Journal of Economic Geography **21** (2021) pp. 67–95
Advance Access Publication 17 December 2020
doi: 10.1093/jeg/lbaa029

The 'China Shock' revisited: insights from value added trade flows

*Adam Jakubik** and *Victor Stolzenburg***,†

*World Trade Organization, Centre William Rappard, Rue de Lausanne, 154, Case postale 1211, Genève 2, Switzerland
**World Trade Organization, Centre William Rappard, Rue de Lausanne, 154, Case postale 1211, Genève 2, Switzerland
†Correspondence to: *email* <Victor Stolzenburg@wto.org>

Abstract

We exploit a decomposition of gross trade flows into their value added components to reassess the relationship between increased imports from China and manufacturing jobs in US local labour markets following the seminal paper of Autor, Dorn, and Hanson (2013, ADH). Decomposed trade flows enable us to address identification and measurement issues inherent to gross trade data. In particular, it allows us to remove US value added in Chinese exports from the exposure measure which is mechanically correlated with the dependent variable and overstates the volume of the trade shock. In addition, the decomposition permits to correct for double counting, to remove primary and services inputs in manufacturing exports, and to assign competition to the upstream industry that supplied the value added rather than the final exporting industry. This further reduces the volume of the shock and improves the accuracy of the import exposure measure. Consequently, we find considerable differences in the pattern of regions that are most affected by the trade shock and show that imports from China can explain less of the decline in US manufacturing than what gross trade data would suggest. We then separate the shock into a China-driven domestic reform and a third-country-driven value chain component, and find in line with ADH that the smaller, but still negative labour market effects are indeed China driven. Finally, we observe that the negative effects identified in ADH are not present in the 2008–2014 period, which is in line with the hypothesis that labour market adjustment has largely concluded.

Keywords: Value added trade, labour market adjustment, local labour markets
JEL classifications: E24, F14, F16, J23, L60, R23
Date submitted: 22 February 2019 **Editorial decision:** 19 October 2020 **Date accepted:** 20 October 2020

1. Introduction

The reintegration of China into the world trading system has been an extraordinary historical achievement that has lifted millions of people out of poverty. It has also set in motion monumental shifts in world trading patterns which provide a unique opportunity to examine the effects of trade policy. This research has found evidence of lower prices and greater investment in innovation due to trade with China (Bloom et al., 2016; Feenstra and Weinstein, 2017; Impullitti and Licandro, 2018; Amiti et al., 2020). On the flip side, trade liberalisation necessitates adjustments in both factor and product markets. As is the case with adjustment due to technological progress or changes in consumer tastes, some individuals will be worse off than before and can face significant adversities in transitioning from job to job. While the gains from trade through lower prices are relatively evenly distributed throughout the USA, the patterns of geographical clustering typical of manufacturing industries cause local communities to be asymmetrically affected by import competition. Highly influential research by (Autor et al., 2013, henceforth ADH) shows that US local labour markets more exposed to increased import competition from China have seen significant losses in jobs and earnings relative to less exposed labour markets. These effects have also been shown to be present to varying degrees in other advanced economies such as Germany, Spain, Norway and France (Dauth et al., 2014; Donoso et al., 2015; Balsvik et al., 2015; Malgouyres, 2017), although in Germany import competition from neighbouring Eastern European countries had a much larger role.

Recent research suggests that these negative effects are either smaller or not present on aggregate at the national level, and that the net welfare effects of trade with China have been positive (Hsieh and Ossa, 2016; Galle et al., 2017; Caliendo et al., 2019; Adao et al., 2019). Indeed, the cost savings made possible by trade with China have allowed certain industries such as construction and services to add workers (Caliendo et al., 2019), and some papers find positive aggregate employment effects (Magyari, 2017; Wang et al., 2018). This, however, does not diminish the significance of the fact that in many locations US manufacturing industries have suffered. The localised pain felt by those adversely impacted has started to feed into the political process and has shaped the discourse on trade at a national level. Colantone and Stanig (2018) show that the vote for Brexit was influenced by import competition from China, and Autor et al. (2020) present evidence on trade with China contributing to the polarisation of US politics. In light of these developments, researchers and policy makers have emphasized the need for adjustment policies, such as place-based or mobility policies, in order to secure the net welfare gains from trade while minimising the hardship for locations and individuals who are affected negatively by trade (IMF, World Bank, WTO, 2017; WTO, 2017; Austin et al., 2018). For such policies it is crucial to correctly identify which regions and sectors are exposed to import competition and to what extent.

In this article, we first show that the statistical concept of trade in value added can greatly enhance the accuracy of import competition measures with important consequences for the spatial distribution and the magnitude of trade shocks. Moreover, value-added decomposed trade flows further allow us to correct for a mechanically endogenous component of the exposure measure, namely US value added in Chinese exports, and to distinguish between the impact of China-specific drivers of the trade shock and that of third countries who use China in final stages of their production but provide much of the value added. The final contribution of this article is to assess whether Chinese import competition continued to have an effect on local labour markets in the US beyond 2008.

We address these questions by exploiting data from Inter-Country Input-Output tables (ICIOs) covering the time period from 2000 to 2015. This expands the time-period analysed by ADH to shed light on whether the negative effect of Chinese import competition persists, and therefore whether the China shock is fundamentally different from other trade shocks with regard to adjustment time. The tables allow us to split gross US imports from China into their individual value added components by industry and country of origin and, thus, separate Chinese value added (CNVA), US value added (USVA) and third country value added (TCVA). This approach entails important methodological improvements over the use of gross trade flow data and allows us to create a more precise measure of local labour market trade exposure by addressing four different measurement issues.

First, goods exported from a downstream industry such as consumer electronics contain inputs from upstream industries such as plastics and fabricated metal products. Therefore, a rise in US consumer electronics imports might actually affect local labour markets which depend on the plastics or fabricated metal industries. Taking mobile phones as an example, assume each worker adds one unit of value and out of all the workers required to produce a phone half are working in the electronics industry, and half are working in the glass, plastics and other upstream industries, that are located elsewhere. This means that when a mobile phone is imported, gross trade data assigns only 50% of the competition correctly, by assigning all of it to the electronics industry and the local labour markets where that industry is present. Meanwhile, it assigns no competition to the local labour markets where the upstream industries are located.

Second, gross imports hide the fact that certain upstream production stages of imported goods are performed in the importing country itself rather than abroad. Returning to our mobile phone example, recall that out of all the workers who produced the imported phone, half are in the electronics industry. Now assume additionally that half of these workers are located in the USA in charge of high-tech components, and only the rest are located in the exporting country in charge of basic components. In this case using gross trade data would overstate competition by 33%, effectively claiming that these workers are competing with themselves.

Third, similar to the previous points, many goods are dependent on primary and services inputs. The value added of such inputs is falsely assigned by gross imports data as competition to the exporting industry, which in the case of mobile phones is the electronics industry, instead of the actual industry facing competition, such as logistic services or mining and quarrying. If the focus is on manufacturing employment, such inputs must be excluded from the analysis which value added data allows us to do.

Fourth, in the age of global value chains gross trade data suffers from double counting, which occurs when embedded intermediate parts and components cross the same border twice. Thus their value added is counted multiple times in gross imports data, inflating measures of import competition. If plastic cases in our mobile phone example are produced in China and shipped to the USA, where high-tech components are inserted before the phone travels back to China for final assembly, then the phone case is counted twice by gross trade data and falsely inflates import competition.

Using data on the value added content of US imports from China we can address these four issues and correctly assign import competition to local labour markets.

Finally and related to the second point above, another methodological improvement relates to the identification strategy. Value added trade data allows us to better control for the endogeneity of import exposure by removing the US value added component in Chinese exports. Johnson and Noguera (2012) show that the US value added content in Chinese exports is considerable which highlights that this adjustment is quantitatively meaningful and relevant. The endogeneity arises since US employment is a major contributor to US value added in Chinese exports and, hence, there is a mechanical correlation between import exposure and US employment in manufacturing. That is, when Chinese exports increase, so does Chinese demand for inputs provided by US manufacturers leading to an upward bias in the coefficients.[1] This mechanical correlation is not addressed by the instrumentation strategy of ADH since US value added is also present in Chinese

1 To be precise, the presence of US value added in Chinese exports creates a positive bias in the coefficient proportional to the US employment share of value added times the share of US value added in Chinese exports.

exports to other high-income countries. By removing this part of Chinese exports from both our value-added exposure measure and the instrumental variable, we address this problem with the validity of the ADH instrument.

Turning to our results, we find that using value-added instead of gross trade flows changes the geography of import competition considerably. As expected, certain locations specialised in downstream industries, in particular electrical machinery and electronic equipment, are much less exposed to import competition than what gross imports would suggest while the opposite holds for certain locations specialised in upstream manufacturing including steel. Two of our most extreme cases in this regard are San Jose, California, home to Silicon Valley and many of the US' main electronic equipment manufacturers, and North-West Indiana, home to the largest steel mill in the US and large aluminium producers. In these commuting zones, import competition in value-added terms is more than a standard deviation different from gross import exposure. In the case of San Jose, value-added exposure per worker is $4000 below gross exposure, while in Gary, Indiana, it is $960 above gross exposure. However, the relative upstreamness (Antràs et al., 2012) of the activities a US local labour market is specialised in, is not a sufficient statistic to arrive at our revised geography of import exposure which depends instead on the sectoral composition of imports. This is because each importing industry has embedded 'upstream' value added from an industry other than the importing industry itself, but this may be in general from an industry that is either more downstream or more upstream than the average US industry. These intuitive results highlight the need to take value added data into account when assessing the geography of trade shocks and when designing policy responses, in particular when these policies are place-based. They also facilitate our understanding of current trade policy developments since they align import competition more closely with recently introduced trade policy measures targeting the steel and aluminium sectors.

Next, we find that Chinese import competition can explain less of the US manufacturing decline than previously considered. Consistent with value-added imports reducing measurement error, which biases estimates towards zero, and correcting for an upward bias introduced by endogeneity, we observe that the corresponding coefficient on Chinese imports increases substantially in absolute value compared to the coefficients obtained using gross import data. This speaks in favour of a larger role of imports. However, since the total volume of the shock is significantly smaller once double counting, US value added, and primary and services inputs are excluded, we find that the total number of jobs affected is in fact smaller than the corresponding gross trade number by 32.3%, despite the increased coefficient. This suggests that China has been relatively less important for the decline of US manufacturing than what ADH find using gross trade flows.

