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U.S.-China Bilateral Trade Flows and U.S. Employment

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Abstract

The U.S.-China diplomatic relationship today is shaped significantly by economic factors. Recent strains of literature have expanded our understanding of how international economic policy choices have effected U.S. workers and labor markets. This paper extends this research by imposing bilateral symmetry in the trade flow calculations of previous works, which historically have considered U.S. exports globally. I build on the net-impact analysis of Feenstra, Ma, and Xu (2017b) and adopt the instrumental variable strategy used in Acemoglu et al. (2016), which uses Chinese trade flows with eight additional high-income countries to avoid endogeneity when comparing U.S.-China trade. From this analysis, I determine that between 1991 and 2011, a one percentage point increase in an industry's exposure to Chinese imports led to a -1.32 percentage point decrease in employment within that industry. I also find that for the same period of time, a one percentage point increase in export exposure led to a 3.51 increase in employment for a given industry.

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I. Introduction:

Modern American political discussions have become dominated by issues concerning economic disenfranchisement. The prominence of issues such as immigration, trade, and automation in the 2016 presidential election, and their continued attention from the Trump administration indicate the severity of economic shifts that have occurred in recent decades.[1] Current culture conflicts between metropolitan and rural areas are underpinned by shifts in each area's ability to be prosperous amid rapid economic change.[2] Within the broader discussion of disruptive forces in the modern economy, the U.S.-China trading relationship has become particularly significant. Reflecting both the geopolitical rise of China as a U.S.-competitor, and the current sentiments of disenfranchisement within the U.S. labor force, polling from Pew Research identified that the share of Americans who hold an unfavorable view of China has reached 60 percent.[3] The specific trading relationship between the United States and China requires significant increased scrutiny.

Recent research has elevated the public understanding of the consequences generated by this trading relationship, beginning with the seminal, Autor, Dorn, Hanson (2013),"China-shock" paper, which evaluated the domestic consequences of U.S.-China

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[1] Wilkie, Christina. 2018. "Trump's first State of the Union will focus on the economy, trade and immigration." *CNBC*, January 27. https://www.cnbc.com/2018/01/26/trump-state-of-the-union-to-focus-on-economy-trade-immigration.html

[2] Hendrickson, Clara, Muro Mark, and Galston, William A. 2018. "Counter the geography of discontent: Strategies for Left-Behind Places." Brookings. https://www.brookings.edu/wp-content/uploads/2018/11/2018.11_Report_Countering-geography-of-discontent_Hendrickson-Muro-Galston.pdf

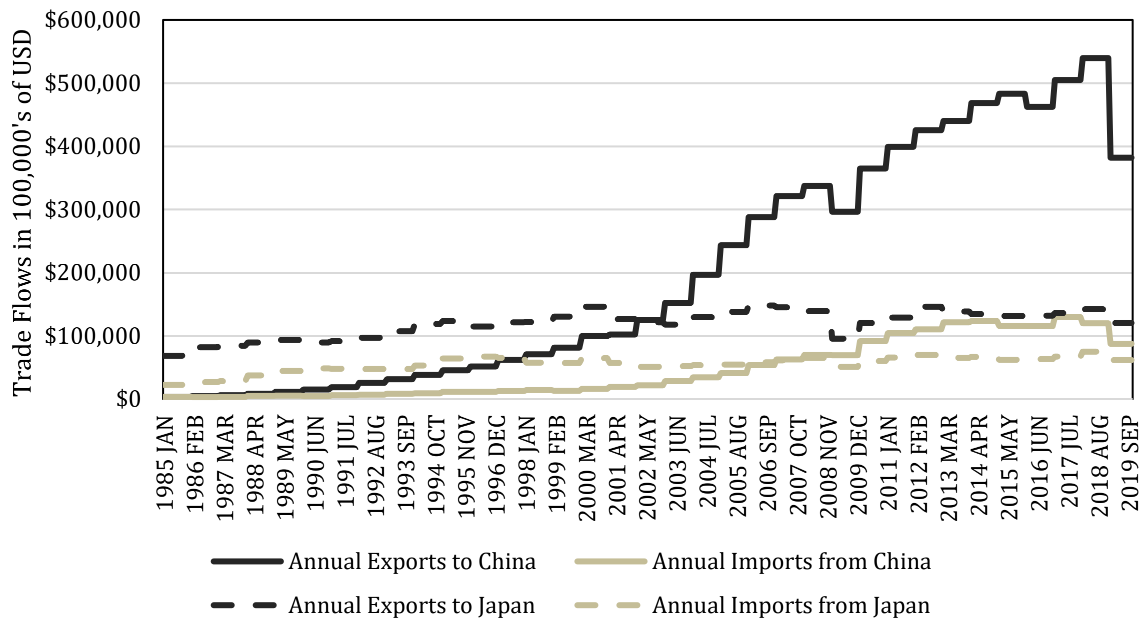
[3] Silver, Laura, Devlin Kat, and Huang, Christine. 2019. "U.S. Views of China Turn Sharply Negative Amid Trade Tensions." *Pew Research*, August 13. https://www.pewresearch.org/global/2019/08/13/u-s-views-of-china-turn-sharply-negative-amid-trade-tensions/

trade through localized effects of import competition from Chinese products. The authors found that these localized effects magnified the job-losses from trade beyond previously estimated levels, which undermined existing assumptions in the literature of labor mobility across sectors and job markets.

