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Recalculating the China Shock to US Manufacturing Employment

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ABSTRACT

This study uses input-output labor-content accounting to estimate the impact of rising imports from China on US manufacturing employment. The salience of this question escalated with the 2018-19 US-China trade war. The estimates take account of partial offsets from substitution for imports from other countries competing with China, as well as increased US exports to China and induced exports to other countries, and job gains in downstream sectors using imported inputs. The estimates do not include further offsets from macroeconomic policy. We find that from 2000 to 2016, the China shock displaced 774,000 direct and indirect jobs in manufacturing, 15.5 percent of the decline in manufacturing employment in this period. Total jobs lost including in other sectors amounted to 749,000 jobs, reflecting gains in non-manufacturing exports and downstream effects. These estimates are substantially smaller than the impacts of about 1 million jobs lost in manufacturing and, especially, the 2 million total job loss in all sectors estimated by Acemoglu et al. (2016). We similarly find much smaller manufacturing job losses than Autor, Dorn, and Hanson (2013) using their commuting-zone data but applying lagged US imports from China as the explanatory variable rather than an instrument based on other advanced economies' imports from China.

A Brief Review of Recent Literature[2]

ADH 2013, Its Sequels, and Other "Large Shock" Studies - In their 2013 study *Autor, Dorn and Hanson* (ADH) applied cross-sectional data on manufacturing employment for 722 commuting zones in the mainland United States to examine the impact of imports from China on manufacturing employment and several socio-economic measures. They identify the distribution of imports from China across 397 manufacturing industry categories, and then calculate the

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[2] Fredrick Toohey provided research assistance for this section.

exposure of manufacturing to imports from China in each commuting zone (CZ) based on the share of the zone in total US employment in each of the manufacturing sectors. They then apply the change in total imports from China in two periods, 1990 to 2000 and 2000 to 2007, to obtain the change in each CZ's exposure to imports from China. After instrumenting this explanatory variable by increases in the corresponding sectoral manufacturing imports from China into eight other advanced economies, they conduct regressions of the change in manufacturing employment on the change in exposure to imports from China. Their main estimates indicate that rising imports from China caused a loss of 2 million US manufacturing jobs from 2000 to 2007. Their "conservative" estimate is 48 percent of this amount.[3] Their public statements of their results have emphasized the conservative estimate of a loss of 1 million manufacturing jobs.[4] ADH (2013) remains by far the most widely cited study on this issue.[5]

Appendix B uses the ADH commuting-zone data to re-estimate the China shock using lagged US imports from China rather than the ADH instrumental variable. We find a much smaller regression coefficient than in the unadjusted ADH version, and our estimate is about 15 percent smaller than their "conservative" variant. But our main estimate using counterfactual input-output analysis is smaller still (table 3 below), suggesting that the cross-sectional approach overstates even when using the direct lagged independent variable rather than the instrumental variable.

A subsequent study by *Acemoglu, Autor, Dorn, Hanson, and Price* (2016) updates and complements the 2013 ADH study. In this paper the ADH authors implicitly recognize possible problems with the geographical cross-section approach by switching to the industrial sector as their unit of observation. This later study again instruments the China shock by using increased imports into other advanced economies. However, its observations are for sectoral import penetration from China at the national level for 392 manufacturing industries, rather than for changes in manufacturing employment at the geographical level for 722 commuting zones. The new estimates are substantially lower for the direct impact: a decline of 560,000 manufacturing jobs from 1999 to 2011, versus a loss of 1 million jobs during 2000-2007 alone in conservative variant of ADH.[6] But the authors then catapult the estimate to about 1 million jobs in manufacturing and another 1 million in non-manufacturing by taking into account indirect inter-industry effects. They find large negative effects for upstream industries and ambiguous effects for downstream industries. They argue that gains in downstream industries from cheaper intermediate inputs imported from China can be offset by the collapse of "existing long-term

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[3] In this apparently unconventional treatment of an instrumental variable estimate, they shrink the estimated coefficient by the ratio of explained to total variance, on grounds that doing so separates the "exogenous supply-driven component" from demand forces; p. 2140.

[4] See for example Chris Arnold, "China Killed 1 million U.S. Jobs, But Don't Blame Trade Deals," National Public Radio, April 18, 2016; and Peter Dizikes, "Trading Places," *MIT News*, March 9, 2016.

[5] As of mid-February 2019, Google Scholar reported 1,945 citations of ADH, 465 citations of AADHP, 505 citations of Pierce and Schott (2016), and 35 citations of Caliendo et al (2019). A corresponding Bloomberg search of news articles in the major press reported 74, 14, 25, and 6, respectively.

[6] Like ADH, AADHP shrink the regression coefficient on the instrumented China exposure variable, this time yielding a fraction of 0.56 instead of 0.48 (p. S160). Unlike ADH, AADHP do not present a job impact estimate using the unadjusted result.

relationships for specialized inputs as domestic input suppliers are driven out of business" (p. S149). They omit any downstream impact because their estimates are not statistically significant and have an unstable sign (positive offset for manufactures, negative for non-manufactures; S173). In contrast, Wang, Wei, Yu, and Zhu (2018) estimate large positive downstream job effects, as discussed below. AADHP place their preferred estimate of job losses from the China shock from 1999 to 2011 at 560,000 for the direct impact on manufacturing jobs, an additional 425,000 manufacturing jobs lost from upstream input-output effects, and another 1.0 million indirect jobs lost in non-manufacturing sectors, for a total of 1.98 million jobs lost (p. S145). This number balloons further to 2.4 million once Keynesian demand effects are incorporated.

Pierce and Schott (2016) are also of the view that China trade had a major role in the "surprisingly swift" decline in US manufacturing employment after 2000, but they argue that the cause was a change in US trade policy rather than a shock from rising supply of Chinese goods to all markets. They posit that it was the granting of permanent normal trade relations (PNTR) by the United States in 2000 at the time of China's entry into the WTO that spurred a sharp increase in US imports from China. They argue that there was no similar reaction in the EU, which had already granted most favored nation status in 1980. Their statistical tests use a "NTR gap" between normal trade relations tariffs and tariffs which would have returned if NTR had not been renewed annually (averaging 37 percent). Although the argument is appealing that the reduction of uncertainty could have stimulated investment and sourcing decisions causing a surge in imports, the aggregate trends in imports from China do not support the proposition that US PNTR was the key change.[7]

Shrinking the Estimates – A subsequent study by *Feenstra, Ma, and Xu* (2018) reruns the ADH tests to examine the sensitivity of the results to the sharp increase in housing prices in 2000-07. They cite the masking effect on employment from rising construction activity in the housing boom. They find that housing prices rose faster in commuting zones where exposure to Chinese imports was lower. Failing to include housing prices as a control variable would therefore bias the impact of import exposure toward a larger absolute value. They find that when changes in local housing prices are included, the response of the total employment-to-population ratio falls by about half. After taking account of endogeneity of housing prices to the China shock, they find that the independent employment effect of the China shock is still reduced by about 30 percent.