Regarding the drivers behind the employment effects, we find that China-specific changes as suggested by ADH are dominant. Autor et al. (2016) discuss extensively the domestic reforms that took place in China and enabled it to integrate into the global economy as a manufacturing powerhouse. At the same time, Johnson and Noguera (2017) and Koopman et al. (2012) research the proliferation of global value chains (GVCs) and in particular the participation of China. Implications for US trade policy depend on the extent to which employment effects are caused by China-specific drivers as opposed to GVCs since the latter tend to be highly mobile and can reroute if faced with bilateral trade policy interventions. Our results show that for the period 2000–2008 increased exposure to Chinese value added is associated with a relative decline in local manufacturing employment, whereas exposure to foreign third-country value added in Chinese exports has a positive point estimate, albeit not significantly different from zero. This means that US employment adjustments are caused by China-specific changes and not by indirect imports as would be consistent with a GVC-driven explanation. The result for third-country value added suggests that the rerouting of exports via China by other advanced economies such as Japan and Korea does not harm US manufacturing. This is potentially explained by lower prices of goods that have been previously imported by the US directly from these countries, which boosts total demand but does not require significant new labour market adjustment in the industries affected. This hypothesis is in line with the fact that most of third-country value added in Chinese exports to the US originates in high-income countries that have traded intensively with the US before the rise of China. An alternative hypothesis is that third-country value added is associated more with horizontal intra-industry trade and Chinese value added with vertical intra-industry trade as defined by Greenaway et al. (1995), and hence the former necessitates relatively little labour market adjustment.

Finally, for the period 2008–2014 we do not find a negative effects of local exposure to Chinese value added. The corresponding coefficients in this latter period are no longer statistically significant, consistent with the hypothesis that the China shock today is not driving regional differences in manufacturing employment across the USA. We conclude that current policy measures aimed at limiting imports from China cannot be vindicated by these results.

The rest of this article is organised as follows. Section 2 reviews the related literature, Section 3 discusses the data followed by Section 4 on the empirical strategy, Section 5 presents the econometric results, and Section 6 concludes.

2. Related literature

Our work is directly related to the seminal paper by ADH and papers that replicate their methodology (e.g. Dauth et al., 2014; Balsvik et al., 2015; Malgouyres, 2017). Our methodological contribution to this line of research is to improve upon the identification as well as the precision of the exposure measure by employing novel trade in valued added data.

In addition, our work is similar in spirit to Shen and Silva (2018) who also adopt a value added perspective of the China shock. Rather than studying the value added decomposition of bilateral gross trade flows as we do, they view the impact of the rise of China through a different lens, focusing on all the Chinese value added that is eventually absorbed by the USA. That is, they exclude foreign value added in Chinese exports to the USA but consider instead also the Chinese value added embedded in third country exports to the USA. For instance, China might export processed rare earth elements to Japan for the production of semiconductors which are then exported to the USA. In technical terms, the value added decomposition we use employs backward linkages whereas theirs employs forward linkages. Their results show that exposure to Chinese value added from downstream sectors is responsible for the adverse labour market effects in the USA. They classify industries as downstream if their ratio of foreign value added to gross Chinese exports is high, for example industries where China's role is mainly assembly and packaging.[2]

2 While this is a very valuable exercise, there are several major differences to this paper that imply that results are not directly comparable. First, it differs from the bilateral trade perspective taken in this paper and in ADH. Our focus is in line with much of the recent policy discussion centred on bilateral US–China trade rather than third country imports and their content of Chinese value-added. Their approach leads to very different exposure measures that are not comparable to ours and by default increase the exposure of downstream industries. Secondly, we show that local exposure measured in gross terms neglects the exposure faced by the locations of upstream

More recent work on the impact of Chinese imports emphasises the importance of input–output linkages. Acemoglu et al. (2016) use industry level data to complement the effects of direct industry exposure with exposure which propagates downstream to a given industry's customers and exposure which propagates upstream to a given industry's suppliers. As one would expect, direct and upstream effects of exposure are found to be negative, however downstream effects are statistically insignificant. While related to our approach in spirit, they continue to rely on gross trade data to calculate the direct exposure measures and based on these direct exposure measures estimate indirect exposure using US national input–output tables. This means that the measurement and identification issues mentioned above are not addressed in their work and affect their direct and indirect measures. By taking into account international, as opposed to only USA, input–output linkages we are able to account for these issues and capture the direct exposure effects more precisely. Like ADH, we focus only on the direct exposure measure.

Wang et al. (2018) examine the propagation of import competition also to downstream sectors, and find statistically significant positive downstream effects. They calculate downstream exposure using imports of only intermediate goods and services. Once effects on services sectors are taken into account, they find that the net effect of trading with China on local employment is modestly positive.

The effects we identify here are but one side of the coin of trade liberalisation: the necessary local labour market adjustment. Magyari (2017) broadens the focus by studying the effects on US manufacturing employment at a firm level, cutting across local labour markets. She finds that US firms involved in manufacturing record net gains in jobs in response to increased Chinese import competition. While specific units of production within the firm shrink, others, in sectors where the USA has a comparative advantage relative to China experience employment growth. These results are attributed to firms reorganising production and a favourable cost shock in the form of cheaper Chinese inputs. This does not contradict the significant effects found at a local labour market level or indeed the adjustment costs faced by individual workers, rather, this methodology is suited to assess the aggregate effects of a trade shock, which are equally important to consider from a policy perspective.

In one of the earliest papers in trade to apply this type of identification strategy, Topalova (2007) emphasises that this methodology is suited to identify short- and medium-run effects at the local level. Rather than identifying the effects of the treatment, in our case the China shock, on the national aggregate levels of the outcome variable, the focus is on identifying differential regional effects based on regional variation in the level of treatment exposure. The fact that manufacturing employment is reduced more in local labour markets that are more exposed to import competition is a good indicator of the geography of locally borne costs of trade adjustment, which are greatly important for domestic policy, as discussed earlier. However, it is not informative about the causal effects of the China shock on the manufacturing employment share at a national level, much less about aggregate welfare implications in general equilibrium, which are more relevant questions from a trade policy angle.

industries. With reference to this measurement issue, in our usage, the term upstream refers to all value added contributed by industries other than the final exporting industry itself, and not the lack of foreign value content in that specific industry. Ultimately, both papers provide novel and complementary insights into the role of US–China trade for US labour markets.

A separate literature analyses employment and welfare changes due to trade with China using structural, general equilibrium models. Caliendo et al. (2019) use a model with spatially distinct labour markets and imperfect labour mobility across sectors and locations. They find that the rise in imports from China from 2000 to 2007 resulted in a decrease in US manufacturing employment, accounting for 16% of the observed decrease, but an increase in US aggregate welfare of 0.2%—an estimate that is in line with Hsieh and Ossa (2016) who base their welfare estimates on a quantitative trade model. Adao et al. (2019) extend this methodology to also incorporate spatial linkages to account for indirect general equilibrium effects of shocks in other regions, and draw similar conclusions regarding the decrease in US manufacturing employment. Galle et al. (2017) employ a structural gravity model where labour is heterogenous with regard to its comparative advantage across sectors. They also find that trade with China increases US aggregate welfare by 0.25%, but with significant heterogeneity across workers in different skill groups, with some groups losing from trade. All papers mentioned use gross trade data to calibrate the respective models, whereas we show that value added trade data would be more accurate.

3. Data description

We use value-added trade flow data generated from the OECD ICIOs covering the years 2000 and 2007 using a decomposition based on the accounting framework proposed by Koopman et al. (2014) but further disaggregated to a bilateral-sector level as in Wang et al. (2013). The database covers 61 countries and 34 industries.[3] We prefer OECD ICIOs and the corresponding OECD Trade in Value Added database (TiVA) compared to alternative datasets since our focus is on China, and OECD and WTO have used elaborate techniques to account for the high level of processing trade from China's special economic zones. Due to China's special role in global value chains and processing trade, this implies a significant improvement for the reliability of the data. As the OECD ICIOs covering the year 2000 currently only extend to 2011, we use for some regressions data for the years 2000, 2008, and 2015 generated from the Asian Development Bank multi-regional input-output tables (ADB-MRIO) and provided by the Research Centre on GVCs at the University of International Business and Economics in Beijing. For robustness exercises we also use equivalent data from the 2016 release of the World Input-Output Tables (WIOT 2016); however, the ADB-MRIO contains five additional Asian economies, and since the focus of this research is on the sources of value added in Chinese exports, accurately measuring input–output linkages in the region is critical.

Our employment data is sourced from the publicly available County Business Patterns (CBP) series of the United States Census Bureau and covers the years 1990, 2000, 2007, 2008 and 2014. This data is cleaned using code made public by David Dorn.[4] Data on working-age population used to compute the dependent variables are sourced from the Population Estimates Program (PEP) of the United States Census Bureau. We concord our employment data to the more aggregated industry classification of our trade flow data using correspondence tables made available by the United Nations Statistics Division.[5]

3 Note, that as a result our data is more aggregated than ADH's gross import data which is aggregated to four-digit SIC industries.

4 http://www.ddorn.net/

5 ISIC Rev. 3 - USSIC correspondence, https://unstats.un.org/unsd/classifications/econ/

Control variables at the local labour market level are taken from the dataset published with ADH, with the exception of beginning-of-period employment in manufacturing (see above).

4. Empirical strategy

4.1. Identification and instrumentation

Our empirical approach builds on the methodology developed by ADH with the aim to deepen our understanding of the local labour market effects of the US–China trading relationship.[6] In this approach, the identification strategy relies on the fact that the USA can be divided into 722 regional markets, termed commuting zones (CZs). Within commuting zones labour is mobile and across them it is highly immobile. This is a key assumption, because if labour were mobile also across CZs, the effects of trade shocks would not be identifiable at a local labour market level. It is thus worth noting that the literature finds support for this assumption (Topel, 1986; Blanchard and Katz, 1992; Glaeser and Gyourko, 2005). These CZs are then subject to differential trade shocks determined by their initial patterns of industry specialisation.

