to aggregate export changes at industry level to the county level. Measurement errors tend to attenuate the point estimate of interest toward zero. In addition, supply shocks that are labor saving will bias the OLS estimates toward zero. Although we try to control for supply shocks using a county's change in manufacturing TFP based on the TFPs estimated in Orr, Trefler and Yu (2018), these measures are not available for 2005-2010 and 2010-2015 periods and are assumed to follow the same trend as those in 2000-2005. Therefore, in the rest of the paper, we report the 2SLS estimates of equation (1).

Columns 5 and 6 report the 2SLS estimates of our preferred specification in equation (1) using the instrument described in equation (6) constructed based on the structural gravity model. First stage results are reported in panel II. The first stage results in columns 5 and 6 suggest that the instrument described in equation (6) passes the under-identification and weak instrument tests.

The coefficient of 1.85 in column 6 indicates that for a $1,000 exogenous 5-year rise in a county's export exposure to the world per worker increases manufacturing employment per working-age population by 1.85 percentage points. Note that the average 5-year change in county-level export exposure growth to the world between 2000 and 2015 is approximately $631 and the interquartile 5-year change is $657. The point estimate in column 6 implies that the share of manufacturing employees in the working-age population in a CZ at the 75th percentile of the export exposure increases by 1.22 percentage points more than in a county at the 25th percentile.

In column 6, we control for a county's change in manufacturing TFP. In the 2SLS estimates, we the labor shares in the start of the previous period when we construct a county's change in manufacturing TFP to mitigate simultaneity bias. Change in TFP may affect manufacturing employment in the following ways. On the one hand, county's change in manufacturing TFP that is labor-saving will reduce the county's manufacturing employment. On the other hand, the same TFP shock can lead to expansion in export product variety and tends to increase employment. The estimate in column 6 suggests that on average, a county's change in manufacturing TFP is labor-saving. One standard deviation change in a county's manufacturing TFP (2.96) is associated with a differential manufacturing employment share decline of 0.38 percentage points. Controlling for the share of manufacturing employment in a county in the start of the previous period addresses the concern that the export exposure variable is in part picking up an overall trend in China's manufacturing. The estimate in column 6 implies that a county with one percentage point higher initial manufacturing share in $t-1$ is associated with a differential manufacturing employment share decline of 0.15 percentage points in period t. Share of a county's population that has a college education, share of population with rural Hukou, share of working-age women that are employed, and share of skilled workers among employed do not have significant effects on the share of manufacturing employment in working-age population. Share of migrant population in the previous period, surprisingly, is negative correlated with the change in manufacturing employment. One possible explanation for this is that counties that already attract many migrant workers pay higher wages. When facing an export shock, firms take costs factors into consideration and may choose to expand in regions with lower wages.

Note that the effect of a county's export exposure to the world affects the relative share of manufacturing employment in working-age population across Chinese counties, but it may or may not affect the absolute change in the share of manufacturing employment in working-age population in China. As seen in Table 1 Panel C, China's share manufacturing employment in working-age population in the country has increased from 10.6% to 11.6% from 2000 to 2015. A county's export exposure to the world is likely to affect the absolute change in the share of manufacturing employment in working-age population in China if China's exports is growing faster than its imports. As seen in Table 1, between 2000 and 2005, China's trade surplus is rising (growth in China's exports to the world is higher than growth in China's imports from the world). However, this pattern reverses itself in 2005-2010, when China's growth in imports exceeds China's growth in exports in percentage terms, leading to a lower trade surplus in 2010 than that in 2005. In 2010-2015 period, China's growth in exports is at a similar rate to growth in imports in percentage terms. In addition, Panel D in Table 1 suggests that the average change in the share of manufacturing employment relative to working-age population is close to 0, with large standard deviations, in each period. As a result, we cannot directly equate the effects of China's export exposures on relative manufacturing employment shares across Chinese counties to the absolute manufacturing employment share of the working-age population in China.

4.2 Other labor market outcomes

Next, we study the impact of export exposures on the share of employment in services, agriculture, unemployment and labor force non-participation to working-age population in columns 1 to 4 in Table 3. These four shares, together with the share of manufacturing employment to working-age population, sum up to one by definition. Columns 1 to 4 suggest that a $1,000 per worker increase in export exposure to the world reduces the share of agricultural employment by 2.0 percentage points, increases the share of unemployment by 0.53 percentage points, and has no significant effect on the share of service employment, and labor force non-participation relative to the working-age population. Note that the increase in the unemployment share to working-age population (or the net decline in employment share to working-age population) is driven by the large decline in the agricultural sectors. This result is intuitive in the sense that export demand shocks drive workers from agricultural sectors to manufacturing sectors, and as workers make the shift, job search frictions may lead to slightly higher unemployment rate.

The two Panels in Table 4 show that while export shocks increase the share of manufacturing employment and unemployment and reduce the share of employment in agriculture to working-age population, these effects are more pronounced for male workers. The dependent variable in column 1 in Panel A is the share of employed male manufacturing workers to male working-age population, and it is the share of employed female manufacturing workers to female working-age population in Panel. Dependent variables in columns 2-5 are constructed similarly for the share of services, agriculture, unemployment and labor force non-participation by gender under Panels A and B. Column 1 in Table 4 Panel A shows that a $1,000 export exposure to the world per worker increases the share of manufacturing employment to working-age population by 2.34 percentage points for male workers. For female workers on the other hand, the effect is only 1.33 percentage points, as shown in Panel B in column 1. The effects on the share of employment in agriculture and unemployment are also larger for male workers.

In Table 5, we analyze the effects of export exposure shocks on rural- and urban-Hukou workers. The dependent variable in Panel A (B) is the share of rural- (urban-) Hukou workers in each category listed under columns 1 to 5 relative to the rural- (urban-) Hukou working-age population in a county. Panel A in columns 1 to 5 suggest that the export increases the share of rural-Hukou workers employed in the manufacturing sectors, reduces the share in the agricultural sectors, increases the unemployed share and has no effect on the share of services and labor force non-participation. These effects suggest that rural-Hukou workers make the transition from agricultural sectors to manufacturing sectors, consistent with the aggregate trend in the shift from agricultural sectors to manufacturing sectors in China between 2000 and 2015.