Feenstra, Ma, and Xu (2017b) continued this effort by expanding the analysis to include not only jobs lost through import competition, but jobs generated through exports. Feenstra et al. introduced a net-impact approach based on the original ADH methodology to determine the employment effects of all U.S. exports to Chinese imports. While this choice is appropriate for an analysis of the available policy options regarding protectionism or export promotion, it does not allow for the isolation of the export and import relationship strictly between the United States and China. This trading relationship is unique in its size. Before the emergence of the U.S.-China trade conflict, U.S.-Japan trade caused great concern among U.S. policymakers. Figure 1 compares historical trade flow data between the U.S. and both China and Japan. As shown by its relative magnitude, growth of U.S. imports from China represent a significant shock to the U.S. economy.

This paper expands on the existing research by introducing symmetry into the already rich literature on the employment effects of U.S. trade with China. Recent papers have focused on characterizing import and export exposure as driving forces behind employment shifts. This paper instead provides an estimate of the employment changes driven by trade flows between the U.S. and China. Policy research from prominent institutions regularly cites the estimates of US-China trading employment effects from this strain of research.[4]

Figure 1: Total Trade in Goods between the U.S., Japan, and China



[5]

However, using global exports from the U.S. overstates the employment generation side of the equation, and in doing so, underplays the degree to which Chinese import competition has displaced U.S. workers. If the debate surrounding the U.S.-China trading relationship is informed by empirical work that does not symmetrically compare trade, the true consequences of this bilateral relationship will be misstated. To impose

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[4] Meltzer, Joshua P. and Shenai, Neena. 2019. "The US-China economic relationship: A comprehensive approach," *Brookings*, https://www.brookings.edu/wp-content/uploads/2019/02/us_china_economic_relationship.pdf.

[5] Data collected from the U.S. Census Bureau, Trade in Goods by Country

symmetry while remaining consistent with the literature, I use the same data sources as Feenstra et al., including but not limited to, the tariff schedules from the UN-Comtrade Database, the County Business Patterns (CBP) surveys, and the NBER-CES Manufacturing Industry Database.

I find that, between 1991 and 2011, a one percentage point increase in an industry's exposure to Chinese imports led to a -1.32 percentage point decrease in employment within that industry. I also find that for the same period of time, a one percentage point increase in export exposure led to a 3.51 increase in employment for a given industry. This number is markedly larger than the figures identified in previous studies, which motivated a secondary analysis of observed effects by sector. It is also noteworthy that my analysis did not find statistically significant effects of export-generated employment for alternative time and methodological specifications of the model, which is inconsistent with previous research.

The next section discusses the relevant literature. Section III discusses the data. Section IV describes the empirical approach and presents the results. The conclusions are discussed in Section V.

II. Literature Review:

Coinciding with growing political attention to the U.S.-China trading relationship is a rapid growth in attempts to better understand the underlying trends that govern the relationship In their seminal paper, Autor, Dorn, Hanson (2013, henceforth ADH) evaluated the role that growing Chinese import competition had in the employment decline seen in the U.S. manufacturing industry between 1990 and 2007. Specifically, ADH used local commuting zones (CZ's) as the unit of analysis, building upon existing literature that emphasizes the mapping of trade shocks to regional labor markets (Borjas and Ramey 1995). The theoretical justification for this approach is the assumption that labor struggles to move across CZ's, so the successful or unsuccessful reallocation of labor after job displacement will heavily determine the net effect of import competition. Moreover, the co-location of buyers and suppliers within industries has the potential to magnify the employment effects of import competition in non-manufacturing industries within the same CZ as aggregate demand suffers from declining employment (Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi, 2012; Pierce and Schott, 2015; Acemoglu, Autor, Dorn, Hanson, and Price, 2016, henceforth Acemoglu et al. 2016). ADH also utilizes an instrumental-variables (IV) strategy to account for the potential endogeneity of US trade shocks.

First, the authors must identify an IV to counter the extent to which growth in US imports of Chinese goods are driven by existing economic fluctuations in the United States. To do this, the authors rely on existing literature and proxy Chinese import penetration into the United States with Chinese import penetration to 8 comparably developed economies (Bloom, Draca, Van Reenen 2011).[6] ADH found that Chinese import competition explains 21 percent of the decline in US manufacturing between 1990 and 2007.

ADH's work led to further detailed examinations of the role of Chinese import competition in the US labor market. The most comprehensive summary of work in this

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[6] The countries used in the IV were Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland

area can be found in Autor, Dorn, Hanson (2016). Only the most relevant additional articles will be discussed here. Acemoglu et al. (2016) identified potentially ambiguous employment effects of Chinese import competition if the replacement of the domestic supplier made the downstream firms more productive. This dynamic required the addition of a national industrial evaluation to complement the regional analysis of ADH. Acemoglu et al. (2016) found that between 1991 and 2011, approximately 3.1 million jobs were lost.

To fully discuss the employment effects of trade, a separate strain of research quantifies the employment generating effects of exports. Feenstra, Ma, and Xu (2017b) used the methods of ADH to determine the number of jobs created through U.S. global exports. They then compared the net employment effect of exports and imports. The authors found that, between 1991 and 2011, 0.2 to 0.3 million jobs were lost on net. Feenstra, Ma, and Xu (2017b) use two instruments for exports. The first is the inverse of the ADH import instrument. It measures the exports of the same 8 developed states to China. The second instrument for U.S. export expansion is comprised of global tariffs and rising foreign demand. This instrument was inspired by the existing literature on the coordinated rise of US exports and global trade liberalization (Romalis, 2007; Caliendo et al. 2015). This area of free-trade agreement literature allows for an estimate of how much export demand is created in the US market by a foreign tariff reduction. Like the instrument in ADH, this variable should not be correlated to U.S. supply shocks. Feenstra, Ma, and Xu (2017b) explicitly recognize the lack of symmetry in their own comparison of US global export expansion and Chinese-only imports in the United States. The authors' research prioritizes an understanding of U.S. labor markets, and therefore they were more concerned with capturing global demand for U.S. goods broadly rather than preserving symmetry in the analysis. This analysis is more interested in questions surrounding symmetric trade flows.