Levy (2016) argues that ADH do not address two major sources of falling manufacturing employment that provide an alternative to causation from increased imports from China: technological change away from unskilled labor; and geographical relocation of manufacturing, such as the shift in auto production from Michigan and Ohio to Tennessee and Alabama. He also argues that the sole focus on China misses the point that in the absence of the large increase in

[7] Thus, ADH (2013, p. 2131) report that the rise in US imports from China (at constant 2007 prices) was actually larger for the United States in the 1990s (a multiple of 4.6) than in the 7 other developed countries (a multiple of 3.3), whereas in the post-PNTR period 2000-2007 the rise was almost identical for the United State (multiple of 2.7) and the 7 other countries (2.8). Note further that if Pierce and Schott are right, ADH would have to be wrong to use the other developed countries for their instrumental variable.

supply from China, there would likely have been more imports from other competing economies such as Vietnam – rather than much larger domestic production. As discussed below, the aggregate labor content estimates in the present study are lower than cross-section-based estimates, lending support to the notion of aggregation bias from geographical reallocation. Similarly, the estimates below calculate a substantial offset to the China shock from a decline in growth in imports from major competing economies.

Rothwell (2017) re-examines the ADH results. He argues that whereas the 1990s were characterized by economic conditions favorable to Information technology, electronic components, and manufacturing more generally, the period 2000-07 was characterized by conditions more favorable to places experiencing rapid population growth. When he "unstacks" the two time periods, he finds the ADH results were biased by the weaker macroeconomic performance of the second period combined with the intensification of the China trade shock in the second period. He estimates neutral or positive impacts of China trade for every labor variable in both periods, except for manufacturing employment in the second period when rising import competition was more intense. His principal focus, however, is general local labor market disruption from trade (e. g. for unemployment and wages) rather than the impact on manufacturing employment (the focus here), and he does not translate his statistical estimates into the number of manufacturing jobs displaced by China trade in the second period.

As shown in estimates below, taking account of the export side of trade reduces the net loss in manufacturing jobs from the China shock. *Feenstra and Sasahara* (2017) seek to place the ADH estimates into perspective by calculating US job gains from increased exports globally. They estimate that from 1995 to 2011, growth in US exports boosted demand for US jobs by 2 million in manufacturing, 0.5 million in resource industries, and 4.1 million in services (of which one-third were due to intermediate demand from the expansion of manufacturing and resource exports). They estimate that in comparison imports from China led to a reduction in demand for 1.4 million jobs in manufacturing (and 0.6 million in services). However, they do not specifically estimate the export jobs that can be associated with US-China trade, examined below.

Caliendo, Dvorkin, and Parro (2019) use a calibrated dynamic general equilibrium model to assess the China shock. They find lower manufacturing job losses than ADH: a decline of 550,000 jobs from 2000 to 2007, reducing the share of manufacturing in total employment by 0.36 percentage point (pp. 29-31). Reallocation of labor to non-manufacturing, in part spurred by cheaper intermediate inputs imported from China, boosted the employment shares by 0.29 percentage point in services, 0.03 percentage point in construction, and 0.028 percentage point in wholesale and retail trade. They emphasize that the shock *increased* US welfare by 0.2 percent, albeit with wide dispersion across individual labor markets (ranging from -0.8% to + 1.0%; p. 40). The authors find that the job losses were concentrated in computers and electronics (about 25 percent of the total decline), as well as furniture, textiles, metal products, and machinery (each in a range of 10 to 15 percent). The largest declines were in California and Texas (each about 9 percent of the total). Normalized by state employment shares, the largest declines were in Mississippi, South Carolina, Kentucky, Michigan, and North Carolina (in a range of 1.6 to 2.2

percent; p. 33). Overall the study significantly moderates the ADH results while confirming the sharp regional dispersion of the impact.

Reversing the Sign – Two recent studies have gone further and calculated that China trade has *increased* US employment. *Magyari* (2017) argues that competitive pressure from imports from China has increased employment in US firms more exposed to imports from China. Using confidential census micro-data, she focuses on employment at the level of the firm, rather than the individual establishments within the firm. At the aggregate level, she found that from 1997 to 2007 the total employment of manufacturing firms rose by 4 percent even though employment in their manufacturing establishments fell by 3 percent, because their employment in non-manufacturing establishments rose by 7 percent. Moreover, manufacturing firms at the 75th percentile of exposure to imports from China experienced 1.5 percent higher annual employment growth than those at the 25th percentile. She infers that the more exposed firms reorganized their activities toward less exposed industries. Her analysis implies that the sharp decline in manufacturing employment in this period would have been even more severe without rising imports from China, but she does not assess the other sources of the decline.[8]

The most dramatic sign reversal in the recent literature is to be found in a study by *Wang, Wei, Yu, and Zhu* (2018). The authors follow the ADH approach of examining commuting-zone exposure to imports from China. However, in addition to the direct-competition effect associated with sectoral production, they add two indirect effects: upstream effect (loss of jobs in supplier sectors as home production declines in response to the China shock) and downstream (increased employment in sectors that *use* output of the home sector as an intermediate input but benefit from the alternative of cheaper inputs from China). They thus seek to combine the ADH reduced-form approach and the general equilibrium approach (e.g. of Caliendo, Dvorkin and Parro, 2019). They conclude that the downstream effect of the China shock is positive and large. They further emphasize that employment in non-manufacturing sectors systematically benefits from China trade.[9] The authors do not provide a specific number for the China shock impact on manufacturing sector jobs. For 2000-2014, their main statistical estimate shows a positive employment effect even in manufacturing (with positive downstream and even upstream effects more than offsetting negative direct competition effects), and positive effects for non-manufacturing). A robustness check turns the manufacturing employment impact negative but leaves the total employment effect strongly positive.[10] Overall, the thrust of the study is that incorporation of indirect effects turns the impact of the China shock strongly positive.[11]

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[8] Note that the paper posted on her website does not provide the database (perhaps in part because of census confidentiality), making verification difficult.

[9] They state: "Even research institutes, hospitals, schools, banks, law firms, government departments, and restaurants use imported Chinese made laptops, desktop computers, electric cables, communication devices, steel parts, tables and chairs, light bulbs, bed sheets, uniforms, or wash towels." (p. 4).

[10] Their tables 8 and 13 respectively. The robustness test eliminates intermediate inputs along the diagonal of the input-output table to avoid double-counting.