A different picture emerges for urban-Hukou workers following a rise in export shock. Panel B columns 1 to 5 suggest that the share of urban-Hukou workers employed in manufacturing and service sectors is reduced, while the share in unemployed, labor force non-participation and agricultural sectors rises following an export shock. One mechanism that potentially accommodates the decline in both manufacturing and service employment and the rise in labor force non-participation for people with urban-Hukou in a county following a rise in export exposure is better social security and welfare benefits for people with urban-Hukou in China ([CITE some work about better benefits for urban-hukou than rural-hukou]).

Next we consider the heterogeneous effects of a county's export exposure to the world by education groups. We investigate the effects on workers with a college degree or above, high school workers, and middle school workers by replacing the dependent variable used in equation (1) by the share of the education group in each panel in Table 6 employed in each category indicated by the column in Table 6 among the working-age population for the corresponding education group. For example, Panel A in column 1 suggests that following a $1,000 rise in export exposure per person, the share of college-educated workers employed in manufacturing sectors to college-educated working-age population is increased by 1.34 percentage points. The effect is slightly higher for workers with a middle school education than those with a high school and college education. This finding is consistent with findings in Yin (2018) that a export shock tends to increase employment of middle school educated workers. Column 2 suggests that the effect of a rising export shock in the share of service employment is not significant for all education groups. Not surprisingly, the point estimates in column 3 suggest that workers with middle school education experience the largest decline in the share of employment in the agricultural sectors among working-age population with a middle school education.

The effect of a export shock on unemployment share is increased for all education groups, as show in column 4. Column 5 suggests that labor force non-participation share is decreased in the share of college and high school workers among college and high school working-age population, respectively. However, the effect is insignificant for workers with middle school education. Note that the point estimates for the export shock in columns 1 to 4 in each panel add up to the effect on the labor force participation rate, or the labor force non-participation rate multiplied by -1, by construction. Workers with middle school education did not see a drop in labor force non-participation rate (or a rise in labor force participation rate) due to the large decline in the share of employment the agricultural sectors these workers.

The increases in manufacturing employment and labor force participation rate following an export shock are more concentrated among young workers (ages 16-34), as shown in Panel A in Table 7. Mid-career and older workers (ages 35-49 and 50-64) see an increase in the share of manufacturing employment but the effect is significantly smaller than the effect for young workers. The labor force participation rate is also decreased for these workers. The decrease in the labor force participation rate is driven by the large decline in the share of agricultural employment for mid-career and older workers. In addition, older workers see a rise in the share of employment in the service sectors following a rise in the export shock, but there is no effect in the service employment shares for other workers.

We also assess the effect of a county's export exposure on labor mobility. If workers can freely reallocated between counties, export shocks are less likely to affect the share of employment in a local labor market since initial local impacts will rapidly diffuse across regions through labor mobility. In Table 8 column 1, the dependent variable is the log change in the working-age population in a county in 2000-2005, 2005-2010, and 2010-2015. We find export shocks do not lead to substantial changes in population. This is consistent with the theory that labor markets are not geographically integrated and fully competitive, and workers face frictions when they reallocate between counties. Columns 2-3 suggest that this is robust for different Hukou types, columns 3-5 suggest that this is robust for all education groups, and columns 5-7 suggest that this is robust for all age groups as well.

4.3 Import exposures

In this section, we also consider the effects of import exposures from the world on China's labor market outcomes. On the one hand, the share of manufacturing employment in working-age population in a county may decline if firms that face import shocks shut down and displace workers (ADH (2013) and Pierce and Schott (2016)). On the other hand, the share of manufacturing employment in working-age population in a county may rise if access to imported inputs raise firms productivity (Halpern, Koren, and Szeidl (2015)) and allow firms to expand and hire more workers.

To construct the instrument for import exposures, we estimate equation (9) and report the results in Appendix A1 columns 4 to 7. We use China's predicted imports from the world using estimates from column 6 to construct the instrument for import exposure described in (11).[12] The first stage results for reported in Panel C in Table 9. It is clear from Panel C that the instrument based on China's predicted exports to the world and the instrument based on China's predicted imports from the world are correlated with a county's export exposure in the direction we expect. Namely, the predicted-exports-to-the-world instrument is positively correlated with the export exposure and the predicted-imports-from-the-world instrument is negatively correlated with the export exposure. Similarly for import exposure, the instrument from predicted imports is positively correlated with the import exposure, and

[12] Using the predicted imports from the world based on columns 4 and 5 to construct the instrument gives rise to qualitatively similar results.

the instrument from predicted exports is negatively correlated with the import exposure. We report the under-identification and weak instrument tests for the first stage estimates. The instruments pass the under-identification and weak instrument tests at 5%. The first stage results for columns 1 to 5 are the same for Panel A where both export exposure and import exposure from the world are used as described in (7). The second stage results in Panel A suggest that the effect from a rise in export exposure for each outcome variable remains robust after controlling for import exposures. Results in Panel A also suggest that a rise in a county's import exposure from the world has no significant effect on the share of manufacturing, service, agricultural employment, unemployment and labor force non-participation to working-age population.

We also consider an alternative measure of exposure exposure using net exports. Panel B in Table 9 reports the effect of exposure to net export to the world, where the exposure to net export to the world is defined as the following:

$$\Delta NPW_{it} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\Delta X^c_{jt} - \Delta M^c_{jt}}{L_{it}}. \tag{12}$$

The instrument for ΔNPW_{it} is constructed on China's predicted exports to the world and its predicted imports from the world as follows:

$$\Delta IV\_NPW_{it} = \sum_j \tfrac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta \widehat{X\_PRE}^c_{jt} - \Delta \widehat{M\_PRE}^c_{jt}}{L_{it-1}}. \tag{13}$$

Panel C column 2 reports the first stage results for net export exposure. The instrument is positively correlated with the endogenous variable, as expected. The instrument passes weak instrument test at 5% but passes under-identification test at 10%. Panel B in Table 9 suggests that the results are robust to using net export exposures.