Other authors have prioritized symmetry in comparing the employment effects of import and export trends. Dauth, Findeisen, and Suedekum (2014) used a global input-output approach to evaluate the manufacturing employment changes in Germany caused by its trading relationships to China and Eastern Europe. The authors sought to capture both the substitution of German products for imports made in labor-abundant economies and the increasing demand for high-quality German products in those same economies. These offsetting dynamics also aptly characterize the United States and China. Dauth, Findeisen, and Suedekum (2014) utilized the same UN-Comtrade Database as Feenstra, Ma, and Xu (2017b), simplifying the coordination of the two papers' methodology. Taken together, the literature stemming from ADH undermines the presumption that labor freely adjusts in response to trade-related economic shocks. The process of creative destruction relies on labor that is flexible across region and industry, something that recent localized approaches to calculating trade consequences has called into question.

The political attention towards the U.S.-China trading relationship requires a more specific understanding of the direct consequences of that relationship. Toward that end, I hope to provide an opportunity for enhanced understanding of this crucial relationship by clearly defining the consequences of the bilateral trade flow. Like Feenstra, Ma, and Xu (2017b), this paper utilizes a dual-IV approach to estimate the employment effects of imports and exports using CZ and national industries as the units of analysis. This paper does not use data after 2011 in order to maintain comparability with previous research.

Of the existing studies inspired by the ADH methodology, I am not aware of any that refine their analysis specifically to the United States and China. This paper's primary contribution is a symmetrical analysis of this bilateral trading relationship.

III. Data:

The data sets used for the analysis are the County Business patterns (CBP), the NBER-CES Manufacturing Industry Database, and the UN-Comtrade Database. These data sources are ideal because they include by-industry data on various employment, bilateral trade flows, and relevant control variables such as region, manufacturing dummy variables, and educational attainment. This array of data can all be merged to present a comprehensive picture of economic outcomes across industries according to the 392 manufacturing and 87 non-manufacturing sector Standard Industrial Classification codes. In addition, the relatively large sample size allows for reasonably precise results across selected intervals of time.

The sample is restricted to the 392 manufacturing industries to offer greater consistency across industries. The remaining non-manufacturing industries hold different relationships between trade flows and employment, and their exclusion helps to promote consistency in the paper's findings. This choice is consistent with the primary literature cited herein. Data is categorized across 3 time periods, 1991-1999, 1999-2007, and 1999-2011. This division enables a stacked first differences approach that can isolate trends surrounding particular shocks. Specifically, the 1991-1999 period assesses dynamics prior to China's accession to the WTO and resultantly large exports. The 1999-2007 period avoids the Great Recession, while the 1999-2011 includes it. These restrictions create 3 time periods, each with 392 observations (one per industry).

My measure of employment, which is the variable of interest, mirrors the approaches of Feenstra et al (2017b) and Acemoglu et al (2016). CBP data provides employment totals across regions and NAICS industry 6-digit codes. Using the crosswalk prepared by Acemoglu (2016), these codes are converted to the 4-digit SIC codes which can be aligned to industry-level export and import exposure. Table 1 shows that between 1991 and 1999, average manufacturing employment by industry contracted by -0.64 percentage points, then by -3.99 percentage points between 1999 and 2007, and by -4.51 percentage points between 1999 and 2011.

Trade flow data from the UN-Comtrade Database presents imports and exports as annual totals. This paper follows the existing literature and converts these aggregate trade flows into normalized annual changes in imports and exports. The process of normalization is outlined in the Empirical Strategy section. Table 1 shows significant growth in the annual difference in import exposure, climbing from 0.39 to 0.99 from the 1991-1999 period to the 1999-2007 period. Import exposure growth declines in the 1999-2011 period to 0.74 annually, reflecting the consequences of the Great Recession. The 1999 to 2011 period was primarily similar to the 1999 to 2007 period, and the table is therefore left unreported. Export growth is more moderate across periods, increasing annually in each period by 0.81, 0.99, and 1.05 percentage points.

Table 1:

1991_1999 Primary Variable Summary Statistics

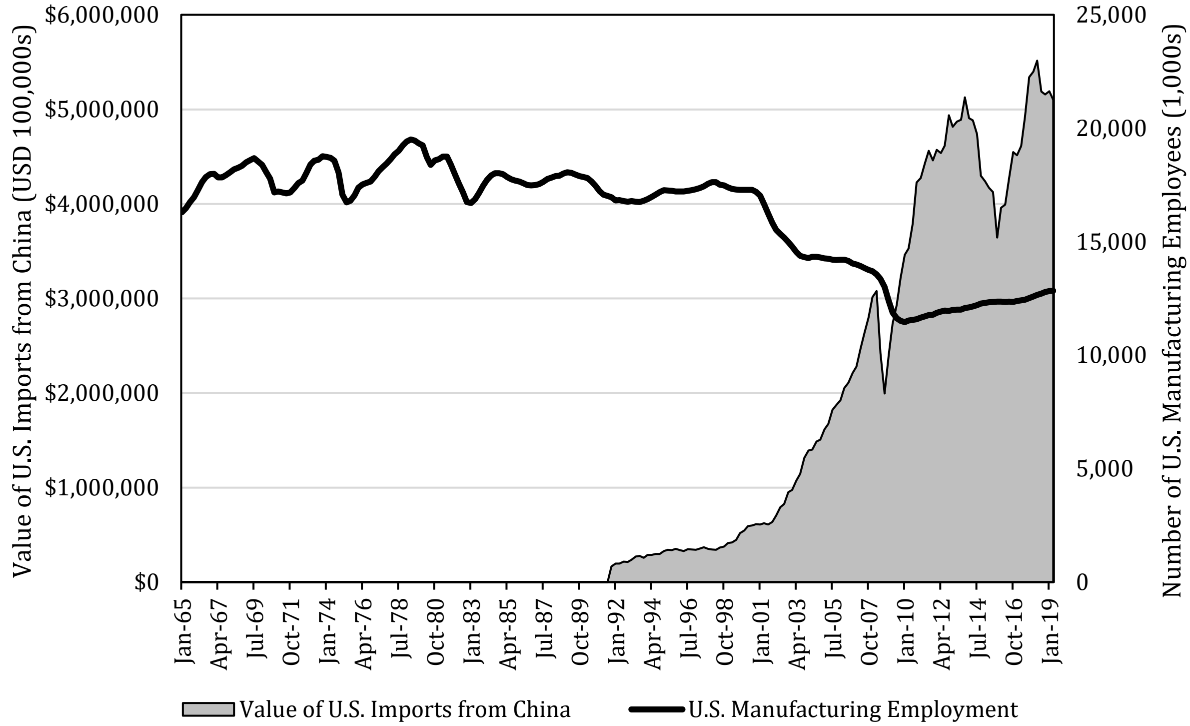
VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Imports	392	0.389	1.038	-0.252	12.15
Imports Other	392	0.259	0.710	-1.510	6.621
Exports	392	0.0442	0.286	-1.703	4.844
Exports Other	392	0.115	0.428	-3.560	4.647
Employment	392	-0.641	3.866	-18.15	14.18

1999_2007 Primary Variable Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Imports	392	0.987	1.918	-1.515	19.69
Imports Other	392	0.738	1.330	-0.269	14.15
Exports	392	0.133	0.522	-1.364	9.149
Exports Other	392	0.501	1.552	-0.938	24.26
Employment	392	-3.986	4.973	-47.50	9.004

In addition to the import and export bilateral flows between the United States and China, the empirical approach constructs an Instrumental Variable comprised of trade flows between the two countries in question, and 8 additional developed states. The summary statistics for these trade flows can also be found in Table 1. To better visualize the discrepant relationship between Chinese imports and employment, Figure 2 shows the total changes in U.S. employment and rising presence of Chinese imports to the United States.

Figure 2: U.S. Imports from China and U.S. Manufacturing Employment



[7]

Trade flow data required some manipulation before use. Raw annual change in U.S. - China imports needs to be normalized by the initial trade absorption level of each industry. This procedure mirrors the normalization performed in both Feenstra et al. (2017b) and Acemoglu et al. (2016). Beginning with the treatment of import exposure, Equation 1 normalizes changes in import exposure to initial domestic absorption,

$$\Delta IP_{s,t} = \frac{\Delta M_{s,t}^{UC}}{Y_{s,t_0} + M_{s,t_0} - E_{s,t_0}}$$

[7] Data collected from the FRED database

where $\Delta IP_{s,t}$is the change in Chinese import penetration at the industry level, as denoted by *s* for the 392 manufacturing sectors with SIC classifications. $\Delta M_{s,t}^{UC}$ is the change in US total imports from China for given period *t*, which has three sub-periods, 1991-1999, 1999-2007, and 1999-2011). $Y_{s,t_0} + M_{s,t_0} - E_{s,t_0}$ is initial absorption, defined as industry shipments, plus industry imports, minus industry exports, all set at the base year, 1991 =t_0. All values are deflated by the Personal Consumption Expenditures (PCE) price index, as done both in Feenstra et al. (2017b) and Acemoglu et al. (2016).

Treatment of export penetration in this paper differs from Feenstra et al. (2017b). They evaluated U.S. exports globally, and were therefore only concerned with export intensity as a share of each sector's total shipments (□$_{□,□0}$). In preserving bilateral symmetry, I apply the same normalization process to exports as just performed on imports to create the variable,

$$\Delta EP_{s,t} = \frac{\Delta X_{s,t}^{UC}}{Y_{s,t_0} + M_{s,t_0} - E_{s,t_0}}$$

where $\Delta EP_{s,t}$ measures export exposure of sector *s* across the three periods *t*. $\Delta X_{s,t}^{UC}$is annual change in exports from the United States to China (UC).

Control variables are presented thoroughly in the Appendix. The Appendix also includes regression outputs with all controls enumerated. These categories were included by Feenstra et al. (2016) and are: 1) Pre-trend controls that describe relevant industries between 1976 and 1991, 2) Sector controls which are a set of 10 dummy variables for primary manufacturing sectors, and 3) Production controls which include 1990 and 1991 initial economic characteristics of each industry.

The remainder of this paper formally evaluates these patterns using these primary variables and the listed controls.