[11] Some of their specific estimates strain credulity, however. Thus, they find that downstream real wage growth rises by 8.5% *a year*, and that "The overall effect of trading with China is a boost to the real wage growth by 4.9%" (p. 24). Few readers will agree with them that real wages in the United States rose by 95 percent from 2000 to

Manufacturing versus Total Employment

The focus in the China shock literature has been primarily on manufacturing, and on employment rather than welfare including consumer benefits. The salience of manufacturing reflects a widespread view that manufacturing jobs are better than jobs available in the service sector for workers of comparable education, as well as the fact that disruption effects tend to be geographically concentrated in (old) manufacturing towns.

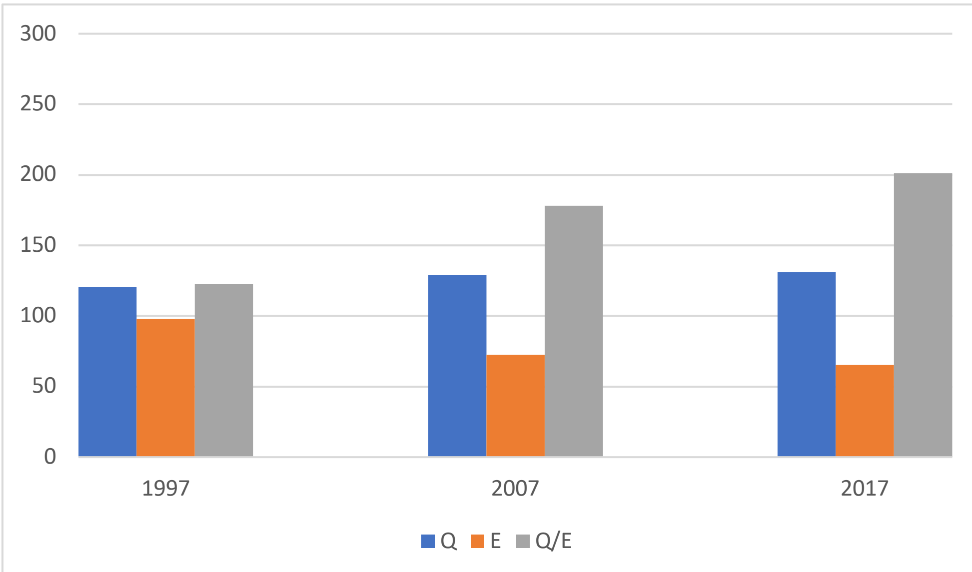
It should be kept in mind, however, that a shock on the order of 1 million or even 2 million manufacturing jobs would have been modest relative to employment in the economy as a whole, which stood at 137.2 million in 2000 and 150.5 million in 2017 (BEA, 2018c). A shift of about one percent of the total labor force from manufacturing to other sectors should not have been difficult in the aggregate even though it was disruptive in some local labor markets concentrated in the manufacturing sectors affected.

Similarly, it is important to recognize that manufacturing output continued to rise over this period, rather than being decimated by imports, and that the substantial reduction of manufacturing employment after 2000 reflected a strong increase in productivity per worker rather than a collapse in production. Figure 1 reports manufacturing output, employment, and output per worker in 1997, 2007, and 2017 as indexes against their respective levels in 1987. From 1987 to 2017, manufacturing output rose by about 30 percent, but productivity gains boosted output per worker by about 100 percent. As a result, employment fell by 35 percent. It should also be kept in mind that the job loss estimates in the China shock literature typically make no allowance for induced policy changes that seek to preserve full employment and hence tend to translate the ex-ante reduction in jobs into ex-post offsets from increased employment outside manufacturing.

2014 (=1.049^{14}) thanks to trade with China, implying that real wages would have fallen by half from their actual 2014 level without China's help.

Figure 1

US Manufacturing Output (Q), Employment (E), and Output per Worker, 1997-2017
(Index, 1987 = 100)



Source: Calculated from BEA (2018b, c; 2019c)

An Input-Output Labor-Accounting Approach

The literature on the China trade shock has been dominated by statistical inference. The search for sufficient observations, in a context with only a few annual data points at the aggregate level for manufacturing and imports from China, has added to the indirect nature of the analysis, particularly through recourse to cross-sectional geographic data. A further layer of indirection has arisen from the use of instrumental variables.

There is a much more direct approach: the use of input-output analysis incorporating sectoral labor coefficients. This "input-output labor-accounting" (IOLA) approach has the additional merit of forcing careful attention to the counterfactual implicit when imputing the consequences of China trade. The literature to date tends to give too little attention to the meaningful counterfactual; that is, what would have been the outcome after taking account of induced effects that partially offset the direct impact of higher imports from China.

The input-output approach takes the Leontief structure of the economy as the point of departure. In this framework, the vector of gross output in each of the economy's *n* sectors must be sufficient to provide intermediate inputs needed in the sector itself and in other sectors, as well as final demand (consumption plus investment plus government use, plus exports but minus the amounts provided by imports). Fixed coefficients of intermediate requirements are represented by the input-output matrix $\boldsymbol{B}$, of the dimension $n \times n$ and with element b_{ij} calculated as the ratio of inputs from sector *i* to gross output in the using sector *j*. The vector of gross output then equals the vector of final demand pre-multiplied by the inverse of the matrix ($\boldsymbol{I} - \boldsymbol{B}$), where $\boldsymbol{I}$ is the identity matrix (with unity at each diagonal element and zeroes otherwise).

The China shock amounts to a surge in imports from China, almost entirely in the subset of sectors representing manufacturing. The impact of this surge on domestic production at the level of each sector is then given by the vector of changes in gross output. This vector is driven by the vector of changes in trade associated with the China shock. Denoting the counterfactual as "*Cf*", actual outcomes as "*A*," and "Δ" as the change from the base period to the terminal period being considered, then the vector of changes in sectoral gross output in the counterfactual in comparison with the actual outcomes is estimate as:

$$1)\;\; \underset{nx1}{(\Delta \boldsymbol{Q}_{Cf} - \Delta \boldsymbol{Q}_{A})} = \underset{nxn}{(\boldsymbol{I} - \boldsymbol{B})^{-1}} \times \underset{nx1}{([\Delta \boldsymbol{X}_{Cf} - \Delta \boldsymbol{X}_{A}] - [\Delta \boldsymbol{M}_{Cf} - \Delta \boldsymbol{M}_{A}])}$$

where $\boldsymbol{Q}$ is gross output, $\boldsymbol{X}$ is exports, and $\boldsymbol{M}$ is imports.

The final expression in equation 1) indicates that in the counterfactual, final demand for domestic output would have been larger by the amount of the surge in imports that would have been avoided. That is, in the counterfactual of no China shock, the rise in imports would have been smaller than actually occurred, leaving more room for an increase in domestic output. The penultimate bracketed expression indicates that this increase of domestic demand from lower imports would have been offset to the extent that exports in the counterfactual would have been lower than actual exports because of incremental exports induced by the shock. These trade shocks are identified at the sectoral level, generating a vector of counterfactual changes in net final demand, which in turn generate the counterfactual vector of changes in domestic output.