4.4 Robustness

Over the time period that we examine, the share of manufacturing employment in China relative to working-age population rose by 1 percentage point as shown in Table 1 Panel C. The service share to working-age population has risen by 11.7 percentage points, while at the same time, the agricultural employment share to working-age population has declined by 25.4 percentage points. As a result, labor force non-participation rate has increased by 12.8 percentage points. To verify that our results capture period-specific effects of exposure to export to the world, and not some long-run common factors that cause change in these shares and the rise in China's export to the world, we conduct a falsification exercise by regressing past changes in the manufacturing employment on future changes in export exposures. Table A2 report the 2SLS estimates using future changes in export exposure to the world. Panel A reports the results using data in 1990-2000 and 2000-2005 for the dependent variable in each column in period t and the export exposure to the world in $t+2$ periods. The full set of controls $\mathbf{X}$ is in period $t+2-1 = t+1$. Column 1 suggests that there is little evidence of reverse causality for the share of manufacturing employment relative to working-age population. The rise in a county's export exposure to the world has no significant effect on the share of manufacturing employment in working-age population in the two periods before. Following a similar logic, we expect that counties that had large export exposures to the world in 2005-2010 and 2010-2015 should not have seen differential rises in manufacturing employment in 1990 and 2000, respectively. Panel B reports the results using the counties with above median export exposures in $t+2$ and results suggest the effects on all past outcomes except labor force non-participation are insignificant.

Panel C reports the results using data in 2000-2005 and 2005-2010 and export exposures in period $t+1$ with the full set of controls. This implies the full set of controls $\mathbf{X}$ is in period $t+1-1=t$. The effect of future export exposure has no significant effect on the share of manufacturing to working-age population. Column 4 shows that in both panels the effect of future trade exposures on unemployment is insignificant. However, results in columns 2, 4 and 5 are less robust.

For comparison purposes, we can compare the effects of U.S. export exposures with the effects of world export exposures. Table A3 in the appendix reports the results using the U.S. export exposure. In Panel A, we report the 2SLS results using the change in China's predicted exports to the world described in equation (6) as the instrument. The identification strategy behind using this instrument is that China's predicted exports to the world should be correlated with China's predicted exports to the U.S. The first stage estimates suggest that the instrument is correlated with the U.S. export exposure and the instrument passes the under-identification and weak instrument tests at 5%. In addition, the coefficient in the first stage is 0.100, suggesting that for a \$1,000 change in China's predicted world export exposure per person is associated with \$100 change in the measured U.S. export exposure per worker. The magnitude is smaller than the coefficient in the first stage estimate in column 6 Table 2 because the measured U.S. export exposure per person is approximately one fifth the size of the measured world export exposure per person. The average U.S. export exposure per person in five years between 2000 and 2015 is \$202 (see Table 1). For a \$200 change in U.S. export exposure per person, a county experiences 2.15 percentage points rise in the share of manufacturing employment, 2.36 percentage points decline in the share of agricultural employment, 0.62 percentage points rise in the share of unemployment, relative to the working-age population. The effect on NILF and service employment is insignificant. The average world exposure per person in five years between 2000 and 2015 is $1,051 or approximately $1,000. Therefore, the effects of a rise in U.S. export exposure per person are not significantly different from the effects of a rise in world export exposure per person in Tables 2 and 3.

The first stage results in Panel B in Table A3 shows that other middle-income countries' exports to U.S. may not be a good instrument for the U.S. export exposure in a Chinese county. Note that the construction of this instrument ($\sum_j \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta X_{jt}^{o,US}}{L_{it-1}}$) follows more closely to the one used in ADH (2013).[13] Among 86 middle-income countries defined in the world bank income classification in year 1990, we select five countries with highest correlations with China's exports to U.S. between 2000 and 2015. We use these five countries' change in exports to U.S. to construct the instrument.[14] First stage results in Panel B suggests that other middle-income countries exports to U.S. exposure is negatively correlated with the measured U.S. export exposure in a Chinese county, suggesting that there may be some substitution between China's exports to the U.S. and these other middle-income countries exports to the U.S. In addition, the instrument does not pass under-identification test at 5% level. Panel B in Table A3 reports the 2SLS results using the other middle-income countries' exports to U.S. The second stage estimates are the in same direction as those in Panel A in the same table. However, they are much larger than the ones reported in Panel A. This suggests that the second stage estimates may be blown up due to weak correlation between

[13]Note that we cannot use eight high-income countries imports from China to instrument for China's exports to U.S. as done in ADH (2013), because this method is to identifying the supply shocks in China, whereas we want to identify the demand shocks from the U.S. to study the effect of U.S. export exposure in a Chinese county.

[14]The top five correlation coefficients are 0.51, 0.36, 0.31, 0.25 and 0.24. If we use eight countries, the correlation coefficients quickly fall to below 0.08.

the instrument and the measured U.S. export exposure in a Chinese county. As a result, we opt to use the predicted world export exposure per person described in equation (6) as the instrument.

5 Conclusion

China's exports to the world grew by 480% from 2000 to 2015. Little previous research has studied the effects of China's exports to the world on the local labor market outcomes. Our paper fills this gap by analyzing the effects of differential trade shocks according to initial industry specialization patterns on local labor market outcomes following the strategy used in ADH (2013). Specifically, we study the effects of changes in local market exposure to world exports on the changes in the share of manufacturing, service, agricultural employment, unemployment and labor force non-participation relative to working-age population across Chinese local labor markets.

The observed trade flows from China to the world are driven by both demand and supply shocks. Our identification strategy ensures that the export expansion in China is driven by foreign demand shocks and *not* driven by supply-side shocks in China. To correct for supply shocks, we employ the following two strategies. First, we control for regional manufacturing productivity changes constructed based on the firm level TFPs estimated in Orr, Trefler and Yu (2018) for all manufacturing firms in China over the 2000-2006 period. Next, we follow the strategy in Feenstra and Ma (2017) and construct China's predicted exports to the world that captures the exports of other countries to the country China exports to and reductions in import tariffs faced by Chinese exporters and their competitors exporting to that country. We construct the predicted regional export exposures per person based on the change in

China's predicted exports to the the world and use it to instrument China's regional world export exposure per person.