IV. Empirical Strategy:

<u>Instrumental Variable Introduction</u>

Trade flows reflect export supply shocks and import demand shocks, which are both subject to concerns of endogeneity within the broader economies of both trading partners. Domestic economic shocks can obscure the identification of trade's effect of labor by simultaneously altering trade and employment data, creating an omitted variable bias. This is accounted for in the literature through the introduction of an IV that measures bilateral trade flows from China to eight non-U.S. developed countries, represented by the variable

$$\Delta IPO_{s,t} = \frac{\Delta M_{s,t}^{OC}}{Y_{s,t_0} + M_{s,t_0} - E_{s,t_0}}$$

where $\Delta IPO_{s,t}$ measures the change in the amount of Chinese imports received by the eight other developed nations, again using the same sector *s* and period *t* indicators as in (1). Data for the eight countries used for the instrument is most available in 1988 as opposed to 1991. Therefore the denominator $t_0 = 1988$. The assumption is that the U.S. will be similarly exposed to Chinese supply shocks as the eight other countries. However, the GFC in 2007 and 2008 presents the potential for a negative demand shock across both the U.S. and IV countries, which is why the sub-period allow for an isolated analysis of pre- and post-GFC.

The export instrument is constructed homologously to the import instrument while substituting in export flows, $\Delta EPO_{s,t}$.

$$\Delta EPO_{s,t} = \frac{\Delta X_{s,t}^{OC}}{Y_{s,t_0} + M_{s,t_0} - E_{s,t_0}}$$

One weakness of this instrument strategy is that the eight high-income countries may have correlated consumption demands and production supplies. If this is the case, the IV estimates may be smaller than the true effects, as a portion of the employment fluctuations are wrongly attributed to domestic changes shared between the U.S. and the eight comparator countries. Feenstra et al. (2017b) constructs a second instrument for U.S. exports that is not included in this paper. This excluded instrument uses global tariff changes to estimate anticipated U.S. export fluctuations. The second instrument is used in the preferred model specification within Feenstra et al. However, global tariff fluctuations are not a valid instrument for bilateral exports from the United States to China. The tariff instrument did not reduce the statistical significance of key variables in the Feenstra specification, therefore its omission in this paper should not cause concern.

Baseline Industry Estimates

In order to evaluate the effect of both import and export exposure on employment fluctuations, I estimate an OLS model of the following form:

$$\Delta \ln(L_{s,t}) = \alpha_t + \beta_1 \Delta IP_{s,t} + \beta_2 \Delta EP_{s,t} + \epsilon_{s,t}$$

where $\Delta \ln(L_{s,t})$ is 100 times the annual log change in employment in sector *s* over time period *t*. $\Delta IP_{s,t}$ and $\Delta EP_{s,t}$ are the annual change in U.S. exposure to imports from China and the annual change in U.S. exports to China. α_t is a period-specific constant, and $\epsilon_{s,t}$ is an error term with the usual properties. Following both Feenstra et al. (2017b) and Acemoglu et al. (2016), I fit this equation to a stacked first difference model that includes the 1991-1999 period and either the 1999-2007 or the 1999-2011 time periods. The above equation is susceptible to concerns of endogeneity, which required the inclusion of instruments to perform a 2SLS estimation of the following form:

$$\Delta \ln(L_{s,t}) = \alpha_t + \beta_1 \Delta IP_{s,t} + \beta_2 \Delta EP_{s,t} + \beta_3 \Delta IPO_{s,t} + \beta_4 \Delta EPO_{s,t} + \epsilon_{s,t}$$

where all terms from equation (6) remain with the addition of the import and export instruments from equations (3) and (4), with observations across sectors *s* and periods *t*. This analysis seeks to isolate the effect of the Chinese export supply shock on U.S. employment. In an OLS specification without instruments, a U.S. demand shock would bias coefficients toward zero as domestic economic shifts would obscure employment shifts caused by import and export changes.

In Table 2, Column (1) is the OLS stacked first difference of the 1991-2007 period. Column two is the same model extended until 2011. Columns (3) and (4) are 2SLS regressions that include both instruments $\Delta IPO_{s,t}$ and $\Delta EPO_{s,t}$. The number of observations doubled from 392 to 784 due to the combination of time period variables in the stacked first difference. These findings imply that a one percentage point increase in industrial exposure to Chinese imports reduced employment in a given industry by -1.26 percentage points between 1991 and 2007 according to Column (2), and by -1.32 percentage points when extended to 2011 according to Column (4).

Row 1 outputs are consistent with the findings of Feenstra et al. (2017b). The inclusion of instruments increases the magnitude of import effect under both time periods, and is the preferred specification.

Table 2: Baseline Specification

VARIABLES	(1) 1991-2007 OLS	(2) 1991-2007 2SLS	(3) 1991-2011 OLS	(4) 1991-2011 2SLS
Imports	-0.709***	-1.263***	-0.816***	-1.320***
	(0.185)	(0.379)	(0.163)	(0.425)
Exports	0.615	1.536	1.013	3.514***
	(0.417)	(1.394)	(0.733)	(1.301)
1{1991-1999}	-0.135	-0.0267	-0.124	-0.102
	(0.369)	(0.390)	(0.370)	(0.386)
1{1999-2007}	-3.104***	-2.760***		
	(0.395)	(0.447)		
1{1999-2011}			-3.918***	-3.919***
			(0.352)	(0.387)
Observations	784	784	784	784
R-squared	0.349	0.323	0.449	0.411

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Row 2 provides coefficients for export exposure across specifications. Coefficients differ significantly from Feenstra et al. (2017b), which found statistically significant positive employment effects across all specifications. Column (4) is the only statistically significant result, with a 1 percentage point increase in U.S. exports to China creating a 3.51 percentage point increase in employment within the exporting industry. The reduced significance of most coefficients is reasonable, given that the global export approach taken previously included larger observations of global trade flows. Shrinking the observations to exports from the U.S. to China significantly increased the standard errors shown across Row 2. However, the significance of marginal effect of export growth in the final specification in Column (4) is notably larger than the estimates of Feenstra et al. (2017b) but consistent with the assumption that the GFC created large domestic shocks that necessitate the inclusion of an instrument. An additional explanation for the large export coefficient is the strength of the instruments. In Feenstra et al. (2017b), the instruments used met the Stock-Yogo F-test critical values across all specifications.[8] In my analysis, the export variable test output of 18.40 did not reach the 10% maximal IV size of 19.93, but is still valid at the 15% maximal IV size critical value of 11.59. Weakness of instrument, as indicated by my below-critical value export test, indicates that the effects of the variable of interest may be overstated. This would bias both the 1991-2007 and 1991-2011 2SLS outputs in columns (2) and (4) upwards.