The following calculations examine five counterfactuals in successive, additive layers of effects. In the Naïve Counterfactual, the entire increase in US imports from China, from 2000 to 2016, is assumed not to have occurred. Then Counterfactual 1 (Cf1) allows for "normal" increase in imports from China, by no more than the same proportion as the increase for imports from all areas. The next counterfactual, Cf2, adds the consideration that some portion of rising imports from China did no more than replace increases that otherwise would have occurred in imports from other competing economies. Counterfactual 3 (Cf3) then turns to the export side and considers that the rise in US exports to China also experienced a "shock" and would almost certainly would have been smaller in the absence of the China shock on the import side. Finally, Cf4 adds the consideration that China likely imported more from other countries than it would have in the absence of the surge in its earnings on exports to the United States, and these third countries in turn likely increased their imports from the rest of the world including the United States (triangular trade).

Naïve Counterfactual: No Increase in Imports from China – In the "Naïve Counterfactual," the entirety of the increase in imports from China is treated as the shock, and there are no offsetting changes in other US imports or exports. Table 1 reports the increases in US imports from China from 2000 to 2016, with the 2000 values inflated to 2016 prices using the personal consumption expenditure (PCE) deflator (FRED, 2018a). The data are for the 19 manufacturing sectors in the 71-sector input-output table.[12]

When the vector of changes in imports shown in the final column of table 1 is multiplied by the 71-sector inverse (***I – B***) matrix as in equation 1), with the vector ($\boldsymbol{\Delta X_{Cf}} - \boldsymbol{\Delta X_A}$) set to zero, the results of this Naïve Counterfactual (NCf) are that total gross output for all sectors rises by 2.0 percent.[13]

The consequences of the China shock for employment in the NCf are then obtained by multiplying the change in gross output in each sector by the sector's labor coefficient, estimated as the ratio of employment to gross output. Appendix E reports these coefficients for 2016. The median labor coefficient for all sectors is 3.53 thousand workers per billion dollars of gross output.[14] For the NCf, multiplication of the changes in final demand for each manufacturing

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[12] The share of China in total imports in each sector is calculated from UN (2018). These shares are applied to the corresponding sectoral total imports reported in the "use" input-output table for 2016 (BEA, 2019a).
[13] From \$32.72 trillion to \$33.37 trillion. Note that the model base, calculated as $\boldsymbol{Q} = (\boldsymbol{I}-\boldsymbol{B})^{-1}\boldsymbol{F}$ where ***B*** is the matrix of intermediate input coefficients calculated from BEA (2019a) and ***F*** is the vector of final demand (consumption + investment + government + exports – imports) from the same source, is extremely close to the simple sum of actual reported gross output by sector (\$32.78 trillion). All comparisons are against the model base.
[14] The median is 3.07 thousand jobs per billion dollars gross output for manufacturing, 3.06 for all goods, and 4.36 for services.

sector (table 1) by the sector's labor coefficient yields a total of 1.22 million additional direct jobs in manufacturing that would have been present in the absence of the absence of the China shock. The corresponding total direct and indirect jobs after applying intermediate requirements (equation 1) would have been 1.64 million in manufacturing and 2.23 million for the economy as a whole. Compared to the shock of $352 billion to final demand (table 1), in the aggregate the labor shock represented a combined direct and indirect labor requirement of about 6.3 thousand jobs per billion dollars of final demand.

Table 1
US Manufacturing Imports from China
(Million dollars at 2016 prices)

Sector	I-O code	Description	2000	2016	Change
8	321	Wood products	1257	4803	3546
9	327	Nonmetallic Mineral products	3875	8180	4305
10	331	Primary metals	2894	5596	2702
11	332	Fabricated metal products	4633	20314	15681
12	333	Machinery	5900	25518	19618
13	334	Computer and electronic prods.	35659	192405	156746
14	335	Electrical equip., appliances	6087	35963	29876
15	3361MV	Motor vehicles and parts	1583	14984	13401
16	3364OT	Other transportation equip.	1012	2582	1570
17	337	Furniture	5598	18808	13210
18	339	Miscellaneous manufacturing	22061	39778	17717
19	311FT	Food, beverage, tobacco prod	771	3871	3100
20	313TT	Textile mills	1414	9863	8449
21	315AL	Apparel, leather products	26729	61092	34363
22	322	Paper products	1275	4772	3497
23	323	Printing	309	1224	914
24	324	Petroleum and coal products	483	817	333
25	325	Chemical products	3012	16033	13021
26	326	Plastics and rubber products	5499	15717	10218
		Total	130049	482318	352268

Source: Calculated from UN (2018), BEA (2019a), and FRED (2018a)

Counterfactual 1: Plus "Normal" Import Growth from China – The first step toward a more realistic counterfactual is to recognize that even if there had been no notable shock, imports from China could have been expected to rise proportionately along with overall US imports. Total US imports of manufactures were $1.06 trillion in 2000; China accounted for $97.6 billion, or 9.18 percent of the total.[15] If this share had remained constant, with total manufactured imports at

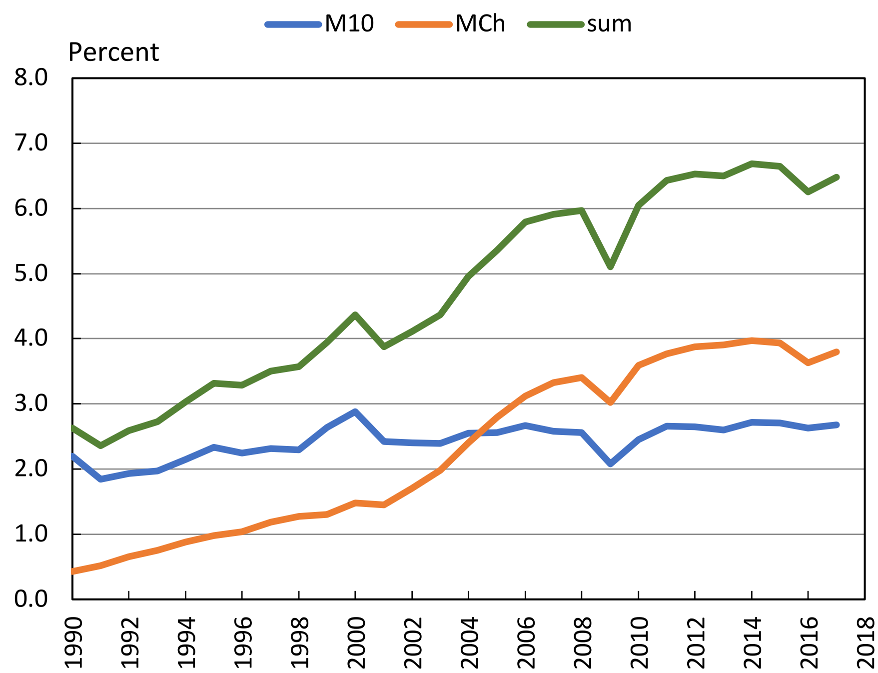
[15] Calculated from UN (2018) and BEA (2019a).