Our empirical results find that world export exposures increase the share of manufacturing employment, reduce the share of agricultural employment, and increase the share of unemployment in working-age population. Regional manufacturing productivity changes tend to be labor-saving in the manufacturing sector but job-creating in the service sector. Men experience a larger increase in the share of manufacturing employment relative to the male working-age population following a rise in the export shock than women do. Rural-Hukou workers experience a rise in manufacturing employment following an export shocks while the share of manufacturing and service employment falls for urban-Hukou workers. This is driven by an increase in labor force non-participation rate for urban-Hukou workers. One possible explanation for this may be that urban-Hukou workers choose not to work due to better social security and welfare benefits for urban-hukou people in China. Middle school educated workers experience a larger increase in manufacturing employment than high school and college educated workers following an export shock. The decline in agricultural employment is also greatest for workers with a middle school education. Workers in the youngest age group 16-34 experience a rise in manufacturing employment, whereas workers in the age group 50-64 experience a rise in service employment.

Note that the effect of a county's world export exposure affects the relative share of manufacturing, service, agricultural employment, unemployment, and labor force non-participation in working-age population across Chinese counties. It would be desirable to further explore the absolute change in the these shares in China using a structural model similar to the model used in Caliendo, Dvorkin and Parro (forthcoming) that studies the general equilibrium effects of the trade shocks in US local labor markets. We leave this task for further research.

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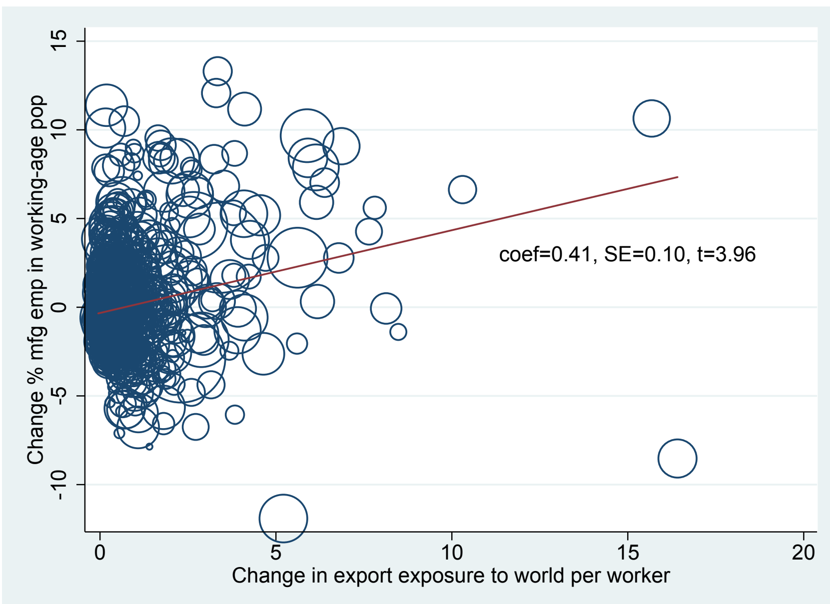
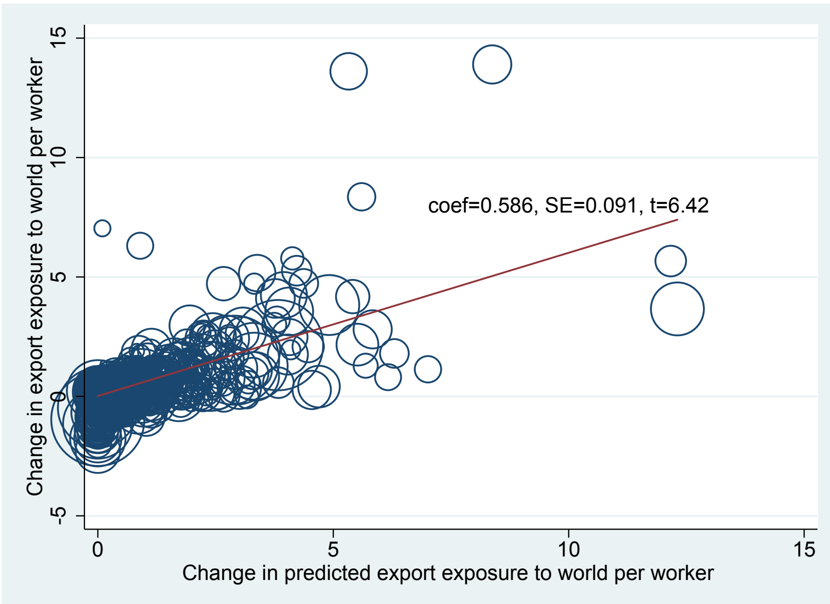
Figure 2: Change in Share of Mfg Emp in Working-age Pop and Regional Exposure to Change in Exports to the World



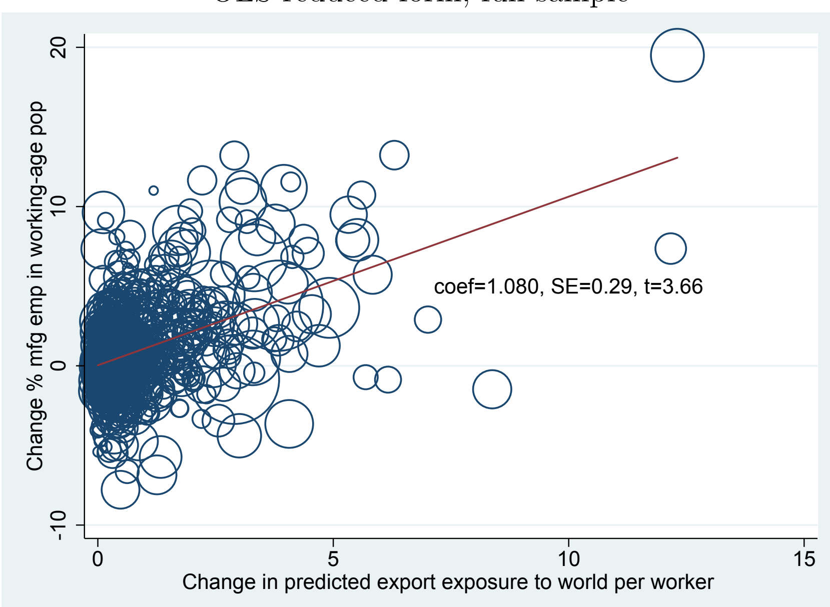
Note: The size of the circle represents the county's population at the start of the period. The scatter plot controls for the start of the period share of employment in manufacturing and changes in manufacturing TFP.