Introducing Sectoral and Industry Controls

Additional factors that vary by industry and sector may alter the way employment responds to import competition. When included with the existing model, controls for these factors create an estimation model of the following form:

[8] 10% IV size was 19.93 with Feenstra et al. variable tests as 30.17 for imports and 20.97 for exports.

$$\Delta \ln(L_{s,t}) = \alpha_t + \beta_1 \Delta IP_{s,t} + \beta_2 \Delta EP_{s,t} + \gamma X_{s,t=0} + \phi Y_s + \upsilon Z_{s,t=0} + \epsilon_{s,t}$$

where $X_{s,t=0}$ is the set of Production Controls across sectors *s* and values reflect the industry's composition in 1990 or 1991 depending on data availability. Y_s is a set of 10 dummy variables for each sector *s*, and are time independent. $Z_{s,t=0}$ is a set of pre-trend controls which characterize industry changes from 1976 to 1991 across sectors *s*, and is also time independent. All other variables are as previously defined in equation (5).

I estimate five specifications where controls are added gradually across columns for the 1991-2007 timespan and is then compared to the 1991-2011 timespan with the full model. The Sector, Production, and Pre-trend controls are tested individually in Columns (1), (2), and (3) respectively. Column (4) includes all three controls and is the preferred 1991-2007 specification. Column (5) is the same all-control specification for the 1991-2011 timespan.

Table 3: Including Controls

VARIABLES	(1)	(2)	(3) 1991-2007	(4)	(5) 1991-2011
Imports	-0.830***	-1.100***	-1.274***	-0.818***	-0.716***
	(0.247)	(0.342)	(0.393)	(0.260)	(0.252)
Exports	0.987	0.844	2.054	1.395	3.121***
	(1.243)	(1.226)	(1.503)	(1.195)	(1.160)
1{1991-1999}	1.349***	-15.28	0.391	0.0444	-8.552
	(0.470)	(15.77)	(0.377)	(17.40)	(15.59)
1{1999-2007}	-1.584***	-18.04	-2.379***	-2.929	
	(0.474)	(15.99)	(0.447)	(17.59)	
1{1999-2011}					-12.57
					(15.73)
Observations	784	784	784	784	784
R-squared	0.530	0.362	0.339	0.554	0.595

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

All estimates are from the 2SLS method that includes both import and export instruments. This is done in conformity with Feenstra et al. and because it allows for a robustness check on the statistically significant export specification in Column (5).Table 3 presents the results from Equation (6) by specification. Row 1 implies that for the full specification, a 1 percentage point increase in import exposure led to a -0.81 percentage point reduction in industry employment between 1991 and 2007, and a -0.72 percentage point reduction between 1991 and 2011. These outcomes are highly consistent with those of Feenstra et al. (2017b). However, there are some noteworthy differences between this specification and the baseline model. The first model showed an increase the employment dislocation effects of import competition between the 2007 and 2011 specifications. However, the control-variable inclusive model finds a slightly smaller marginal effect in the 2011 period. This implies that sector-specific features determined some of the added labor dislocation that occurred between 2007 and 2011. This is a minor revision as the significance and direction of each effect are still consistent with the baseline model.

Row 2 estimates the effect of changing export exposure. As in the non-robust case, only the 1991-2011 2SLS model is statistically significant. It implies that the marginal effect of increasing export exposure of an industry by 1 percentage point is an employment increase by 3.12 percentage points. This finding reflects only a modest adjustment to the magnitude of the observed effect relative to the baseline estimation. As seen in Feenstra et al. (2017b), the industry-specific controls confirm the robustness of the baseline effects. However, the magnitude increase of 3.12 percentage points is large enough to require further exploration. My finding for exports deviates from Feenstra et al. in two crucial ways. The first is that across both OLS regressions and the 1991-2007 period 2SLS specification, my model did not yield statistically significant results. This was due to significantly increased standard errors, which reflects the reduced scale of data used in this analysis by focusing on U.S.-China exports instead of global U.S. exports. The second deviation is in the magnitude of the 1991 to 2011 2SLS specification, which jumped to a 3.51 percentage point increase (without controls) in employment for each percentage point increase in export exposure, over the OLS estimation which showed a statistically insignificant 1.01 percentage point increase. This highlights the importance of the instrument. The 2SLS regression more than tripled the magnitude of observed effect over the OLS for the same 1991 to 2011 period. In addition to the explanation relating to the instrument, the difference could be attributed to the composition of U.S.-China exports relative to U.S.-global exports.