$1.85 trillion in 2016 the amount from China would have been only $169.9 billion instead of $482.3 billion. At 2016 prices the increase from 2000 to 2016 would have been only $312.4 billion instead of $352.3 billion. On this basis, the first step in refining the counterfactual multiplies all results of the naïve counterfactual by the fraction 0.887 (= 312.4/352.3). The corresponding Counterfactual 1 (Cf1) yields China shocks of 1.08 million direct manufacturing jobs, 1.46 million total manufacturing jobs including indirect, and total direct and indirect jobs for all sectors of 1.98 million.

Substitution of Imports from Other Countries

As emphasized by Levy (2016), a major portion of increased imports from China represented substitution of imports from other emerging market and newly industrialized economies. Figure 2 shows imports from China and a group of 10 major competing economies over the period 2000-2017, as a percent of US total consumption (in GDP) during 2000-2017. The competing economies include seven emerging market economies (Brazil, India, Indonesia, Malaysia, Philippines, Thailand, and Vietnam) as well as three newly industrialized economies (Korea, Singapore, and Taiwan).[16]

Figure 2
Imports as a percent of US Consumption: China and 10 Competing Economies[a]



a. Brazil, India, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, and Vietnam.

Source: calculated from BEA (2018a), BEA (2018f), and IMF (2018c)

[16] We omit Mexico from this group of competing economies because of major changes in US-Mexico trade in this period associated with the 1994 North American Free Trade Agreement.

Figure 2 shows that total imports from China and this group of 10 has risen from about 2.5 percent of US total consumption in 1990-91 to about 4 percent by 2000-01 and about 6 percent by 2007, but has plateaued at about 6.5 percent since 2011. Imports relative to US consumption have stayed at a plateau in the past 7 years not only for the competing 10 economies but also for China.

In contrast, from 1990 through 2007 there was a sharp rise in China's share of these imports. From 1990-91 to 2000-01, imports from the 10 competitors rose from 2.02 percent of US consumption to 2.66 percent, representing an annual increase by 0.064 percent of US consumption. If this trend had continued through 2007, imports from these countries would have reached 3.11 percent of US consumption. Instead, the share of these imports in US consumption *fell* to 2.58 percent, a decline of 0.53 percentage point. In comparison, the share of imports from China in US total consumption rose from 1.47 percent in 2000-01 to 3.33 percent in 2007, an increase of 1.86 percentage point. The implication is that 0.53/1.86 or 28.5 percent of the China shock from 2000 to 2007 was a substitute for imports from close competitors. On this basis, a reasonable gauge of the substitution effect is that *about one-fourth of the rise in US imports from China was offset by a reduction of imports from competing emerging market and newly industrialized economies* from levels those imports would have reached in the absence of the surge from China.

Counterfactual 2: Plus Higher Imports from China's Competitors – The next step in refining the counterfactual, to arrive at Counterfactual 2, is thus to cut by one-fourth the sectoral demand shock estimates of Cf1. Thus, whereas Cf1 had already cut the China import shock from $352.3 billion (table 1) to $312.5 billion (= 0.887 x 352.3), the additional import-switching consideration of Cf2 cuts the impact by an additional 25 percent to $243.3 billion (= 0.75 x 312.5). When this additional cut is imposed on each sectoral import shock and the resulting revised vector of ($\boldsymbol{\Delta M_{Cf}} - \boldsymbol{\Delta M_A}$) is applied to equation 1, the employment impact estimates shrink to the following: 812,000 direct manufacturing jobs; 1.09 million manufacturing jobs including indirect; and 1.48 million total jobs in all sectors.

Additional Export Jobs Associated with the China Shock

Measurement of the impact of increased trade with China on US manufacturing employment is incomplete if it excludes jobs gained from increased exports, both directly to China and indirectly to other countries as a consequence of China's re-spending export earnings on purchases from other countries that in turn purchase imports from the United States. US exports of goods to China rose from $16.4 billion in 2000, or 2.1 percent of total US exports, to $115.9 billion in 2016. (BEA, 2018a).

Counterfactual 3: Plus More Normal Growth of US Exports to China – The third counterfactual posits that in the absence of the shock to US-China trade, US exports to China would have remained at an unchanged share of 2.1 percent of total US exports. On this basis, exports to China would have been only $30.6 billion in 2016. Thus, in counterfactual 3 (Cf3), in addition to the elements of Cf2 there is a decline of $85.3 billion in US exports in 2016 from their actual level.

The calculations distribute this decline across sectors in accordance with sectoral shares in US exports to China in 2016.[17]

When the loss of about $85 billion in 2016 US exports to China in 2016 is incorporated into the input-output analysis, Cf3 yields the result that the total counterfactual gain in US jobs shrinks further, to 654,000 direct manufacturing jobs, 816,000 direct plus indirect manufacturing jobs, and 930,000 total direct and indirect jobs for the economy as a whole. In this result, the economy-wide job impact is considerably smaller relative to the impact in manufacturing, because the losses in agricultural exports partially offset gains in manufacturing.

Counterfactual 4: Plus Reduction in Induced US Exports to Other Countries – The expansion of China's trade also contributed to an indirect expansion of US exports to other countries. China's trade with the US is highly triangular, in the sense that it tends to export to the United States and import from other countries, which then in turn tend to import from the United States. Table A.1 in Appendix A shows country shares in China's imports in 2007 for its 43 largest trading partners, as well as the 2007 US share in imports of each of those countries. For each country, the product of these two shares yields a "reflection ratio" indicating the fraction of increased imports of China from those countries that is likely to be re-spent on imports from the United States. Aggregating these ratios gives 8.53 percent as the overall reflection ratio from increased Chinese imports to additional US exports to China's other trading partners.

China's total exports rose from $249 billion in 2000 to $2.14 trillion in 2016; its imports rose from $225 billion to $1.59 trillion (IMF, 2018c). At 2016 prices (again using the US PCE deflator), the 2000 base was $332 billion for exports and $300 billion for imports. On this basis, China has tended to re-spend 71 percent of its export earnings on imports (with the residual going mainly to a large buildup in reserves).