Figure 3: 2SLS first stage and OLS reduced form regression

2SLS first stage, full sample



OLS reduced form, full sample



Note: The size of the circle represents the county's population at the start of the period. The scatter plot controls for the full set of controls in equation (1) Regressions are weighted by the county's start of the period population and robust standard errors are clustered at province level.

Table 1. China Trade Flows and Local Market Exposures

	World			US	
	Exports	Imports		Exports	Imports
	(1)	(2)		(3)	(4)
Panel A. China's exports					
2000	437.6	272.7		105.8	23.2
2005	1385	660.2		256.1	43.8
2010	2144	1747		411.1	100.0
2015	2563	1972		516.4	140.0
Growth 2000-2015	4.8	6.2		3.9	5.0
Panel B. Changes in China's local market exposures					
2000-2005	1.434	0.588		0.225	0.032
	(2.136)	(0.811)		(0.384)	(0.034)
2005-2010	1.082	1.608		0.219	0.081
	(1.424)	(1.997)		(0.303)	(0.078)
2010-2015	0.637	0.349		0.161	0.064
	(0.840)	(0.399)		(0.190)	(0.060)
Average 2000-2015	1.051	0.848		0.202	0.059
	(1.591)	(1.377)		(0.304)	(0.063)
Panel C. China's share of each below to working-age population at the country level					
	mfg	service	agri	unemp	nilf
2000	10.6%	19.5%	50.1%	0.03%	19.8%
2005	10.8%	23.0%	41.2%	0.06%	25.0%
2010	12.5%	26.3%	35.8%	0.03%	25.4%
2015	11.6%	31.2%	24.6%	0.06%	32.6%
Panel D. County's change in share of each below to working-age population					
	mfg	service	agri	unemp	nilf
2000-2005	-0.301	2.177	-5.869	-0.281	4.427
	(2.619)	(3.136)	(5.207)	(1.128)	(2.947)
2005-2010	0.924	3.455	-5.590	0.230	0.981
	(2.627)	(4.085)	(6.227)	(1.240)	(3.156)
2010-2015	-0.366	5.167	-10.962	2.356	3.804
	(3.871)	(5.408)	(9.108)	(2.328)	(3.337)
Average 2000-2015	0.086	3.600	-7.474	0.768	3.020
	(3.148)	(4.478)	(7.457)	(2.010)	(3.468)

Note: Trade flows are in billions of U.S. dollars. The change in China's local market exposures is in thousands of U.S. dollars per person. Standard deviations for changes in trade exposures are reported in parentheses.

Table 2. China's Export Exposures to the World and Change in Share of Manufacturing Employment

	OLS				2SLS stacked first differences	
	(1)	(2)	(3)	(4)	(5)	(6)
(Δ exports to world)	0.869**	0.832**	0.272	0.298	1.789***	1.845***
worker	(0.345)	(0.311)	(0.267)	(0.278)	(0.612)	(0.620)
Δ Mfg TFP		0.143*		-0.049		-0.127*
		(0.083)		(0.094)		(0.088)
County's start-of-the-previous-period controls						
% of employment			-0.064	-0.061	-0.161***	-0.154***
in manufacturing$_{t-1}$			(0.043)	(0.043)	(0.029)	(0.028)
% of college-educated			-0.073	-0.064	-0.016	0.024
population$_{t-1}$			(0.065)	(0.072)	(0.054)	(0.059)
Percentage of migrants in			-0.098***	-0.095***	-0.137***	-0.145***
population$_{t-1}$			(0.015)	(0.018)	(0.041)	(0.043)
% of rural-hukou in			0.020	0.022	0.014	0.016
population$_{t-1}$			(0.019)	(0.019)	(0.018)	(0.018)
% of empoyment			0.014	0.014	0.008	0.008
among women$_{t-1}$			(0.016)	(0.016)	(0.022)	(0.022)
% of employment in			0.105*	0.105*	0.065	0.063
skilled occupations$_{t-1}$			(0.058)	(0.058)	(0.061)	(0.061)
County's start-of-period controls						
% of employment	-0.128***	-0.135***				
in manufacturing$_t$	(0.043)	(0.046)				
% of college-educated	0.037	0.028				
population$_t$	(0.046)	(0.047)				
% of migrants in	-0.102***	-0.115***				
population$_t$	(0.024)	(0.028)				
% of rural-hukou in	0.003	-0.000				
population$_t$	(0.018)	(0.017)				
% of empoyment	-0.024	-0.026				
among women$_t$	(0.021)	(0.021)				
% of employment in	-0.078**	-0.078**				

skilled occupations$_t$	(0.028)	(0.028)				
Observations	945	945	945	945	945	945
R-squared	0.358	0.359	0.318	0.319		
Province FE, Time FE	YES	YES	YES	YES	YES	YES
IV	NO	NO	NO	NO	YES	YES
					II. 2SLS first stage	
(Δ Predicted exports					0.595***	0.586***
to world) / worker					(0.0944)	(0.091)
R-squared					0.68	0.68
KP rk LM statistic					5.77	5.57
KP rk Wald F statistic					39.75	41.26
(both pass 5%)					YES	YES

Notes: $N = 945$ (315 counties x 3 time periods). Dependent variable is the share of manufacturing employment x 100. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. First stage estimates in panel II also include the control variables that are used in the corresponding columns of panel I. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 3. China's Export Exposures to the World and Other Employment Outcomes