Adding Section on By-Industry Analysis

Using the same methods described above, I evaluated the effects of import and export exposure on each unique sector. The sector categorizations match the dummy variables provided by Feenstra et al. This method was not reported in Feenstra et al., and the subsequent analysis first performs the by-industry analysis on the original data used by these authors. Subsequently, I compare these findings to a by-industry analysis performed on my symmetric data. All model specifications use the 1991 to 2011 specification with an OLS regression. This was done because the 2SLS specifications presented erratic estimations, likely caused by applying too strict an instrument on too few observations per industry. Each column of Tables 4 and 5 contain coefficients for one sector.

Table 4: U.S.-Global By-Industry Baseline Effects

VARIABLES	(1) Foodstuffs	(2) Textiles	(3) Wood Products	(4) Paper	(5) Chemicals/Petrol	(6) Clay/Stone	(7) Metals	(8) Equipment	(9) Transp.	(10) Other
Imports	-3.987***	-0.482***	-0.938*	0.0274	-2.512	-1.454***	0.421	-0.505***	-1.342	-0.794*
	(1.039)	(0.155)	(0.419)	(1.023)	(1.780)	(0.432)	(0.929)	(0.166)	(2.662)	(0.311)
Exports	1.551**	0.0575	1.246	1.289*	0.783***	0.736*	0.312	0.540***	0.206	-0.0217
	(0.674)	(0.302)	(1.074)	(0.667)	(0.196)	(0.404)	(0.209)	(0.153)	(0.447)	(0.0222)
1{1991-1999}	0.172	-4.152***	2.297***	-0.371	-1.260***	1.781*	0.483	-1.166*	-1.467	1.834
	(0.627)	(1.024)	(0.511)	(0.540)	(0.364)	(0.844)	(0.825)	(0.609)	(2.623)	(1.542)
1{1999-2011}	-1.123**	-11.02***	-4.217***	-3.816***	-3.092***	-3.480***	-3.746***	-4.219***	-2.804**	-3.698*
	(0.398)	(1.045)	(0.637)	(0.456)	(0.748)	(0.289)	(0.565)	(0.414)	(0.761)	(1.611)
Observations	90	104	46	48	66	74	90	202	32	32
R-squared	0.238	0.812	0.772	0.686	0.410	0.701	0.474	0.614	0.284	0.648

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Bilateral By-Industry Baseline Effects

VARIABLES	(1) Foodstuffs	(2) Textiles	(3) Wood Products	(4) Paper	(5) Chemicals/Petrol	(6) Clay/Stone	(7) Metals	(8) Equipment	(9) Transp.	(10) Other
Imports	-3.987***	-0.482***	-0.938*	0.0274	-2.512	-1.454***	0.421	-0.505***	-1.342	-0.794*
	(1.039)	(0.155)	(0.419)	(1.023)	(1.780)	(0.432)	(0.929)	(0.166)	(2.662)	(0.311)
Exports	1.551**	0.0575	1.246	1.289*	0.783***	0.736*	0.312	0.540***	0.206	-0.0217
	(0.674)	(0.302)	(1.074)	(0.667)	(0.196)	(0.404)	(0.209)	(0.153)	(0.447)	(0.0222)
1{1991-1999}	0.172	-4.152***	2.297***	-0.371	-1.260***	1.781*	0.483	-1.166*	-1.467	1.834
	(0.627)	(1.024)	(0.511)	(0.540)	(0.364)	(0.844)	(0.825)	(0.609)	(2.623)	(1.542)
1{1999-2011}	-1.123**	-11.02***	-4.217***	-3.816***	-3.092***	-3.480***	-3.746***	-4.219***	-2.804**	-3.698*
	(0.398)	(1.045)	(0.637)	(0.456)	(0.748)	(0.289)	(0.565)	(0.414)	(0.761)	(1.611)
Observations	90	104	46	48	66	74	90	202	32	32
R-squared	0.238	0.812	0.772	0.686	0.410	0.701	0.474	0.614	0.284	0.648

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Across both data-sets, import coefficients are largely consistent by approximate magnitude and significance. The sole exception is the Wood Products and Furniture sector, for which a one percentage point increase in import exposure led to a -0.94 percentage point reduction in employment under Feenstra et al. parameters and a statistically insignificant amount under my parameters. The coefficients for exports differ significantly. Under my parameters, only Foodstuffs and Agriculture, and Chemicals/Petroleum retain statistical significance. A one percentage point increase in export exposure led to a 6.91 percentage point and 1.67 percentage point increase in each industry respectively. This compares to the Feenstra et al. parameters, which 1.55 percentage point and 0.78 percentage point employment responses in each industry. The particularly large increase in Food and Agriculture could be attributed to the types of crops exported to China from the US and their relative employment flexibility.

More broadly, the statistical insignificance of export data is driven by rising standard errors with still large amplitude responses. Given that the inclusion of instruments has raised statistical significance and pushed coefficients away from 0, it is possible that the overall high effect observed for the 1991-2011 2SLS specification may be unreliably inflated by the instrument. Specific exporters within industrial codes may fluctuate heavily, influencing the sector outputs severely. With the previous Feenstra et al. methodology, these exceptions would have been less capable of biasing estimates given the overall higher amount of trade flows being observed.

Caution is encouraged before ascribing too much significance to the role of the Food/Agriculture and the Chemical/Petroleum sectors in shaping the overall estimations. Crucially absent from this phase of analysis is weighting estimates by total employment within each industry. Without that element, a discussion only of the econometric implications of this by-industry analysis is appropriate.

Conclusion:

The U.S.-China economic relationship is, and will continue to be a source of geopolitical tension. The future of this relationship could range from de-escalation, to decoupling, or even more contentious outcomes. To avoid conflict, it is crucial that policymakers are properly informed on the consequences of the relationship as it stands.