We use a measure of CZ trade exposure created in the spirit of ADH but based on value added imports from China to the USA:

$$\Delta EXP_{it} = \frac{1}{L_{it}} \sum_{s} \frac{L_{ist}}{L_{st}} \Delta IMP_{st}. \tag{1}$$

The above expression represents the change in exposure, *EXP*, for a particular CZ i with the base year t. It is normalised per worker. The change in imports, *IMP*, from each exporting sector s is weighted by the national prominence of the CZ in the sector, using the CZ's share of total US employment, L, in that sector. In our analysis, our benchmark specifications measure *IMP* as the value added provided by sector s embedded in the imports of all sectors. For comparison with previous work, other specifications use the conventional gross value of imports *IMP* by exporting sector s.

The issue of potential endogeneity stemming from the correlation of both US employment outcomes and imports with unobserved and omitted shocks to US demand or supply, is addressed by instrumenting the exposure measure with an analogous one where employment is lagged by one period and US imports from China are replaced by Chinese exports to a group of other developed economies.[7]

$$\Delta IV_{it} = \frac{1}{L_{it-1}} \sum_{s} \frac{L_{ist-1}}{L_{st-1}} \Delta IMP^{OTH}_{st}. \tag{2}$$

6 We are interested in precisely identifying the causal effects on manufacturing employment through the import competition channel, so we do not seek to simultaneously include a treatment variable for downstream exposure to intermediate goods in order to identify input price effects. Industries which are downstream from the imported product presumably benefit, so the expected effect would be positive. For example, Topalova and Khandelwal (2011) show that trade liberalisation leads to some firm-level efficiency gains due to import competition but much bigger gains due to increased access to foreign inputs. Furthermore, our identification strategy is agnostic about the employment effects, whether positive or negative, through the aggregate demand channel, which is not locally determined, as well as welfare effects more generally. Therefore, our conclusions are most relevant not for national trade policy but for employment policies, particularly those aimed at facilitating local adjustment to shocks.

7 We follow ADH in using Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland from OECD TiVA data; however, New Zealand and Switzerland are not included in ADB-MRIO data.

We estimate the specification in equation (3), that is we regress $\Delta MANUF_{it}$, the change in the share of manufacturing employment in the working-age population of CZ i, on the change in local trade exposure, ΔEXP_{it}.

$$\Delta MANUF_{it} = \beta_0 + \beta_1 \Delta EXP_{it} + \mathbf{X}'_{it}\gamma + \epsilon_{it} \tag{3}$$

4.2. Value added exposure

If trade adjustment policies are to be implemented, it is important to correctly identify the industries and local labour markets affected by import competition. It is here that trade in value added statistics come into play. By accounting for input–output linkages on the supply side they allow us to identify the industries and countries which contribute value added to the production of a manufactured good. This information enables us in turn to create a more precise measure of local labour market exposure.

The reason is that gross trade data assigns a substantial amount of import competition to wrong labour markets due to four issues. First, goods exported from a downstream industry such as consumer electronics contain inputs from upstream industries such as plastics or fabricated metal products. Therefore, a rise in US consumer electronics imports might actually affect local labour markets which depend on plastics or fabricated metal products and not only labour markets specialised in electronics. As a result, ignoring the components of a final good leads downstream labour markets to appear overexposed and upstream labour markets underexposed. Consider the following simple example, with two industries $s \in \{1, 2\}$ each employing one unit of labour and respectively located in different CZs $i \in \{1, 2\}$. Then equation (1) simplifies to

$$\Delta EXP_i = \Delta IMP_s, \tag{4}$$

where $s = i$. Assume industry 1 (downstream) produces a consumer good using intermediate inputs from industry 2 (upstream) so that half of its value-added comes from industry 2. Intuitively, growth in gross imports of industry 1 goods implies equal import competition facing workers on both domestic industries. If the growth in gross imports is $\Delta IMP_1^G = 2$ and $\Delta IMP_2^G = 1$, then this implies growth in value-added imports of $\Delta IMP_1^{VA} = 1$ and $\Delta IMP_2^{VA} = 2$. It is then straightforward to note that the gross-imports based import exposure measure ΔEXP_i^G is twice as large for the CZ housing the downstream industry than for the CZ housing the upstream industry. Using the value-added based import exposure measure ΔEXP_i^{VA} reverses this to a more intuitive ordering where the upstream industry is more exposed to import competition.

Secondly, primary and services inputs account for an important share of the value of manufacturing imports, around 42.3% in 2000, but do not compete with manufacturing workers. Not removing this value added leads to overstating the exposure of those local labour markets which are specialised in manufacturing products using these inputs relatively more extensively.

Third, a similar mismeasurement arises due to the double counting problem in gross trade data. The increasing complexity of production networks causes some intermediates to cross the same border several times which leads them to enter gross trade statistics several times without actually adding competition. This overstates the exposure of local labour markets specialised in more complex products such as electronics.

The fourth issue is that a non-negligible share of US manufacturing imports from China is made up of US value added, around 6.25% in 2000, that should not be counted as foreign competition. Not removing US value added would overstate the exposure of those local labour markets where upstream US industries which supply inputs to China are located.

In addition to this measurement issue, the presence of US value added in Chinese exports introduces an identification issue not addressed by ADH. It mechanically correlates dependent and independent variable by creating a partial identity between the two. To be precise, US value added can be separated into a capital and a labour share where the latter is generated by employment and wages. That is, a certain share of US value added is accounted for by US employment in manufacturing, the numerator of our dependent variable. Since US value added is also a component of Chinese exports, our independent variable, we have a one-to-one relationship between this overlapping component in both variables which is equal to the share of employment in US value added times the share of US value added in Chinese exports. This creates a bias proportional to the value of the overlapping component (which is positive) and, hence, causes an upward bias in ADH's estimates. The instrumental variable of ADH does not address this problem because Chinese exports to other developed countries also contain US value added, which violates the exclusion restriction. We can address this by using value added decomposed trade data and removing the US value added component, thereby focusing on the portion of the variation in import exposure due to the surge in Chinese manufacturing which avoids this concern with the validity of the instrumental variable.

In Figure 1 we present a side-by-side comparison of the value of US imports from China based on the industry of the imported good, i.e. a gross trade perspective, with the imported value added by industry. Given the focus of the literature on the decline of manufacturing industries in the USA, we focus here on manufacturing goods and the manufacturing value added, so while embedded primary commodities and services value added is included in the first panel, these industries are not shown in the second panel, albeit they are also indirectly exposed. As expected, we observe that the imported value added is significantly less than the gross import value for some industries such as Textiles (4), Leather and Footwear (5), Machinery (13), Electrical and Optical Equipment (14), and other Manufacturing and Recycling (16). The most dramatic difference is in the Electrical and Optical Equipment sector where in 2008 US imports from China were close to $130 billion by gross import value of the goods, yet only above $47 billion of the value added embedded in those goods came from the Electrical and Optical Equipment sector. This illustrates how using gross trade statistics may give a distorted picture of labour market exposure to import competition. In contrast to the downstream sectors listed above, we observe that for some upstream sectors which serve more often as inputs to production, such as Pulp, Paper, Printing and Publishing (7), Coke, Refined Petroleum and Nuclear Fuel (8), Chemicals (9), and Basic and Fabricated Metal (12), the embedded value added imported is significantly greater than its gross import counterpart. This implies that local labour markets specialised in these products are affected more than one might expect from studying gross import data.

Figure 2 illustrates that the value added content of Chinese exports to the USA does not solely originate from the exporting industry, but also from other upstream industries that supply inputs to the exporting industry. Different shades represent the source industries of the value added content in the exports of each manufacturing industry. The industry with the largest share is usually the nominal exporting industry, however it is clear that a

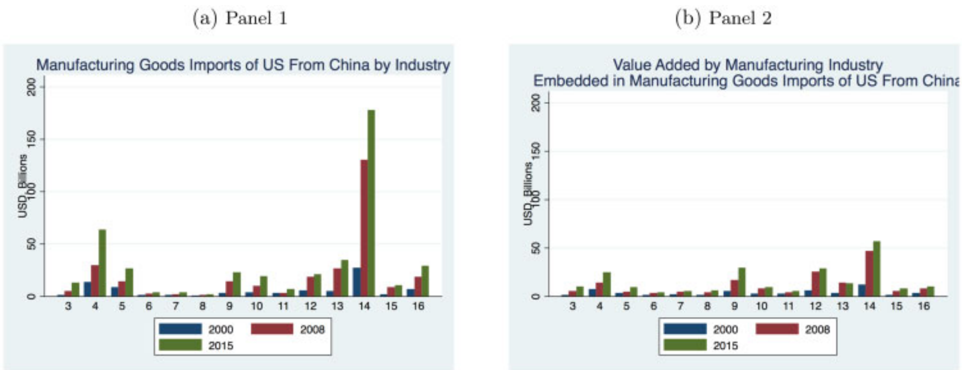

Figure 1. Gross US imports from China and imported value added by manufacturing industry. *Notes*: WIOD codes for manufacturing industries: 3 Food, Beverages and Tobacco; 4 Textiles and Textile Products; 5 Leather, Leather and Footwear; 6 Wood and Products of Wood and Cork; 7 Pulp, Paper, Paper, Printing and Publishing; 8 Coke, Refined Petroleum and Nuclear Fuel; 9 Chemicals and Chemical Products; 10 Rubber and Plastics; 11 Other Non-Metallic Mineral; 12 Basic and Fabricated Metal; 13 Machinery, Nec; 14 Electrical and Optical Equipment; 15 Transport Equipment; 16 Manufacturing, Nec; Recycling. Trade data is in 2008 US dollars and sourced from the WIOD database.

significant share of value added—and labour—content is contributed by other manufacturing industries, as well as primary and services industries. It is important to note that the value added decomposition of bilateral exports does not simply take into account the direct inputs to production but also the inputs of these inputs, and so on.

Given these insights, we follow ADH in constructing an exposure measure based on beginning-of-period local employment in manufacturing industries, but assign import competition to labour markets according to which industries supplied the value added content rather than to the exporting industry in order to better understand the local geography of exposure to the rise of China.[8] As expected and as first result, we observe that the geographic pattern differs markedly from gross import based exposure measures.

In Figure 3 we highlight the differences in local labour market exposure using the two different approaches. For comparability the two types of exposure are both calculated from the same source, TiVA, and are reported in units of $1000 per worker. The colour scale in Figure 3 differentiates between below and above one standard deviation (of 2000–2007 gross trade exposure) differences between the two exposure measures in either direction. The exposure measure described in equation (1) is calculated with s representing the exporting industry in gross trade flows or with s representing the value added industry.