	2SLS stacked first differences			
Share of	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)
(Δ exports to world)	-0.326	-2.015***	0.528***	-0.033
/ worker	(0.596)	(0.497)	(0.146)	(0.226)
Δ Mfg TFP	0.206**	-0.029	0.004	-0.054
	(0.100)	(0.091)	(0.045)	(0.069)
County's start-of-the-previous-period controls				
% of employment	-0.011	0.184***	-0.035***	0.017
in manufacturing$_{t-1}$	(0.037)	(0.048)	(0.010)	(0.024)
% of college-educated	-0.269***	0.230**	-0.013	0.029
population$_{t-1}$	(0.083)	(0.106)	(0.033)	(0.065)
% of migrants in	0.029	0.148***	-0.023**	-0.009
population$_{t-1}$	(0.039)	(0.026)	(0.012)	(0.014)
% of rural-hukou in	0.028	-0.053*	0.006	0.004
population$_{t-1}$	(0.021)	(0.029)	(0.008)	(0.017)
% of empoyment	0.042*	-0.059*	-0.003	0.011
among women$_{t-1}$	(0.023)	(0.034)	(0.012)	(0.021)
% of employment in	0.271***	-0.190	-0.024	-0.120***
skilled occupations$_{t-1}$	(0.101)	(0.122)	(0.025)	(0.041)
Observations	945	945	945	945
Province FE, Time FE	YES	YES	YES	YES
IV	YES	YES	YES	YES

Note: $N = 945$ (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 4. China's Export Exposures to the World by Gender

	2SLS stacked first differences				
Share of	Mfg emp	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)	(5)
Panel A. Male workers					
(Δ exports to world)	2.341***	-0.612	-2.138***	0.542***	-0.133
/ worker	(0.802)	(0.891)	(0.496)	(0.152)	(0.226)
Δ Mfg TFP	-0.202*	0.306**	0.004	0.012	-0.120*
	(0.120)	(0.128)	(0.094)	(0.045)	(0.069)
Panel B. Female workers					
(Δ exports to world)	1.334***	-0.084	-1.884***	0.515***	0.120
/ worker	(0.476)	(0.372)	(0.517)	(0.152)	(0.355)
Δ Mfg TFP	-0.046	0.123	-0.056	-0.006	-0.015
	(0.063)	(0.078)	(0.092)	(0.047)	(0.085)
Observations	945	945	945	945	945
Province FE, Time FE	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES

Note: N = 945 (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 5. China's Export Exposures to the World by Hukou Type

	2SLS stacked first differences				
Share of	Mfg emp	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)	(5)
Panel A. Rural-hukou workers					
(Δ exports to world)	1.438***	0.072	-2.062***	0.462***	0.090
/ worker	(0.454)	(0.747)	(0.616)	(0.138)	(0.296)
Δ Mfg TFP	0.004	0.234**	-0.224*	-0.025	0.011
	(0.072)	(0.097)	(0.135)	(0.036)	(0.082)
Panel B. Urban-hukou workers					
(Δ exports to world)	-1.204***	-2.242***	2.236***	0.466***	0.744*
/ worker	(0.386)	(0.535)	(0.542)	(0.149)	(0.417)
Δ Mfg TFP	-0.115	0.382**	-0.049	0.041	-0.259***
	(0.082)	(0.150)	(0.101)	(0.070)	(0.089)
Observations	945	945	945	945	945
Province FE, Time FE	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES

Note: N = 945 (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 6. China's Export Exposures to the World by Education

	2SLS stacked first differences				
Share of	Mfg emp	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)	(5)
Panel A. College					
(Δ exports to world)	1.338***	-0.100	-0.681***	0.526***	-1.083*
/ worker	(0.322)	(0.620)	(0.136)	(0.116)	(0.588)
Δ Mfg TFP	-0.060	0.550**	0.045***	0.008	-0.543***
	(0.079)	(0.228)	(0.017)	(0.047)	(0.171)
Panel B. High school					
(Δ exports to world)	1.485**	0.609	-0.854**	0.606***	-1.847***
/ worker	(0.702)	(0.808)	(0.350)	(0.178)	(0.491)
Δ Mfg TFP	-0.154	0.258	-0.043	-0.042	-0.019
	(0.129)	(0.159)	(0.063)	(0.070)	(0.184)
Panel C. Middle school					
(Δ exports to world)	1.829***	0.273	-2.646***	0.485***	0.059
/ worker	(0.529)	(0.643)	(0.596)	(0.158)	(0.279)
Δ Mfg TFP	-0.106	0.115	0.011	0.011	0.063
	(0.069)	(0.107)	(0.044)	(0.044)	(0.057)
Observations	945	945	945	945	945
Province FE Time FE	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES

Note: N = 945 (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 7. China's Export Exposures to the World by Age Groups

	2SLS stacked first differences				
Share of	Mfg emp	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)	(5)
Panel A. Age 16-34					
(Δ exports to world)	2.952***	-0.698	-1.260**	0.679***	-1.673***
/ worker	(0.749)	(0.622)	(0.501)	(0.173)	(0.371)
Δ Mfg TFP	-0.138	0.331***	-0.054	0.008	-0.147
	(0.094)	(0.115)	(0.116)	(0.056)	(0.112)
Panel B. Age 35-49					
(Δ exports to world)	1.883***	-0.575	-2.385***	0.383**	0.694***
/ worker	(0.728)	(0.805)	(0.614)	(0.189)	(0.255)
Δ Mfg TFP	-0.207*	0.187	0.055	-0.018	-0.018
	(0.124)	(0.152)	(0.105)	(0.051)	(0.068)
Panel C. Age 50-64					
(Δ exports to world)	0.528*	0.786***	-2.581***	0.546***	0.720**
/ worker	(0.274)	(0.258)	(0.594)	(0.135)	(0.326)
Δ Mfg TFP	-0.110	-0.024	0.024	0.005	0.105
	(0.072)	(0.082)	(0.121)	(0.037)	(0.116)
Observations	945	945	945	945	945
Province FE, Time FE	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES

Note: N = 945 (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 8. China's Export Exposures to the World and Changes in Working Age Population