The decline in China's exports to the United States represented by Counterfactual 1 amounts to $312 billion. This decline would have induced a reduction in China's imports from all countries by $222 billion in China's 2016 imports (71 percent of the reduction in its exports to the US). The portion associated with imports from the United States is already addressed in Counterfactual 3. The US share in China's imports in 2016 was 10 percent, so the Counterfactual 4 reduction in China's imports from other countries would be 90 percent of $222 billion, or $200 billion. The US reflection ratio of 8.53 percent, applied to this base, generates losses of US exports to other countries (excluding China) of $17 billion. This total is distributed across I-O sectors in proportion to their shares in total US exports (calculated from UN, 2018; BEA, 2019a). Applying the input-output analysis of equation 1), Counterfactual 4 further shrinks the US job gains from avoidance of the China shock, to the following magnitudes: direct manufacturing, 617,000 jobs; direct plus indirect manufacturing, 755,000 jobs; and total for the economy, 825,000 jobs.

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[17] Calculated from UN (2018) and BEA (2019a). Leading I-O sectors were farms (18.4 percent), machinery (17.7 percent), electrical equipment (13.6 percent), motor vehicles (11.8 percent), and chemical products (13.6 percent).

Counterfactuals Summary

Table 2 summarizes the results of the successive counterfactual calculations. The final rows indicate the total job impacts of each counterfactual in three concepts: direct manufacturing jobs lost, indirect plus direct manufacturing jobs lost, and total jobs lost after including direct and indirect effects in non-manufacturing sectors. As shown, whereas the naïve counterfactual indicates a direct and indirect loss of 1.64 million manufacturing jobs, the preferred counterfactual 4 (Cf4) shrinks this estimate to 755,000 jobs. The shrinkage is even greater for total jobs including direct, indirect, and other sectors: from a total of 2.2 million jobs in the naïve counterfactual to 825,000 in Cf4, reflecting the sacrifice of export jobs (especially in agriculture) in this more complete counterfactual.

The table reports the impact on total jobs by individual manufacturing sectors as well as broader aggregates of non-manufacturing sectors in the 71-sector input-output table. Incorporation of export losses in Cf3 and Cf4 turns the impact of avoiding the China shock from significant job gains in the naïve counterfactual to significant losses in agriculture, mining, machinery, automobiles, and food, beverages, and tobacco. Sizable reductions in potential job gains from avoiding the China shock are also evident in the transit from the naïve counterfactual to counterfactual 2 which takes account of switching of imports from competing economies. These differences are most notable for computers and electronics (a decline of job gains from 481,000 to 361,000 in the shift from Cf1 to Cf2) and in apparel and leather products (a decline from 260,000 to 195,000). There are also large declines in the extra jobs in professional, scientific, and administrative services in the successive counterfactuals (from 210,000 extra jobs in Cf1 to 158,000 in Cf2 taking account of switching from imports from competing countries, and to 73,000 by Cf4 incorporating export losses).

A possibly counterintuitive finding in table 2 is that for key service sectors, such as wholesale and retail trade, and professional services, the employment effect of avoiding the China shock is estimated as being positive, even though the shock would have reallocated labor from manufacturing to these sectors so avoiding the shock would have done the opposite. The explanation of this paradox is that the partial equilibrium estimates of table 2 do not hold the economy-wide employment constant, but instead implicitly allow total employment to rise as a consequence of avoiding the shock. This outcome reflects the fact that the estimates do not take account of induced macroeconomic policy changes. From this standpoint, all of the counterfactuals tend to exaggerate the additional employment that would have been possible through avoiding the China shock. Thus, in the naïve counterfactual, total gross output is 2 percent larger than in the actual 2016 outcome. It is likely that this much pressure on capacity would have meant greater inflationary pressure and some offsetting tightening of monetary policy. Even in Cf4 the increment to total gross output is 0.6 percent, exerting some albeit more modest macro pressure for monetary tightening.

The estimates of table 2 overstate job losses because they do not include increased activity in downstream sectors that benefitted from cheaper inputs as a consequence of greater availability of imports from China. As noted above, Wang et al (2018) emphasize that these gains were large. An additional analysis of downstream effects is incorporated below. Working in the opposite direction, the estimates of table 2 tend to understate the size of the job loss in the important sector of computers and electronics products, where imports from China tend to be concentrated in subsectors that are more labor intensive than for the aggregate 3-digit input-output code (334). A special calculation for this sector is thus also added.

Table 2
Employment by Sector, 2016, and Change by Counterfactual
(1,000 jobs)

I-O Sector		Actual	Change: Naive	Cf1	Cf2	Cf3	Cf4
1, 2	Agriculture	1417	31.2	27.7	20.8	-58.9	-65.2
3-5	Mining	611	7.0	6.2	4.7	-2.6	-4.4
6	Utilities	554	7.3	6.5	4.9	1.8	1.3
7	Construction	6883	7.0	6.2	4.6	1.0	0.3
8	Wood products	391	28.2	25.0	18.8	5.6	4.5
9	Nonmetallic Mineral products	407	23.5	20.9	15.6	10.4	9.2
10	Primary metals	374	50.5	44.8	33.6	13.8	8.6
11	Fabricated metal products	1420	129.5	114.8	86.1	55.4	48.1
12	Machinery	1073	76.7	68.0	51.0	-5.3	-15.9
13	Computer and electronic prods.	1048	542.6	481.3	361.0	347.9	344.6
14	Electrical equip., appliances	382	109.1	96.7	72.5	29.7	21.0
15	Motor vehicles and parts	945	32.2	28.5	21.4	-1.7	-5.7
16	Other transportation equip.	681	5.0	4.4	3.3	2.7	1.7
17	Furniture	391	74.9	66.4	49.8	48.4	47.7
18	Miscellaneous manufacturing	592	69.1	61.3	46.0	42.9	40.6
19	Food, beverage, tobacco prod	1798	12.5	11.1	8.3	-4.9	-7.8
20	Textile mills	230	75.8	67.3	50.5	46.2	44.9
21	Apparel, leather products	159	293.3	260.2	195.1	191.0	189.7
22	Paper products	370	18.3	16.3	12.2	3.3	1.8
23	Printing	448	7.8	6.9	5.2	3.3	2.8