In Washington, Oregon and California, we observe several CZs that display high gross import exposure but much lower value added exposure. Even though these CZs appear directly exposed to import competition, it is actually jobs located elsewhere that are at

8 Since the OECD-WTO, ADB-WIOD, and WIOD databases have been balanced so that worldwide trade flows are mirrored, we first confirmed that the differences in the geography of exposure are not due to using a different dataset compared to UN Comtrade, the database used by ADH.

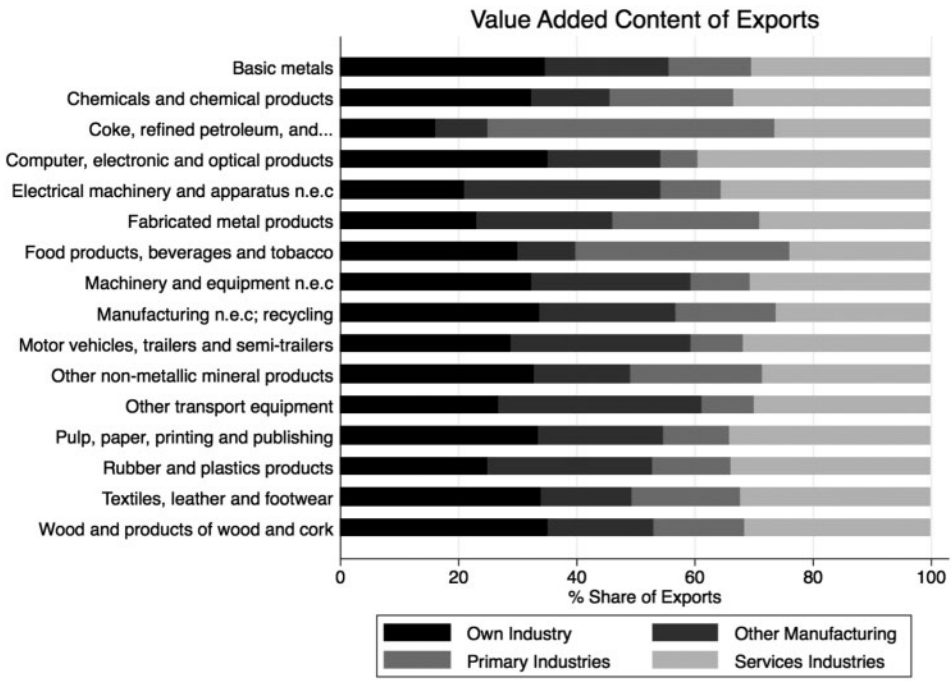

Figure 2. Industry-level value added content of Chinese exports.
Notes: Trade data is sourced from the TiVA database.

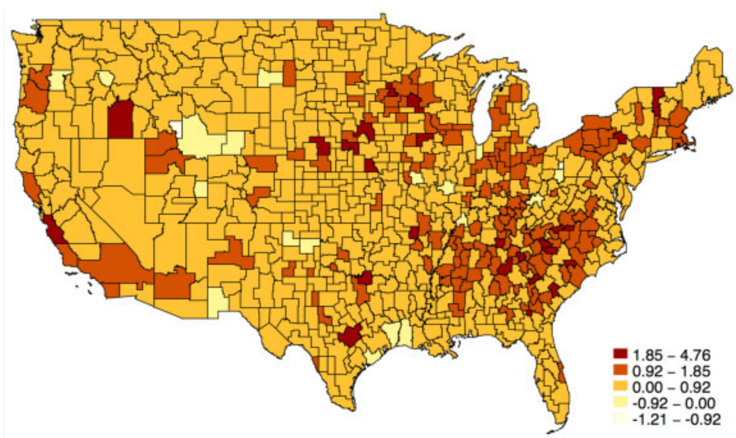

Figure 3. Differences between gross and value added exposure measures.
Notes: Exposure is calculated based on import growth over the 2000–2007 period and reported in units of $1000 per worker in 2007 US dollars. Trade data is sourced from the TiVA database.

risk. The opposite holds amongst others for Indiana and Texas. There are six local labour markets where exposure calculated using gross trade flows rather than value added flows differs by more than one standard deviation. The regions in question are located in or around Minneapolis, Minnesota; Nashville, Tennessee; San Jose, California; Northwest

Indiana; Central New York; and Jackson, Mississippi. As an example, San Jose is famously associated with Silicon Valley and plays host to a large number of high tech and electronics jobs. As we know from Figure 1, it is this sector in particular where value added imports were much lower than gross imports. While San Jose has one of the largest differences in exposure between the two measures—$6400 of gross exposure versus $2400 of value added exposure per worker—it remains in the top 97th percentile by value-added exposure due to the high concentration of the US electronics industry. However, nearby CZs with a lower concentration of workers in electronics do change their position in the exposure distribution: San Diego moves from the 74th to the 57th percentile and Santa Rosa from the 80th to the 64th percentile under gross and value added exposures respectively.

Turning attention to areas where value added exposure was greater than gross import exposure, such areas typically have high employment in sectors where value added imports are greater than gross imports, i.e. in sectors where China does not export much directly, but whose outputs are embedded as value added in Chinese exports in other sectors. We observe that out of the top ten such areas three are located in Texas. This is not surprising given the prominence of the Petroleum and Chemical sectors in Texas which are located upstream in the value chain of typical manufactured imports. For example, Beaumont, Texas moves from the 40th to the 84th percentile, and Corpus Christi, Texas from the 23rd to the 46th percentile under gross and value added exposures respectively. Even less surprising is the increase in some of the rust belt areas, and most strongly in Northwest Indiana which is the seat of the largest North American steel factories for both US Steel (Gary, Indiana) and ArcelorMittal (East Chicago, Indiana). Gary, Indiana is only at the 57th percentile by gross exposure but is at the 100th percentile by value added exposure.

We note, however, that while upstream value added embedded in imported goods is misallocated under a gross exposure measure, local labour market specialisation in what are on average upstream sectors is not alone a sufficient measure to capture this distortion. This is due to two reasons. First, imports from all manufacturing sectors contain value added from other sectors (see Figure 2 above) which are considered to be upstream to specifically these sectors, so it is the precise sectoral composition of Chinese imports which determines in which labour market the mismeasurement is the greatest (Figure 3) rather than the average upstreamness of the local industries. Secondly and relatedly, some downstream and upstream sectors do not face intense import competition from China which weakens the relationship between the position of an industry in the value chain and the misallocation of import competition. To see the contrast, we map each CZ's average upstreamness based on Antràs et al. (2012) in Figure 4 below. While Silicon Valley in California is highly downstream (electrical equipment) and coastal areas of Texas are highly upstream (chemicals) and these areas are indeed respectively over- and underexposed using the gross exposure measure (Figure 3), the same correlation does not generally hold for the rest of the USA. For example, states in the North-West that are high in upstreamness are not notably underexposed.

Returning to our findings, revising the spatial distribution of exposure to import competition has important ramifications for policy makers attempting to understand and respond to the impact of trade shocks on their constituencies. It can help to design better local policies as well as federal place-based policies that are needed to share the gains from trade as widely as possible as has recently been emphasised by various researchers and institutions (e.g. IMF, World Bank, WTO, 2017; WTO, 2017; Criscuolo et al., 2019). It can also

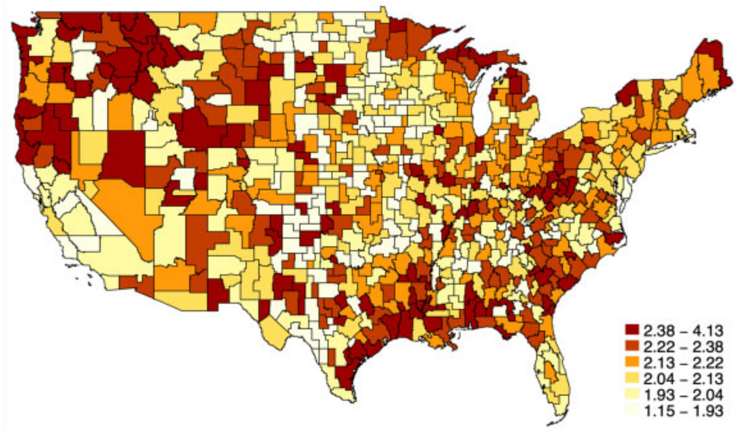

Figure 4. The average upstreamness of manufacturing in local labour markets.
Notes: Upstreamness index is sourced from Antràs et al. (2012) and weights are based on employment in 2000.

help improve our understanding of the political economy processes underlying trade policy making in legislatures since it matches electoral districts more precisely to import competition and shows more clearly which constituencies are competing with foreign suppliers.

Finally, there are implications of using a more accurate geographic exposure measure for the expected causal effects of the trade shock. For instance, some labour markets specialised in downstream industries are falsely assigned to the treated group rather than the control group. If detrimental employment effects have been less severe in these places, such as California or Oregon, then correcting this mis-assignment would change the coefficient of trade exposure in the negative direction. However, since the shift of exposure is not random but systematic from downstream to upstream industries, there is a shift of the coefficient in the positive direction if upstream industries are systematically more resilient to import competition than are downstream industries. One reason for this could be that upstream sectors can more easily switch between supplying various downstream industries depending on demand conditions, and may have benefitted from the aggregate demand boosting effects of trade liberalisation through lower consumer prices and increases in disposable income. Ultimately, the expected effect of using a value added exposure measure on the coefficient of interest remains an empirical question, which we seek to answer in the section below.

5. Econometric results

5.1. Comparison with gross trade

We are interested in the effects of trade exposure on local manufacturing employment and we follow closely the preferred specification of ADH with the full set of controls, as shown in equation (5). The dependent variable is the change in the share of working-age population employed in manufacturing in each CZ. Each observation is weighted by population.

$$\Delta MANUF_{it} = \beta_0 + \beta_1 \Delta EXP_{it} + \mathbf{X}_{it}'\gamma + \epsilon_{it}. \tag{5}$$

Summary statistics for the main variables used in the estimations using TiVA data for the 2000–2007 period are reported in Table 1 below. For ease of comparison with ADH, we adjust changes to be 10-year equivalent and use 2007 US dollars.