	2SLS Log changes in								
		By Hukou type		By education level			By age group		
	All	Urban	Rural	College	High	Middle	16-34	35-49	50-64
	(1)	(2)	(3)	(3)	(4)	(5)	(6)	(7)	(8)
(Δ exports to world)	0.007	-0.019	0.053	-0.063	-0.003	0.024	0.043	-0.005	-0.007
/ worker	(0.053)	(0.071)	(0.054)	(0.062)	(0.055)	(0.050)	(0.056)	(0.051)	(0.060)
Δ Mfg TFP	-0.050***	-0.054***	-0.051***	-0.051***	-0.052***	-0.053***	-0.048***	-0.053***	-0.052***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Observations	945	945	945	945	945	945	945	945	945
Province FE Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: $N = 945$ (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

Table 9. China's Export and Import Exposures to the World

	2SLS stacked first differences				
Share of	Mfg emp	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)	(5)
Panel A. Exports and Imports					
(Δ Exports to world)	1.917***	-0.495	-1.963***	0.532***	0.009
/ worker	(0.563)	(0.532)	(0.402)	(0.176)	(0.237)
(Δ Imports to world)	-0.155	0.365	-0.111	-0.008	-0.090
/ worker	(0.191)	(0.375)	(0.416)	(0.178)	(0.267)
Δ Mfg TFP	-0.132	0.218**	-0.033	0.004	-0.057
	(0.084)	(0.095)	(0.091)	(0.045)	(0.068)
Panel B. Net exports					
(Δ Net exports to world)	3.215***	-0.591	-3.491***	0.918***	-0.051
/ worker	(0.791)	(0.993)	(0.845)	(0.326)	(0.388)
Δ Mfg TFP	-0.225**	0.225**	0.076	-0.024	-0.053
	(0.092)	(0.109)	(0.129)	(0.053)	(0.071)
Observations	945	945	945	945	945
Province FE Time FE	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES

Panel C. 2SLS first stage estimates			
	(1)		(2)
	Panel A		Panel B
	(Δ Exports to world) / worker	(Δ Imports to world) / worker	(Δ NX to world) / worker
(Δ Predicted exports to world) / worker	0.692***	-0.265*	
	(0.084)	(0.145)	
(Δ Predicted imports to world) / worker	-5.547*	27.8***	
	(2.74)	(7.659)	
(Δ Predicted NX to world) / worker			0.346***
			(0.059)
KP rk LM statistic	6.82		3.66
KP rk Wald F statistic	17.888		34.159
(both pass 5%)	Yes		No (Yes at 10%)

Note: $N = 945$ (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. The firs stage results are reported in Panel C. Note that the first stage results for all columns in Panel A are the same and are thus reported in column (1) under Panel C. Similarly, the first stage results for all columns in Panel B are reported in column (2) under Panel C. *** p <0.01, **p<0.05, * p<0.1.

Appendix

A1. Predicted Exports to and Imports from the World

	China's exports to m				China's imports from m			
	(1)	(2)	(3)		(4)	(5)	(6)	(7)
$\ln\left(\tau_{jt}^{c,m}\right)$	-0.010***	-0.010***	-0.007**	$\ln\left(\tau_{jt}^{m,c}\right)$	-0.081***	-0.045***	-0.082***	-0.039***
	(0.004)	(0.003)	(0.003)		(0.014)	0.011	(0.015)	(0.010)
$\ln\left(\sum_{k\neq c} X_{jt}^{k,m}\right)$		0.102***	0.096***	$\ln\left(\sum_{k\neq m} X_{jt}^{k,c}\right)$		0.603***		
		(0.006)	(0.006)			(0.047)		
α_{jm}	YES	YES	YES	α_{jm}	NO	NO	NO	YES
α_{mt}	YES	YES	YES	α_{mt}	YES	YES	YES	YES
α_{jt}	NO	NO	YES	α_{jt}	NO	NO	YES	YES
Observations	16,803	16,803	16,803		3,758	3,758	3,758	3,500
Predicted		$\widehat{X\_PRE}_{jt}^{c}$				$\widehat{M\_PRE}_{jt}^{c}$		
mean	42.8	42.6	16.1		0.85	1.41	2.70	7.76
sd dev	(82.2)	(80.9)	(7.72)		(0.73)	(2.39)	(0.972)	(1.9)

Note: Columns 1 to 3 report the results for equation (4) and columns 4-7 report the results for equation (9). Robust standard errors are clustered at the country level and reported in parentheses. *** p <0.01, **p<0.05, * p<0.1.

B. Data construction

B1. Trade Data

We obtain trade flows from the UN Comtrade Database at the six-digit Harmonized System (HS) product level. We follow the approach in Feenstra, Lipsey, Deng, Ma, and Mo (2015) to clean up the trade data. Because countries may have incentives to misreport export values, we sum up other countries' imports from country s and count it as country s' export value at the HS 6-digit product level whenever possible. If the sum of other countries' imports from country s is missing or zero, then we use country s's export value as its exports. If both are missing, we treat it as zero. We use country s's reported imports as its imports. If trade flows are less than \$10,000 a year at HS 6 digit product level, we label them as 0. In addition, if the reported trade flow at 4-digit (2-digit) level is higher than the trade flow aggregated from 6-digit levels, we create an artificial product with product code xxxx00 (xx0000) where xxxx (xx) indicates the 4-digit (2-digit) product to reflect the additional trade flow reported at the 4-digit level but not observed at the 6-digit level. Next, we drop all trade flows that are less than \$10,000 a year.

We obtain trade flows for the following years 2000, 2005, 2010, and 2015. Trade flows in these years are reported using classifications HS1992 (HS0), HS1996 (HS1), HS2007 (HS3), and HS2012 (HS4). We construct a crosswalk from each HS classification year to HS2002 (HS2) based on the concordance files between different HS classifications from UNStats. For the artificial products, we add two (four) 0's at the end of the product code for the concordances between 4-digits (2-digits). Lastly, we utilize the crosswalk from Liu and Lu (2015) to obtain trade flows at 2-digit CIC 2002 sector levels.