Table 2, continued

I-O Sector		Actual	Change: Naive	Cf1	Cf2	Cf3	Cf4
24	Petroleum and coal products	111	0.9	0.8	0.6	0.0	-0.3
25	Chemical products	813	39.1	34.7	26.0	3.2	-1.5
26	Plastics and rubber products	702	54.8	48.6	36.4	23.8	20.7
27-32	Wholesale & retail trade	21863	119.0	105.5	79.1	34.2	25.8
33-39	Transportation	5020	65.4	58.0	43.5	19.7	15.1
40-43	Information	2817	6.2	5.5	4.1	2.1	1.7
44-50	Finance, Insurance, Real Estate	8324	37.6	33.4	25.0	10.1	7.3
51-56	Professional, scientific, admin.	20210	237.2	210.4	157.8	87.5	73.1
57	Education (a)	3608	0.8	0.7	0.5	0.2	0.2
58-61	Health, social assistance	19205	0.0	0.0	0.0	0.0	0.0
62-63	Arts, entertainment	2281	2.0	1.8	1.3	0.6	0.5
64-65	Accomodation, food svcs	13420	27.5	24.4	18.3	8.5	6.7
66	Other private services	7061	28.8	25.5	19.2	8.6	6.5
67-71	Government (b)	24585	6.3	5.6	4.2	1.7	1.3
	Total	150194	2227.2	1975.6	1481.7	930.2	825.2
	Mfg total	12335	1643.8	1458.1	1093.6	815.5	754.9
	Mfg dir.		1220.6	1082.7	812.0	653.7	617.2

a. Excluding state & loc. Govt.
b. Including education

Decomposing the Large Shock in Computers and Electronics

As shown in the final column of table 2, just two of the 19 manufacturing sectors account for almost two-thirds of the total China shock: computers and electronics products (345,000 jobs) and apparel and leather products (190,000 jobs). Whereas the large impact in apparel is consistent with intuition regarding competition from labor-intensive imports, the even larger impact in computers and electronics is less so, and warrants further examination.

Imports of computer and electronics products (NAICS 334) amounted to $186.1 billion in 2016, or 40 percent of total US imports of goods from China that year. It should thus not be surprising that approximately this same percent of the total impact of the China shock on jobs is also located in this industry. As noted earlier, Caliendo, Dvorkin and Parro (2019) also identify computers and electronics as the sector with the largest job loss attributable to the China shock (25 percent of the total). For the estimates here, a reasonable question is whether the use of a single labor coefficient for this large aggregate sector may misrepresent the impact of the imports from China because of compositional effects.

As it turns out, imports from China in this aggregate sector are more concentrated in computer manufactures (subsector 3341) than is domestic output, whereas the reverse is true for electronic instruments (subsector 3345). The labor intensity of the computer subsector is considerably larger than the average for the aggregate sector 334, whereas the labor intensity of the electronics instruments subsector is lower than the average. After taking account of corresponding labor intensities and sectoral composition of the four other subsectors, the weighted average labor intensity of imports from China is 19.2 percent higher than the average for US domestic output.[18] If this higher labor intensity is applied to the $102.5 billion increase in 2016 domestic demand for the broad sector in Cf4, the effect is to boost the estimate of the job loss by 60,000. This more detailed examination of the most important sector thus boosts the size of the estimate, from 755,000 manufacturing jobs (direct and indirect) to 815,000; and from a total of 825,000 jobs in all sectors to a total of 885,000.[19]

Downstream Job Creation from Cheaper Intermediate Inputs from China[20]

The approach of input-output labor-accounting used in this study, as a more direct alternative to cross-sectional statistical inference, can also be used to examine the magnitude of downstream jobs created by the China shock. Availability of imports from China for use as intermediate inputs would have tended to reduce the price of inputs needed by downstream

[18] This disaggregation applies more detailed sectoral labor data available in BLS (2019).
[19] In the estimates using the aggregated sector 334, 91.5 percent of the job impact is found to be "direct," namely, the product of the change in final demand for the sector multiplied by the sectoral labor coefficient, as opposed to "indirect" for induced intermediates. This same ratio is applied to the 60,000 job impact increment from sectoral decomposition for purposes of the direct-indirect detail shown in table 3 below.
[20] The downstream estimates of this section, and further details in Appendix F, are included for the first time in the September 2019 revision of this working paper.

sectors. Lower prices would have meant greater demand and hence output in each using sector. The increase in output would have increased employment.

The Bureau of Economic Analysis (BEA, 2019d) has developed data for imported intermediate goods by using sector, available for 2012 at a detail level of 405 input-output sectors. Define this matrix of intermediate imports as $\boldsymbol{M}^{Int}$. Data on imported intermediate inputs are not available separately for imports from China alone. However, if one assumes that for any given product the typical China share in use as an intermediate good is equal to the typical China share in total imports for the category in question, it is possible to approximate the input-output matrix of imports from China used as intermediate inputs into production.

Let ϕ_i be the share of China in total imports of sector i goods. Define $\boldsymbol{\Phi}$ as a vector containing these shares, and define $\boldsymbol{\Phi}^D$ as the corresponding diagonal matrix with vector $\boldsymbol{\Phi}$ along its diagonal and zeroes otherwise. Then the estimated matrix of imported goods from China used as intermediate inputs into the using input-output sectors becomes:

$$2)\ \underset{k \times k}{M_C^{Int}} = \underset{k \times k}{M^{Int}} \times \underset{k \times k}{\boldsymbol{\Phi}^{D}}$$

The potential for cheaper intermediate inputs from China to benefit a particular using sector "j" in the input-output table will depend on the sum of sector j's intermediate inputs from China from all supplying sectors. Define the sensitivity of each sector to intermediate imported inputs from China as z_j. Then:

$$3) z_j = \left[\sum_{i=1}^{k} m_{ij}^{C}\right] / Q_j$$

where Q_j is gross output in the using-sector j. That is, the sensitivity measure z is the ratio of the value of all intermediate inputs imported from China to the gross value of output in the using sector j.

Suppose the price of the Chinese input is typically cheaper than the price for alternative domestic or foreign supply by the proportion π. Then the availability of Chinese supply for intermediate inputs reduces the output price of good j by the proportion $z_j\pi$. Suppose the price elasticity of demand for product j is η_j. Then the corresponding increment in demand for the product thanks to its relatively cheap inputs from China will be $\Delta D_j = z_j \pi \eta_j$. If one assumes for simplicity that all products have a price elasticity of demand of -1, then $\Delta D_j = z_j\pi$.[21]

[21] Both π and η are negative, so ΔD_j is positive.

The impact of downstream benefits from cheaper intermediate inputs from China will thus be a vector of increased demand, $\boldsymbol{\Delta D}$.[22] The corresponding change in gross sectoral output will then be determined as before by pre-multiplying the **I-B** inverse matrix. Applying sectoral labor coefficients to the vector of change in gross output will show the employment gains induced by downstream benefits of the China shock. After aggregating the sectoral changes in demand to the same level of detail as available for sectoral labor coefficients, the resulting changes in gross output induced by downstream effects will be:

$$4)\ \underset{nx1}{\boldsymbol{\Delta Q}_{ds}} = \underset{nxn}{[\boldsymbol{I}-\boldsymbol{B}]^{-1}}\underset{nx1}{\Delta \boldsymbol{D}}$$

With estimates of the changes in sectoral gross output in hand, the corresponding changes in employment can be calculated as before, applying sectoral labor coefficients. However, two further steps are required to arrive at the downstream job creation from the China shock. First, the calculation so far is applied to the entirety of imports from China in 2016. However, only that portion that represents the relevant shock should be included. The germane counterfactual for this purpose is Counterfactual 1: increase in imports (at 2016 prices) from 2000 to 2016 above and beyond what would have been expected if China's share of total US imports had remained constant. This increment amounts to \$312.4 billion, or 65 percent of total actual imports from China in 2016. Accordingly, the final output and labor effects are set at 65 percent of the magnitudes calculated using the actual 2016 trade flows.