In Table 2 we present the results of 2SLS estimates of our main specification. In Column 1 we use our data to construct a gross-trade-based trade exposure measure adjusted to be 10-year equivalent for comparability to ADH, and we compare these results with our benchmark results in Column 2 using our value added based exposure measure.

We confirm that the qualitative conclusions of ADH are robust using both exposure measures, however the coefficient for value added exposure is much larger. In our benchmark results, a $1000 increase in imports per manufacturing worker decreases the share of manufacturing employment by 1.20 rather than 0.80 percentage points. This difference can be explained by at least two points. First, in addition to the differences in the geographic distribution of the two measures illustrated in Figure 3, value added exposure is substantially smaller on average and yet can still explain a significant part of the variation in US manufacturing employment between local labour markets as illustrated in the following paragraph. Secondly, we correct for an upward bias caused by the presence of US value added in Chinese exports.

A benchmarking exercise assuming that trade exposure not only explains relative differences between commuting zones but also absolute differences is conducted in ADH. While useful as a comparison between models, we believe the assumption that unexposed local labour markets did not benefit from increased trade with China through a demand boosting price reduction channel is not plausible, and therefore the absolute decline in the level of manufacturing shares explained by the model in this benchmarking exercise is overestimated. Nevertheless this exercise helps to compare the value added with the gross approach. Taking the results in Column 1, the coefficient of the change in exposure is -0.799 and the average change in exposure over 2000–2007 weighted by CZ population was 1.50. Therefore the actual effect of exposure is the product of the two, a 1.20 percentage points decline. Given that the actual decline was 2 percentage points, the model explains 59.8% of the manufacturing jobs lost. Using our value added based exposure measure in Column 2, the coefficient of exposure is -1.202 while the average change in exposure over 2000–2007 weighted by CZ population was only 0.75 due to the deduction of services and primary inputs and US value added in Chinese exports, yielding an effect of exposure of -0.903 percentage points or 45.2% of manufacturing jobs lost.[9] Therefore, we find that using gross trade exposure overstates by 32.3% the share of jobs lost which can be attributed the trade shock under these strong assumptions.

Given large decreases in exposure for certain local labour markets such as Silicon Valley and large increases for the Texas Bay Area and North-West Indiana, this difference in coefficients between gross and value added trade can translate into very different conclusions for some localities. Consequently, there is a remarkable geographic dispersion of differences in predicted labour market outcomes when comparing our value added based exposure measure versus the gross trade exposure measure. In Table 3 we illustrate these differences in the local labour markets where the difference between the two exposure

9 If we were to consider only the exogenous supply-driven component of exposure, a simple variance decomposition that uses the relationship between OLS and 2SLS estimates would indicate that its effects are only about half of this.

Table 1. Summary statistics for the regression variables

Variable	Mean	Median	SD	Min	Max
$\Delta MANUF_{i2000}$	−2.661	−2.142	3.402	−22.574	8.225
$\Delta GROSSEXP_{i2000}$	1.974	1.755	1.320	0.013	10.933
$\Delta IVGROSSEXP_{i2000}$	1.902	1.666	1.408	0.028	16.434
$\Delta VAEXP_{i2000}$	1.062	0.950	0.453	0.006	4.512
$\Delta CNVAEXP_{i2000}$	0.566	0.509	0.352	0.003	2.152
$\Delta TCVAEXP_{i2000}$	0.177	0.147	0.139	−0.001	1.135
$\Delta IVVAEXP_{i2000}$	0.977	0.898	0.659	0.022	5.779
$\Delta IVCNVAEXP_{i2000}$	0.521	0.483	0.337	0.012	2.311
$\Delta IVTCVAEXP_{i2000}$	0.163	0.137	0.144	0.002	1.883
% manufacturing employment$_{i2000}$	20.122	18.894	10.972	0.210	56.548
% college educated population$_{i2000}$	48.317	49.184	8.551	26.320	70.555
% foreign born$_{i2000}$	6.015	3.743	6.468	0.621	48.908
% employment among women$_{i2000}$	64.330	64.262	7.109	41.339	79.606
% employment in routine occupations$_{i2000}$	28.810	28.844	2.878	22.227	36.656
avg offshorability of occupations$_{i2000}$	−0.614	−0.670	0.422	−1.636	1.240

Table 2. A Comparison of local labour market exposure measures

Dependent variable: 10-year equivalent change in manufacturing employment/working-age population in % pts		
	(1) Gross trade approach	(2) Value added approach
(Δ Local exposure to Chinese exports)/worker	-0.799^{***}	-1.202^{***}
	(0.147)	(0.295)
% manufacturing employment	-0.129^{***}	-0.163^{***}
	(0.0305)	(0.0279)
% college educated population	0.00122	−0.0102
	(0.0228)	(0.0237)
% foreign born	−0.00728	−0.00968
	(0.0233)	(0.0244)
% employment among women	0.0221	0.0268
	(0.0438)	(0.0470)
% employment in routine occupations	-0.248^{***}	-0.228^{***}
	(0.0655)	(0.0820)
avg offshorability of occupations	−0.154	−0.508
	(0.478)	(0.579)
Constant	6.528^{*}	6.166
	(3.590)	(4.112)
Observations	722	722
R^2	0.651	0.632
Census division dummies	Yes	Yes
2SLS first stage estimates		
Instrumental variable	0.755^{***}	0.740^{***}
	(0.0326)	(0.0321)
Adjusted R^2	0.905	0.928
Robust F	527.251	521.698

Notes: Robust standard errors in parentheses are clustered by state.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3. CZs most affected by the change to the value added measure

Largest city	Gross exposure minus VA exposure ($1000)	Predicted outcome gross exposure (percentage point change)	Predicted outcome VA exposure (percentage point change)
Top 5 CZs by difference in gross exposure and VA exposure			
Hutchinson city, MN	6.79	−11.80	−8.98
Binghamton city, NY	4.08	−7.18	−5.57
San Jose city, CA	4.02	−6.60	−5.67
McMinnville city, TN	3.90	−11.02	−10.07
Mountain Home city, AR	3.78	−7.79	−6.28
Bottom 5 CZs by difference in gross exposure and VA exposure			
Steubenville city, OH	−1.73	−4.90	−8.16
Soda Springs city, ID	−1.70	−3.95	−8.06
Gary city, IN	−0.96	−3.95	−5.95
Pampa city, TX	−0.94	−1.17	−3.13
Lake Charles city, LA	−0.45	−0.85	−1.61

measures is the greatest—first for the top five instances where gross exposure is larger, and below for the top five instances where value added exposure is larger.

The prior group includes, as discussed in Section 4.1, San Jose, California, which has a high gross import exposure due to its specialisation in the electronics sector but a lower value added exposure since Chinese electronics imports contain a high percentage of non-electronics as well as US value added. The latter group includes Gary, Indiana, which is specialised in steel production, and therefore its value added exposure is greater since steel value added is embedded in Chinese imports from many other industries besides steel. As expected, for the prior group, the predicted decrease in the share of manufacturing employment using the value added exposure measure is substantially smaller than when the gross trade exposure measure is used; and for the latter group the predicted decrease is larger. Figure 5 below illustrates the differences in the predicted percentage point change in local manufacturing employment share associated with the two exposure measures.

Finally, as regards control variables, we use the same set as ADH, who include start-of-decade labour market and demographic characteristics of CZs that may independently determine future changes in the manufacturing employment share. That means we include percentage of manufacturing employment in order to rule out trade exposure (which is higher in locations where there is more manufacturing) picking up a declining trend in US manufacturing. Like ADH we find this variable to have a negative and significant effect. Similarly, the percentage of employment in routine occupations is correlated with more manufacturing jobs and thus greater trade exposure, but instead captures the effects of the trend for increasing automation. Like ADH, we also find this variable to have a negative and significant effect. The other control variables are percentage of college educated population, percentage of foreign born, percentage of employment among women, and average offshorability of occupations, none of which are statistically significant, which is mostly in line with ADH with the exception of the coefficient for percentage of foreign born population, for which they find a small but positive coefficient.

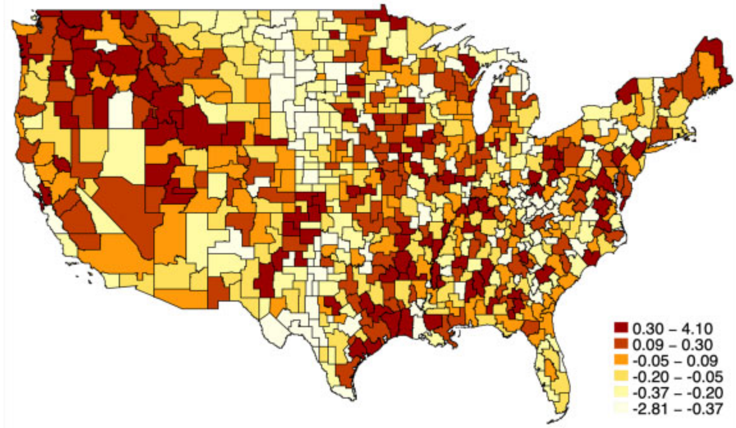

Figure 5. Differences in predicted outcome using gross and value added exposure measures.
Notes: Outcome variable is the percentage point change in local manufacturing employment share. Exposure is calculated based on import growth over the 2000–2007 period. Trade data is sourced from the TiVA database.

5.2. Trade flows decomposed by origin of value added

Beyond improving the accuracy of the exposure measure, our data also allows us to distinguish between the true geographic origins of the value added embedded in Chinese exports to the USA. Given the remarkable expansion of global value chains in the 1990s and 2000s this is relevant because it enables us to test whether the labour market effects of Chinese imports are driven by factors specific to China, such as domestic productivity-enhancing reforms, or whether they are due to third countries gaining competitiveness by using China as assembly hub. This has important implications for bilateral trade policy because in the latter case China could easily be replaced by alternative low-cost countries if bilateral trade policy barriers were to be erected while in the former case relocation would imply losing access to a China-specific productivity multiplier.