B2. China Census Data

China census 1990, 200, 2005, 2010, and 2015 are conducted at the following sampling rate: 1%, 0.95%, 0.1%, 0.1%, 0.1%, respectively. We divide the data we obtain from China census at county-industry level by the corresponding sampling rate and obtain the relevant employment measures at county-industry level. We end up with 30 consistent 2-digit CIC industries using the crosswalks for China's industry classification codes over time (GB/T 4754-2002, GB/T 4754-1994 and GB/T 4754-1984). We construct a crosswalk between county codes (GB Codes of China for county level administrative units) across different census years and obtain 315 consistent counties.

Local market controls include the following characteristics in a county. The percentage of the employment in the manufacturing sector is defined as the share of manufacturing employment in total employed. The percentage of the college-educated population is the share of population with a college education. The percentage of migrant population is the share of migrants, or those without Hukou, in the population. The percentage of population with rural Hukou is the share of workers with rural Hukou in the population. The percentage of employment among women is the share of employed women in working-age women. The share of high-skilled employement is the share of high-skill job employment in total employment. High-skill jobs are defined as the first two occupation categories (managers and professionals) in eight broad occupation categories.

Other outcome variables include share of non-manufacturing employment in working-age population, share of agricultural employment in working-age population, share of unemployed in working-age population, and the share of those not in labor force in working-age

A2. Robustness: China's Future Export Exposure to the World

	Pre-exposure 2SLS stacked first differences				
	(1)	(2)	(3)	(4)	(5)
Share of	Mfg emp	Nonmfg emp	Agr emp	Unemp	NILF
Panel A. 1990-2005					
(Δ exports)	4.194	-1.944*	-6.049	0.853	2.945***
to world / worker$_{t+2}$	(5.181)	(1.078)	(4.330)	(0.911)	(0.821)
Δ Mfg TFP	-0.658***	-0.382	1.038**	0.044	-0.042
	(0.195)	(0.277)	(0.403)	(0.048)	(0.135)
Observations	630	630	630	630	630
Panel B. 1990-2005 counties with above median exposures					
(Δ exports)	9.624	-2.557	-10.449	0.242	3.140***
to world / worker$_{t+2}$	(10.085)	(1.934)	(8.027)	(1.646)	(1.303)
Δ Mfg TFP	-0.685	-0.602	1.214*	0.155*	-0.082
	(0.455)	(0.540)	(0.481)	(0.082)	(0.244)
Observations	258	258	258	258	258
Panel C. 2000-2010					
(Δ exports)	-1.476	5.614***	-3.295***	0.321	-1.164
to world / worker$_{t+1}$	(1.496)	(1.798)	(1.186)	(0.421)	(0.844)
Δ Mfg TFP	0.023	0.331	-0.511*	-0.035	0.191***
	(0.155)	(0.211)	(0.278)	(0.044)	(0.066)
Observations	630	630	630	630	630
Province FE Time FE	YES	YES	YES	YES	YES
IV	YES	YES	YES	YES	YES

Note: N = 630 (315 counties x 2 time periods). The full set of controls used in Table 2 column (6) are used. Panel A uses 1990-2000 and 2000-2005 periods, and includes a period dummy for 2000-2005. Panel B uses 2000-2005 and 2005-2010 periods, and includes a period dummy for 2005-2010 . Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. *** p <0.01, **p<0.05, * p<0.1.

A3. China's Export Exposures to the US

	2SLS stacked first differences				
Share of	Mfg emp	Service emp	Agr emp	Unemp	NILF
	(1)	(2)	(3)	(4)	(5)
Panel A. Instrument: Δ predicted China's exports to world					
(Δ exports to US)	10.787***	-1.908	-11.777***	3.089***	-0.191
/ worker	(2.933)	(3.363)	(2.924)	(0.890)	(1.323)
Δ Mfg TFP	-0.111	0.203**	-0.046	0.008	-0.055
	(0.072)	(0.096)	(0.089)	(0.043)	(0.069)
Observations	945	945	945	945	945
Province FE Time FE	YES	YES	YES	YES	YES
	First stage estimates				
(Δ Predicted exports)	0.100***				
to the world / worker	(0.012)				
KP rk LM statistic	4.32				
KP rk Wald F statistic	68.60				
Both pass 5%	YES				
Panel B. Instrument: Δ other middle income countries exports to US					
(Δ exports to US)	29.184***	1.803	-34.965***	3.164**	0.813
/ worker	(5.471)	(10.193)	(9.922)	(1.499)	(5.081)
Δ Mfg TFP	-0.350***	0.155	0.255*	0.007	-0.068
	(0.135)	(0.161)	(0.141)	(0.046)	(0.093)
Observations	945	945	945	945	945
Province FE Time FE	YES	YES	YES	YES	YES
	First stage estimates				
(Δ Other MI exports)	-1.392***				
to the world / worker	(0.343)				
KP rk LM statistic	2.25				
KP rk Wald F statistic	16.46				
Both pass 5%	No				

Note: N = 945 (315 counties x 3 time periods). The full set of controls used in Table 2 column (6) are used. All regressions include a constant and dummies for 2005-2010 and 2010-2015 periods. Robust standard errors are clustered at province level. Counties' share of national population at the start of the period are used as weights. Note that the first stage results for all columns in Panel A are the same and thus are reported only once. Similarly for the first stage results for Panel B. *** p <0.01, **p<0.05, * p<0.1.

population. In addition, we construct these outcome variables by gender (men vs. women), by Hukou type (rural vs. urban), by education level (college, high school, and middle school), and by age groups (16-34, 35-49, and 50-64) in the corresponding group's working-age population.

To study the effects on labor mobility, we construct log changes in working age population in each period. This is defined as $\log(y_{t+1}) - \log(y_t)$, where y_t is the working-age population.

Note that the census data in those years did not have information on wages, therefore we cannot study the effects of export shocks on wages.

B3. Regional Trade Exposures

We construct regional trade exposures using changes in trade flows at the CIC 2-digit consistent sectors and labor employment at the GB consistent counties. To construct the instruments for regional trade exposures, we obtain the tariff data from the UNCTAD TRAINS database on the World Bank's WITS website. Tariff schedules are at the HS 6-digit level. We use the crosswalk between HS and CIC 2-digit consistent sectors to construct tariff schedules at the 2-digit consistent sector weighted by the trade values at HS 6-digit level.