The current literature develops our understanding of the relationship between trade and labor market adjustment. The Autor, Dorn, Hanson (2013) “China Shock” highlighted the importance of local labor market conditions in determining the long-term effects of worker displacement from trade. Using this methodology, Feenstra, Ma, and Xu (2017b) constructed a net-impact model that offset the employment generation effects of export growth with the labor displacement effects of import competition. From this literature, we know that job losses from trade competition have been chronically underestimated. However, the job losses from Chinese import competition are almost offset by job growth resulting from U.S. global exports. While for various apt reasons, research thus far has not prioritized a symmetrical analysis of U.S.-China bilateral trade flows, symmetry is nevertheless important. Policies that shape this relationship should be informed by analysis specific to the bilateral relationship as opposed to research that broadens our understanding of economic dynamics generally. This paper hopes to offer this narrowed focus.

The current literature has taken a variety of approaches in quantifying the relationships between trade, employment, and local labor markets. Autor, Dorn, Hanson (2013) introduced the consideration that local labor markets do not adjust smoothly to external trade shocks, undermining the existing of labor mobility. Feenstra, Ma, and Xu (2017b) introduced methodology to evaluate the employment-generating effects of exports, and reconciled the two effects through a net-impact analysis. Their finding was that an increase in one percentage point increase of import or export exposure led to a -1.41 percentage point reduction, or 0.65 percentage point increase in employment for a given industry.

This paper largely confirms these findings for imports, but differ sharply on exports. It finds that a one percentage point increase of import exposure leads to a -1.32 percentage point reduction in employment from 1991 to 2011. Meanwhile, a 1 percentage point increase in export exposure led to a 3.51 percentage point increase in employment across the same period. Two possible explanations for such a large jump include the significance of the instrument, which raises observed effects significantly, or the composition of industries that export to China, compared to those that export globally.

Future work could further evaluate the underlying composition differences between U.S. exports to China and U.S. exports globally. Subsequent analyses could also prioritize the aggregate employment effects instead of the marginal effects dimension of the trade and employment relationship. Alternative approaches can also seek to work around the data complications that this paper encountered when using smaller amounts of U.S. to China export data. Such research would further inform policymakers on direct consequences of the U.S.-China trade relationship.

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Appendix:

Appendix Table 1: Enumerated Controls

VARIABLES	(1)	(2)	(3) 1991-2007	(4)	(5) 1991-2011
Imports	-0.830***	-1.100***	-1.274***	-0.818***	-0.716***
	(0.247)	(0.342)	(0.393)	(0.260)	(0.252)
Exports	0.987	0.844	2.054	1.395	3.121***
	(1.243)	(1.226)	(1.503)	(1.195)	(1.160)
1{1991-1999}	1.349***	-15.28	0.391	0.0444	-8.552
	(0.470)	(15.77)	(0.377)	(17.40)	(15.59)
1{1999-2007}	-1.584***	-18.04	-2.379***	-2.929	
	(0.474)	(15.99)	(0.447)	(17.59)	
Textiles	-6.998***			-7.078***	-7.336***
	(1.140)			(1.278)	(1.169)
Wood Products	0.728			0.546	-1.130**
	(0.710)			(0.676)	(0.493)
Paper	-1.184**			-0.651	-1.443***
	(0.535)			(0.480)	(0.456)
Chemicals/Petrol	-1.156			0.162	-0.217
	(0.716)			(1.099)	(0.945)
Clay/Stone	0.116			0.418	-0.584
	(0.675)			(0.496)	(0.437)
Metals	-0.679			-0.0106	-0.734
	(0.747)			(0.596)	(0.545)
Equipment	-1.512**			-0.385	-1.144
	(0.744)			(0.868)	(0.788)
Transp.	-1.676			-1.105	-2.141**
	(1.209)			(1.225)	(1.066)
Other	0.297			0.408	-1.055
	(1.248)			(1.136)	(0.962)
Production workers share of employment (1991)		-0.0169		0.00267	0.0150
		(0.0174)		(0.0199)	(0.0169)
Log average wage in 1991 (in 2007 $)		1.683		0.222	1.021
		(1.536)		(1.688)	(1.514)
Capital/value added (1991)		-0.825*		-0.962**	-0.913**
		(0.463)		(0.462)	(0.393)
Computer investment as share of total (1990)		-0.123**		-0.0591	-0.0327
		(0.0565)		(0.0547)	(0.0440)
High-tech investment as share of total (1990)		0.0286		-0.0326	-0.0663
		(0.0704)		(0.0844)	(0.0761)
Change in industry share of total employment (1976-1991)			7.588*	1.832	2.151
			(4.321)	(3.416)	(2.720)
Change in log real wage (1976-1991)			-0.0517**	-0.0549**	-0.0462*
			(0.0209)	(0.0269)	(0.0247)
1{1999-2011}					-12.57
					(15.73)
Observations	784	784	784	784	784
R-squared	0.530	0.362	0.339	0.554	0.595

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2: Industry-Level Control Variables

VARIABLES	(1) mean	(2) sd	(3) min	(4) max
Computer investment as share of total (1990)	5.986	5.728	0	43.48
High-tech investment as share of total (1990)	8.467	5.088	1.201	18.25
Log average wage in 1991 (in 2007 $)	10.50	0.281	9.783	11.09
Change in log real wage (1976-1991)	4.150	10.43	-32.01	48.06
Production workers share of employment (1991)	70.68	12.64	18.72	97.62
Capital/value added (1991)	0.963	0.570	0.186	3.523
Change in industry share of total employment (1976-1991)	-0.0172	0.0364	-0.418	0.0720