Therefore, we separate US imports from China into CNVA, representing Chinese value added, and TCVA, representing foreign third-country value added, which excludes US value added. Figure 6 presents two maps contrasting the geographic distribution of CNVA and TCVA. The specification used in this section is described in equation (6) in which CNVA and TCVA are separately instrumented using the same variable as before but adjusted for this exercise, i.e. CNVA and TCVA in Chinese exports to other developed economies serve as instruments respectively.

$$\Delta MANUF_{it} = b_0 + b_1 \Delta CNVAEXP_{it} + b_2 \Delta TCVAEXP_{it} + \mathbf{X}'_{it} b_3 + e_{it}. \tag{6}$$

In order to separately identify the causal effects of these two treatment variables on manufacturing employment, it is a prerequisite that the industry compositions of CNVA and TCVA are sufficiently different. We can confirm from Figure 6 that the geographic pattern of these two exposures indeed varies and allows for an identification. Even though CNVA exposure is generally greater in magnitude, we see important heterogeneity across industries. What stands out is that downstream industries, in particular electrical machinery and electronic equipment, contain a high share of foreign third-country value added (72%

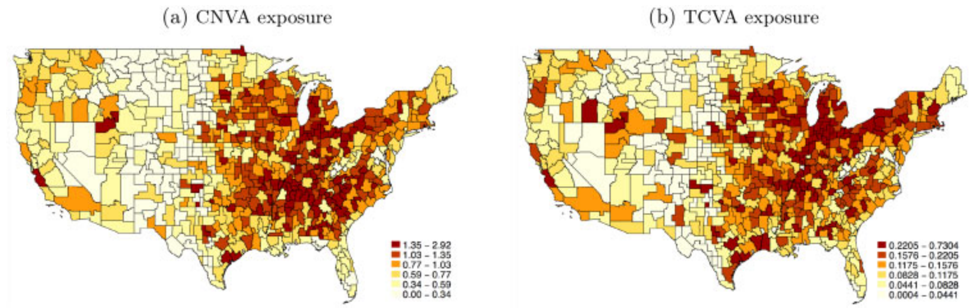

Figure 6. Comparison of CNVA and TCVA exposure.
Notes: CNVA represents Chinese value added in US imports from China, TCVA represents foreign third-country value added with US value added excluded. Exposure is calculated based on import growth over the 2000–2007 period. Trade data is sourced from the TiVA database.

TCVA in 2000) while upstream industries such as the basic metals industry (e.g. steel) contain predominantly Chinese value added (28% TCVA in 2000).

Table 4 reports results from this decomposition exercise. We see that the coefficient of CNVA exposure is negative and significant. Contrary to this, the coefficient of TCVA exposure is not significantly different from zero, although the point estimate is positive. This suggests that the negative effect on exposed local labour markets is caused exclusively by imports of Chinese value added. Given that the CNVA content is particularly high in certain upstream industries and the opposite holds for certain downstream industries, the results mirror our findings on the difference between effects obtained using value added and gross imports. As discussed, using value added instead of gross imports shifted exposure from downstream to upstream industries. This, in turn, increased the coefficient that reports the impact of imports on manufacturing employment considerably. As a result, our decomposition result is consistent since these upstream imports that lifted the coefficient contain mostly CNVA.

While this type of reduced form analysis cannot identify the exact source of the shock, whether it is a Chinese productivity increase or simply the political decision to integrate more deeply into the world economy, we can say that the drivers of the shock are Chinese in origin as hypothesised by ADH. We can also discount the hypothesis that the shock is driven by other advanced economies rerouting production through China via global value chains. In fact, the negative effect of CNVA indicates that manufacturing employment has been affected the most in CZs whose industry structure corresponds to industries in which Chinese value added has expanded, highlighting a degree of substitutability. In contrast, manufacturing employment was unaffected in CZs whose industry structure mirrors the industry composition of increased TCVA. This could indicate a broad shift across developed countries to expand manufacturing sectors where they maintain a comparative advantage over China in response to increased import competition in other sectors.

It is also the case that the TCVA component does not necessitate new adjustment as the USA has been exposed to imports from third countries such as Japan and Korea for a long time. Moreover, if we sum up the total value added that key exporters send to the USA, independent of the exact route these exports take, that is, independent whether they travel to the USA directly or via China, we observe in the data that the expansion of Japanese, German, or Korean exports to the USA via China comes at the expense of direct

Table 4. Local labour market exposure by origin of value added for the period 2000–2007

Dependent variable: 7-year change in manufacturing employment/working-age population in % pts	(1)
(Δ Local exposure to the Chinese value added content of Chinese exports)/worker	-2.991^{***}
	(1.476)
(Δ Local exposure to the foreign third-country value added content of Chinese exports)/worker	1.149
	(2.056)
% manufacturing employment	-0.0817^{***}
	(0.0252)
% college educated population	−0.0128
	(0.0178)
% foreign born	0.00771
	(0.0177)
% employment among women	0.0153
	(0.0340)
% employment in routine occupations	-0.137^{**}
	(0.0564)
avg offshorability of occupations	−0.424
	(0.431)
Constant	4.017
	(2.944)
Observations	722
R^2	0.629
Census division dummies	YES
2SLS first-stage estimates	
Instrumental variable CNVA	$0.533^{***}/-0.0832^{**}$
	(0.0644)/(0.0355)
Instrumental variable TCVA	$0.252^{***}/0.920^{***}$
	(0.0851)/(0.0501)
Adjusted R^2	0.9490/0.8872
Sanderson–Windmeijer F stat	278.59/427.82
Cragg–Donald Wald F stat	604.32
Kleibergen-Paap Wald rank F stat	129.29

Notes: Robust standard errors in parentheses are clustered by state.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

exports. This means that there is no TCVA import shock but simply a rerouting that does not affect the growth rate of total imported value added from these countries. CNVA on the other hand expanded dramatically causing the observed response.

5.3. Extending the analysis until 2014

A similarly important question for trade policy with regards to Chinese import competition is whether labour markets can adjust to import competition. This is particularly important in light of our previous results because while the expansion of global value chains has stalled since the early 2010s, exports of Chinese value added, which, as we have shown, are responsible for labour market adjustment in 2000–2007, continued to rise. As Figure 7

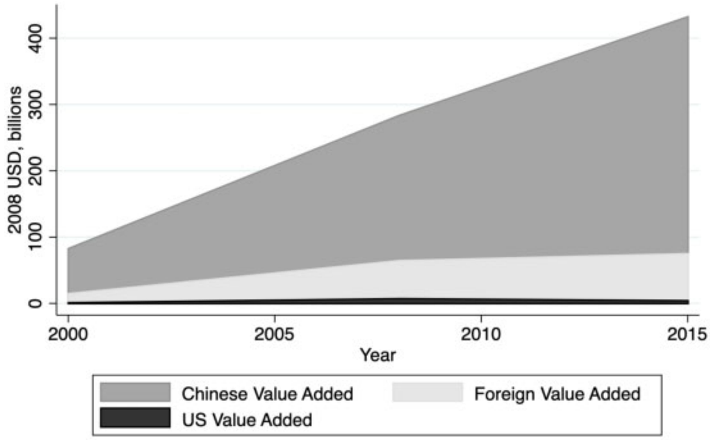

Figure 7. Chinese manufacturing exports to the US decomposed by source country of value added.
Notes: Trade data is sourced from the ADB-MRIO database.

illustrates, the expansion of the import shock up until 2015 is due to the CNVA component, whereas after 2008 the TCVA component has on aggregate remained level, and the US value added component has slightly contracted.

We proceed to analyse the persistence of negative labour market effects using employment data for the more recent period 2008–2014. For this exercise, instead of the TiVA data used thus far, we use data from the Asian Development Bank multi-regional input-output tables (ADB-MRIO), which span 2000–2008 and 2008–2015 and are in 2008 US dollars. Adjusting the data to even 8-year equivalent period lengths, we test our specification for each period separately, allowing covariates to have time dependent effects. Summary statistics for the main variables used for the two time periods are reported in Table 5 above.

Column 1 in Table 6 uses data only for the first period, without any period length adjustment for comparability with ADH. These results replicate our benchmark specification using the ADB-MRIO data. Column 2 shows that the import shock from the 2000 to 2008 period no longer has significant effects in the second (2008–2014) period. Column 3 shows that, despite the continued expansion of Chinese imports, the shock has no significant employment effects in the second period, whereas employment in routine occupations and offshorability are significant factors.

Given that the second period contains the aftermath of the 2008 global financial crisis where presumably there were strong demand co-movements between advanced economies, one concern is that the estimates of the effects of the import shock are biased towards zero because of the invalidity of the ADH instrumentation strategy under these conditions. We therefore redo this analysis in Column 4 using the pre-crisis 2000–2008 instrument for the post-crisis 2008–2014 trade shock. We find a larger but statistically insignificant coefficient in this specification. Finally, in Column 5 we include both the first period and second period import shocks together, and find no statistically significant effects. These results are consistent with a hypothesis that US firms and industries have successfully adjusted to Chinese import competition.

Table 5. Summary statistics for additional variables

Variable	Mean	Median	SD	Min	Max
$\Delta MANUF_{i2000}$	−2.001	−1.682	2.672	−15.045	18.212
$\Delta MANUF_{i2008}$	−5.787	−5.436	3.660	−32.694	0.309
$\Delta VAEXP_{i2000}$	1.005	0.919	0.662	0.005	3.747
$\Delta VAEXP_{i2008}$	0.641	0.562	0.437	0.005	3.588
$\Delta IVVAEXP_{i2000}$	0.951	0.877	0.584	0.027	3.619
$\Delta IVVAEXP_{i2008}$	0.284	0.221	0.264	−0.043	3.388
% manufacturing $employment_{i2000}$	20.122	18.894	10.972	0.210	56.548
% manufacturing $employment_{i2008}$	16.502	15.188	9.086	0.256	51.348
% FIRE $employment_{i2000}$	4.406	3.953	1.795	0.423	20.690
% FIRE $employment_{i2008}$	4.531	4.089	1.961	0.510	23.973
% construction $employment_{i2000}$	5.537	5.208	2.371	0.808	28.364
% construction $employment_{i2008}$	5.644	5.159	2.849	0.187	33.389

Another concern is that in the post-crisis period, omitting to control for local employment in crisis-hit industries, such as finance, insurance and real estate (FIRE), and construction, may bias our estimates due to local demand and supply effects. While countrywide demand and supply shocks that are homogenous across industries are removed through the difference-in-difference design, local shocks that might have arisen as a consequence of the financial crisis due to differences in the industrial composition of CZs, could bias the results. In Table 7 we show that our estimates are robust to controlling for employment shares in particularly affected industries.

The main conclusion from this section is that the case for implementing bilateral trade policy measures that restrict imports from China may be premature for two reasons. First, the evidence does not point to any negative differential effect of import exposure in the more recent period. Secondly, while a local labour market difference-in-difference analysis is not sufficient to draw conclusions about the aggregate effects on employment, an aggregate negative effect seems implausible given the absence of a significant negative differential effect in more exposed local labour markets.[10]

6. Conclusion

The literature on the local labour market effects of Chinese import competition has been cited extensively in the media as an argument for limiting trade with China, despite the fact that the results do not support this conclusion. While the differential effects of trade with China at a local labour market level are clear, its aggregate effects on manufacturing employment are subject to debate.

In this article, we argue that even if policy were narrowly focused on direct import competition effects—ignoring price and indirect effects—the available empirical evidence does not support limiting trade with China. Using recent trade data, we show that rising US local labour market exposure to Chinese imports in the recent 2008–2014 period no longer has a statistically significant effect on the relative shares of manufacturing

10 We thank an anonymous referee for helpful suggestions on making this point.

Table 6. Extending the analysis to cover 2000–2014

Dependent variable: 8-year equivalent change in manufacturing employment/working-age population in % pts

	(1)	(2)	(3)	(4)	(5)
Period analysed (*t*)	(2000–2008)	(2008–2014)	(2008–2014)	(2008–2014)	(2008–2014)
(Δ Local exposure to Chinese exports)/worker$_{2000}$	−1.219***	−0.335			−0.347
	(0.363)	(0.374)			(0.458)
(Δ Local exposure to Chinese exports)/worker$_{2008}$			−0.175	−1.036	0.0383
			(0.541)	(1.278)	(0.669)
% manufacturing employment$_t$	−0.111***	−0.340***	−0.354***	−0.315***	−0.341***
	(0.0286)	(0.0289)	(0.0341)	(0.0596)	(0.0340)
% college educated population$_{2000}$	−0.00581	0.0115	0.0108	0.0101	0.0116
	(0.0163)	(0.0138)	(0.0139)	(0.0142)	(0.0142)
% foreign born$_{2000}$	−0.0000	0.0141	0.0150	0.0148	0.0140
	(0.0172)	(0.0139)	(0.0135)	(0.0125)	(0.0141)
% employment among women$_{2000}$	0.0279	−0.0526**	−0.0514*	−0.0586**	−0.0523**
	(0.0331)	(0.0262)	(0.0266)	(0.0263)	(0.0267)
% employment in routine occupations$_{2000}$	−0.176***	−0.105***	−0.105***	−0.0965***	−0.106***
	(0.0591)	(0.0316)	(0.0321)	(0.0352)	(0.0312)
avg offshorability of occupations$_{2000}$	−0.502	−1.033***	−1.065***	−1.046***	−1.032***
	(0.416)	(0.288)	(0.294)	(0.281)	(0.287)
Constant	4.121	4.840**	4.709**	4.924**	4.837**
	(3.038)	(2.157)	(2.191)	(2.090)	(2.173)
Observations	722	722	722	722	722
R^2	0.642	0.874	0.874	0.871	0.874
Census division dummies	Yes	Yes	Yes	Yes	Yes
2SLS first-stage estimates					
Instrumental variable Period 1	0.678***	0.765***		0.247***	0.753*** /0.165***
	(0.0349)	(0.0374)		(0.0510)	(0.0310) /(0.0302)
Instrumental variable Period 2			0.866***		0.117*/0.775***
			(0.0966)		(0.0712)/(0.0910)
Adjusted R^2	0.946	0.939	0.769	0.718	0.940/0.784
Sanderson–Windmeijer F stat	370.97	410.74	78.76	23.04	154.09/103.13
Cragg–Donald Wald F stat					99.79
Kleibergen-Paap Wald rank F stat					37.94

Notes: Robust standard errors in parentheses are clustered by state.
***p < 0.01, **p < 0.05, *p < 0.1.

employment in US local labour markets. These results are consistent with a hypothesis that manufacturing industries most vulnerable to import competition have for the most part already adjusted, leaving behind an industry structure that is more resilient to increasing volumes of import competition.

This points to an important research agenda that examines which industries, firms and occupations were particularly affected by the shock and the different paths they have followed to adjust. Initial work in this direction has been undertaken by Bloom et al. (2016) who posit that firms accelerate technological and organisational innovation to inoculate themselves against import competition, which could explain our findings. In other recent research, Magyari (2017) presents evidence showing that firms reorganise their production activities towards less exposed industries in response to trade shocks. While this may

Table 7. Extending the analysis to cover 2000–2014

Dependent variable: 8-year equivalent change in manufacturing employment/working-age population in % pts			
	(1)	(2)	(3)
Period analysed (t)	(2000–2008)	(2008–2014)	(2008–2014)
(Δ Local exposure to Chinese exports)/worker$_{2000}$	-1.243^{***}		
	(0.366)		
(Δ Local exposure to Chinese exports)/worker$_{2008}$		−0.101	−0.117
		(0.551)	(0.547)
% FIRE employment$_{2000}$	0.0141		−0.00468
	(0.0424)		(0.0490)
% FIRE employment$_{2008}$		−0.00796	
		(0.0337)	
% construction employment$_{2000}$	0.0550		−0.0282
	(0.0506)		(0.0458)
% construction employment$_{2008}$		−0.0262	
		(0.0435)	
% manufacturing employment$_t$	-0.104^{***}	-0.361^{***}	-0.359^{***}
	(0.0283)	(0.0365)	(0.0359)
% college educated population$_{2000}$	−0.00574	0.0109	0.0110
	(0.0166)	(0.0140)	(0.0140)
% foreign born$_{2000}$	0.00123	0.0150	0.0143
	(0.0172)	(0.0137)	(0.0133)
% employment among women$_{2000}$	0.0265	-0.0491^{*}	-0.0500^{*}
	(0.0327)	(0.0254)	(0.0265)
% employment in routine occupations$_{2000}$	-0.178^{***}	-0.105^{***}	-0.106^{***}
	(0.0602)	(0.0307)	(0.0321)
avg offshorability of occupations$_{2000}$	−0.505	-1.077^{***}	-1.067^{***}
	(0.419)	(0.291)	(0.296)
Constant	3.843	4.739^{**}	4.835^{**}
	(3.124)	(2.210)	(2.221)
Observations	722	722	722
R^2	0.643	0.875	0.875
Census division dummies	Yes	Yes	Yes
2SLS first-stage estimates			
Instrumental variable period t	0.665^{***}	0.870^{***}	0.871^{***}
	(0.0329)	(0.0905)	(0.0911)
Adjusted R^2	0.947	0.770	0.772
Robust F	401.664	90.44	89.48

Notes: Robust standard errors in parentheses are clustered by state.
***p < 0.01, **p < 0.05, *p < 0.1.

happen across CZ boundaries, leaving certain CZs no better off, it may to some extent attenuate the average local negative effects estimated. Further, given that some reorganisation takes place in the first period, the effects of further expansion of imports during the second period are likely to be smaller, as long as the industry composition of imports does not change significantly.

Importantly, if adjustment has indeed concluded, restricting imports after this development has taken place would necessitate renewed costly adjustment. Conversely, it is reasonable to assume that positive effects of imports, such as lower consumer and input prices, continue to increase with rising imports, which would further speak against new trade barriers.

While bilateral trade barriers cannot be justified on empirical grounds, the rationale for adjustment policies to trade remains. Such adjustment policies require a precise understanding about which industries and regions are most affected by import competition. By exploiting a value added decomposition of trade flows, we improve on the accuracy of gross-trade-based measures of import exposure. We find that the geography of the trade shock changes in line with expectations. Local labour markets specialised in relatively upstream manufacturing sectors, such as steel or chemicals, are actually more exposed than what gross trade data would suggest. In contrast, local labour markets dependent on final goods producing industries, such as electronics, are considerably less exposed. Representative examples of these differences are the steel and aluminium hub Gary, Indiana, and San Jose, California, home to Silicon Valley.

We further find that using gross trade exposure, as done by ADH and much of the recent literature, overstates the direct impact of Chinese imports on US manufacturing jobs by 32.3% over the 2000–2007 period. These differences are partly because the volume of the trade shock is smaller once only value added from manufacturing industries is considered, and partly because the geographical distribution of import exposure is different. Using our value-added exposure measure changes the spatial distribution of import exposure markedly with important implications for location based interventions to facilitate adjustment and political economy analyses. Moreover, the decomposition allows us to contribute an important methodological innovation to the empirical strategy of ADH allowing for a cleaner identification of the causal effects of import exposure. This is achieved by removing US valued added from Chinese exports to the USA, which constitutes a mechanically endogenous component.

Finally, this paper adds to our understanding of the drivers behind the rise of China. By splitting value added from Chinese exports into a Chinese part and a part due to third-country inputs into Chinese production, we provide evidence that confirms the hypothesis of Autor et al. (2016) that US local labour market effects are driven by changes that have boosted productivity in China rather than the proliferation of global value chains which have increasingly incorporated China in downstream production stages.

We find it important to emphasise and to make clear that while the focus of this line of research has so far been on the effects of import competition which necessitates labour market adjustment in the short run, there are other channels in general equilibrium through which bilateral trade relations with China have welfare improving effects, and an evaluation of policy should take into account both sides of the coin. While the China shock was a unique historical event, we can expect the labour market to be affected by disruptive technology shocks in the future, and therefore, the lessons from the China shock and its impact in different countries could potentially inform the debate about optimal domestic labour market policies aimed at facilitating adjustment.

Acknowledgements

The authors wish to thank David Dorn, Aksel Erbahar, Bernard Hoekman, Bob Koopman, Marc-Andreas Muendler, Marcelo Olarreaga, Veronica Rappoport, Stela Rubinova, Peri da Silva, Jens Suedekum, Thierry Verdier, Christian Viegelahn, Yuan Zi, and participants at NCCR Trade Regulation Brown Bag Series, World Trade Institute, University of Bern; Geneva Trade and

Development Workshop, Graduate Institute of International and Development Studies; ILO Research Seminar; ETSG 2017; Sixth IMF-WB-WTO Trade Conference at the International Monetary Fund; Bank of Canada Research Seminar; and RMET 2018 for helpful comments and suggestions and are especially grateful to Zhi Wang and colleagues at RCGVC, UIBE for providing data on the value added decomposition of trade flows. The opinions expressed in this article should be attributed to its authors. They are not meant to represent the positions or opinions of the WTO and its Members and are without prejudice to Members' rights and obligations under the WTO.

References

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

Adao, R., Arkolakis, C., Esposito, F. (2019) Spatial linkages, global shocks, and local labor markets: theory and evidence. National Bureau of Economic Research Working Paper.

Amiti, M., Dai, M., Feenstra, R. C., Romalis, J. (2020) How did China's WTO entry affect US prices?, *Journal of International Economics*.

Antràs, P., Chor, D., Fally, T., Hillberry, R. (2012) Measuring the upstreamness of production and trade flows. *American Economic Review*, 102: 412–416.

Austin, B., Glaeser, E., Summers, L. H. (2018) Saving the heartland: place-based policies in 21st century America. In *Brookings Papers on Economic Activity*, Conference Draft. Washington, DC: Brookings Institution.

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: 2121–2168.

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

Autor, D. H., Dorn, D., Hanson, G. H., Majlesi, K. (2020) Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review*.

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

Blanchard, O., Katz, L. (1992) Regional evolutions. *Brookings Papers on Economic Activity*, 23: 1–76.

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

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

Colantone, I., Stanig, P. (2018) Global competition and Brexit. *American Political Science Review*, 112: 201–218.

Criscuolo, C., Martin, R., Overman, H. G., Van Reenen, J. (2019) Some causal effects of an industrial policy. *American Economic Review*, 109: 48–85.

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: 1643–1675.

Donoso, V., Martín, V., Minondo, A. (2015) Do differences in the exposure to Chinese imports lead to differences in local labour market outcomes? An analysis for Spanish provinces. *Regional Studies*, 49: 1746–1764.

Feenstra, R. C., Weinstein, D. E. (2017) Globalization, markups, and US welfare. *Journal of Political Economy*, 125: 1040–1074.

Galle, S., Rodríguez-Clare, A., Yi, M. (2017) Slicing the pie: quantifying the aggregate and distributional effects of trade. National Bureau of Economic Research Working Paper.

Glaeser, E. L., Gyourko, J. (2005) Urban decline and durable housing. *The Journal of Political Economy*, 113: 345–375.

Greenaway, D., Hine, R., Milner, C. (1995) Vertical and horizontal intra-industry trade: a cross industry analysis for the United Kingdom. *The Economic Journal*, 1505–1518.

Hsieh, C.-T., Ossa, R. (2016) A global view of productivity growth in China. *Journal of International Economics*, 102: 209–224.

IMF, World Bank, WTO (2017) Making trade an engine of growth for all: the case for trade and for policies to facilitate adjustment. International Monetary Fund, World Bank, and World Trade Organization joint paper, Geneva and Washington D.C.

Impullitti, G., Licandro, O. (2018) Trade, firm selection and innovation: the competition channel. *The Economic Journal*, 128: 189–229.

Johnson, R. C., Noguera, G. (2012) Accounting for intermediates: production sharing and trade in value added. *Journal of International Economics*, 86: 224–236.

Johnson, R. C., Noguera, G. (2017) A portrait of trade in value-added over four decades. *Review of Economics and Statistics*, 99: 896–911.

Koopman, R., Wang, Z., Wei, S.-J. (2012) Estimating domestic content in exports when processing trade is pervasive. *Journal of Development Economics*, 99: 178–189.

Koopman, R., Wang, Z., Wei, S.-J. (2014) Tracing value-added and double counting in gross exports. *The American Economic Review*, 104: 459–494.

Magyari, I. (2017) *Firm Reorganization, Chinese Imports, and US Manufacturing Employment*. *Mimeo*, Colombia University.

Malgouyres, C. (2017) The impact of Chinese import competition on the local structure of employment and wages: evidence from France. *Journal of Regional Science*, 57: 411–441.

Shen, L., Silva, P. (2018) Value-added exports and US local labor markets: does China really matter? *European Economic Review*, 101: 479–504.

Topalova, P. (2007) Trade liberalization, poverty and inequality: evidence from Indian districts. In Ann, Harrison (ed.) *Globalization and Poverty*, pp. 291–336. University of Chicago Press.

Topalova, P., Khandelwal, A. (2011) Trade liberalization and firm productivity: the case of India. *Review of Economics and Statistics*, 93: 995–1009.

Topel, R. H. (1986) Local labor markets. *Journal of Political Economy*, 94: S111–S143.

Wang, Z., Wei, S.-J., Zhu, K. (2013) Quantifying international production sharing at the bilateral and sector levels. National Bureau of Economic Research Working Paper.

Wang, Z., Wei, S.-J., , Zhu, K., Yu, X., Zhu, K. (2018) Re-examining the effects of trading with China on local labor markets: a supply chain perspective. National Bureau of Economic Research Working Paper.

WTO (2017) *World Trade Report 2017: Trade, Technology, and Jobs*. Geneva: World Trade Organization Publication.

Appendix

The China Shock revisited: Insights from value added trade flows: Value added decomposition of gross trade flows at bilateral-sector level

In this section, we aim to familiarise the reader with the basics of value added decomposition frameworks in order to provide some insight on how our more detailed trade data is generated. Getting to the value added structure of gross trade at a disaggregated level requires taking into account the differences between final and intermediate goods using more techniques that go beyond the standard Leontief decomposition. Wang et al. (2013) propose an accounting framework which builds on Koopman et al. (2014) using additional information found in ICIOs on the subsequent uses and final destinations of foreign value added inputs to domestic industry. For a detailed exposition we refer the reader to original papers. Our data applies their framework to the OECD TiVA and ADB-MRIO tables and completely decomposes gross exports into four major categories: domestic value added absorbed abroad, domestic value added that returns home, foreign value added, and double-counted intermediate trade.

Below is the final decomposition for a simple two country one industry model (equation (22) in Wang et al. (2013)).

$$\begin{aligned}
E^{kl} =& (V^k B^{kk})^T * F^{kl} + (V^k L^{kk})^T * (A^{kl} B^{ll} F^{ll}) \\
&+(V^k L^{kk})^T * \left(A^{kl} \sum_{t \neq k,l}^{G} B^{lt} F^{tt} \right) + (V^k L^{kk})^T * \left(A^{kl} B^{ll} \sum_{t \neq k,l}^{G} F^{lt} \right) \\
&+(V^k L^{kk})^T * \left(A^{kl} \sum_{t \neq k}^{G} \sum_{l,u \neq k,t}^{G} B^{lt} F^{tu} \right) + (V^k L^{kk})^T * (A^{kl} B^{ll} F^{lk}) \\
&+(V^k L^{kk})^T * \left(A^{kl} \sum_{t \neq k,l}^{G} B^{lt} F^{tk} \right) + (V^k L^{kk})^T * (A^{kl} B^{lk} F^{kk}) \\
&+(V^k L^{kk})^T * \left(A^{kl} \sum_{t \neq k}^{G} B^{lk} F^{kt} \right) + (V^k B^{kk} - V^k L^{kk})^T * (A^{kl} X^l) \\
&+(V^l B^{lk})^T * F^{kl} + (V^l B^{lk})^T * (A^{kl} L^{ll} F^{ll}) + (V^l B^{lk})^T \\
&*(A^{kl} L^{ll} E^{l*}) + \left(\sum_{t \neq k,l}^{G} V^t B^{tk} \right)^T * F^{kl} + \left(\sum_{t \neq k,l}^{G} V^t B^{tk} \right)^T \\
&*(A^{kl} L^{ll} F^{ll}) + \left(\sum_{t \neq k,l}^{G} V^t B^{tk} \right)^T * (A^{kl} L^{ll} E^{l*}),
\end{aligned} \tag{7}$$

Here E^{kl} represents exports from country k to l, F^{kl} is the final demand in l for goods of k, L^{ll} refers to the national Leontief inverse as opposed to the Inter-Country inverse B, and T indicates a matrix transpose operation. As can be seen from equation (7), this decomposition splits gross exports into 16 linear terms with four main categories which are subdivided by final destination, as described below.

- Domestic value added absorbed abroad (*vax_g*, T1-5)
    - Domestic value added in final exports (*dva_fin*, T1)
    - Domestic value added in intermediate exports (*dva_intt*, T2-5)

- Domestic value added in intermediate exports absorbed by direct importers (*dva_int*, T2)
- Domestic value added in intermediate exports re-exported to third countries (*dva_intrex*, T3-5)
- Domestic value added in intermediate exports re-exported to third countries as intermediate goods to produce domestic final goods (*dva_intrexi1*, T3)
- Domestic value added in intermediate exports re-exported to third countries as final goods (*dva_intrexf*, T4)
- Domestic value added in intermediate exports re-exported to third countries as intermediate goods to produce exports (*dva_intrexi2*, T5)
- Domestic value added returning home (*rdv*, T6-8)

  - Domestic value added returning home as final goods (*rdv_fin*, T6)
  - Domestic value added returning home as final goods through third countries (*rdv_fin2*, T7)
  - Domestic value added returning home as intermediate goods (*rdv_int*, T8)

- Foreign value added (*fva*, T11-12/14-15)
  - Foreign value added in final good exports (*fva_fin*, T11/14)

- Foreign value added in final good exports sourced from direct importer (*mva_-fin*, T11)
- Foreign value added in final good exports sourced from other countries (*ova_fin*, T14)
  - Foreign value added in intermediate good exports (*fva_int*, T12/15)

- Foreign value added in intermediate good exports sourced from direct importer (*mva_int*, T12)
- Foreign value added in intermediate good exports sourced from other countries(*ova_int*, T15)
- Pure double counting (*pdc*, T9-10/13/16)
  - Pure double counting from domestic source (*ddc*, T9-10)

- Due to final goods exports production (*ddf*, T9)
- Due to intermediate goods exports production (*ddi*, T10)
  - Pure double counting from foreign source (*fdc*, T13/16)

- Due to direct importer exports production (*fdf*, T13)
- Due to other countries' exports production (*fdi*, T16)

It is due to this decomposition that we are able to disregard double counted terms in our analysis, and to split our bilateral exports into country-industry level *DVA* and *FVA* components. Note that Koopman et al. (2014) split the *PDC* term further into domestic and foreign content based on the origins of the double counted terms whereas here the entire *PDC* term is kept intact and apart from domestic value-added in order to allow total bilateral *DVA* to remain net of double counting.