The second key step is to assign a plausible parameter value to π, the proportion by which Chinese intermediate inputs are cheaper than alternatives from other sources (including domestic US sources). The calculations set this margin at 20 percent. This fraction seems more likely to be understated than overstated.[23] However, a uniform price elasticity of demand of unity would likely be biased in the opposite direction, exaggerating rather than understating effects.

The overall result of this exercise is that *downstream employment effects* of the China shock from 2000 to 2016 amounted to *136,000 jobs created*, of which *41,000* were in manufacturing and 95,000 were in non-manufacturing. Further details of the downstream calculations, and a description of the data sources, are presented in Appendix F. Inclusion of the downstream job gains reduces the estimate of US job losses from the China shock during 2000-2016 to 774,000 jobs in manufacturing and only 749,000 jobs in all sectors. In non-manufacturing, employment gains exceeded losses by 25,000 jobs.

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[22] This vector, to be used as a column vector for change in final demand, is the transpose of the horizontal row vector comprising ΔD_j, j=1,k.

[23] An extreme example is the iPhone, mainly manufactured and assembled in China. One technology expert has estimated that the cost of components in each iPhone would rise from \$190 to \$600 if they were produced in the United States. See Stacey Vanek Smith, "How Much Would an iPhone Cost If It Were Entirely Made in the U.S.?", *Marketplace*, National Public Radio, May 20, 2014.

Comparison to Other Estimates

Table 3 summarizes estimates in the recent literature for the impact of the China trade shock on US employment, especially manufacturing. The central estimate of this study uses the results for counterfactual Cf4 from table 2, combined with the special adjustment for sector 334 and the special estimate for downstream gains. Our central estimate is well below the AADHP estimate even for manufacturing alone, at a total of loss of 774,000 jobs versus 985,000 in AADHP. The difference is far larger for the impact on jobs in all sectors: 749,000 in this study versus 1,979,000 in AADHP. This comparison shows the importance of careful attention to the counterfactual. The AADHP framework is essentially Counterfactual 1 considered here.[24] In that counterfactual the estimates of the present study are larger than those of AADHP (manufacturing job loss of 1.46 million, total loss of 1.98 million; table 2).[25]

[24] They normalize by considering import penetration (import share in domestic absorption); Counterfactual 1 normalizes by holding China's share in imports constant.

[25] Comparison of the Naïve counterfactual (NCf) in table 2 to the AADHP estimate does suggest that the method used by them to estimate indirect effects tends to exaggerate. Thus, their ratio of the total-economy impact to the impact in manufactures is 2.0, whereas this ratio in the NCf is 1.35. AADHP use an indirect statistical regression approach with the instrumented China-exposure explanatory variable, far more circuitous than application of the $(\boldsymbol{I}-\boldsymbol{B})^{-1}$ matrix as done here.

Table 3

Alternative Estimates of US Jobs Displaced by the China Trade Shock
(1000)

Study	Approach	Period	Manufacturing	Total
ADH	Cross-section by US commuter zone change in manufacturing employment share in working age population regressed on base period exposure to imports from China; instrumental variable using China imports by other major economies	2000-2007	Preferred: 2,044 Conservative: 982	Not estimated
AADHP	Regresses growth across 392 manufacturing sectors against instrumented change in imports of corresponding products from China; incorporates indirect effects	1999-2011	985 Direct: 560 Indirect: 425	1,979
Pierce-Schott	Regresses growth of sectoral employment after 2000 to gap between Normal Trade Relations (NTR) and non-NTR tariff; emphasizes impact of US move to permanent NTR for China	2000-2007	Not reported	Not reported
Feenstra-Ma-Xu	Applies ADH parameters; finds that controlling for exogenous housing price changes cuts total job loss from 2.4 to 1.65 million	1990-2007	1,715	1,651
Caliendo et al	General equilibrium model including regional labor supply and migration response. Applies ADH instrument but finds that employment losses in manufacturing are exceeded by gains in non-manufacturing, with access to cheaper inputs from China	2000-2007	550	< 0
Wang et al	Adds indirect upstream and downstream impact to ADH approach of commuter zone exposure to China imports; finds large downstream benefits in non-manufacturing	2000-2014	No preferred estimate identified	
This study	Input-output labor-content accounting. Incorporates partial substitution for imports from other countries and induced exports (counterfactual 4, table 2), special adjustment (sector 334), and downstream job gains.	2000-2016	774 Direct: 672 Indirect: 102	749

ADH: Autor, Dorn, and Hanson (2013); AADHP: Acemoglu, Autor, Dorn, Hanson, and Price (2016); Pierce and Schott (2016); Feenstra, Ma, and Xu (2018); Caliendo, Dvorkin, and Parro (2019); Wang, Wei, Yu, and Zhu (2018)

Conclusion

We conclude that the loss of US manufacturing employment to the China trade shock over the period 2000-16 amounted to 774,000 jobs. Manufacturing employment fell from 17.3 million to 12.3 million over this period (BEA, 2018c). The China shock was thus responsible for 15.5 percent of this decline. This impact is far lower than the widely cited estimates of Autor, Dorn, and Hanson (2013, p. 2139), whose "preferred" estimate was that the China shock was responsible for 56 percent of the decline in US manufacturing employment from 2000 to 2007.[26] Our estimate of total US employment lost to the China trade shock, 749,000 jobs, is even further below the 1.98 million job loss as estimated by Acemoglu, Autor, Dorn, Hanson, and Price (2016).

The US-China trade war that began in 2018 is potentially the most severe disruption to open international trade since the 1930s. It is important that the economic analytics informing policy-making on US-China trade be as thorough and well-considered as possible. This study seeks to contribute to that effort.

[26] The authors also reported that even in their "more conservatively" estimated variant the China shock was responsible for 26 percent of the decline in this period (p. 2140). Their more conservative estimate shrank the main Instrumental variable coefficient estimate by the ratio of explained to total variance in the IV model. In their subsequent study with two additional co-authors (Acemoglu, Autor, Dorn, Hanson, and Price, 2016), the conservative method became the only method, but the total of manufacturing jobs lost remained about the same because of the new inclusion of indirect (intermediate input) jobs.

Appendix A

Reflection Ratio for US Exports to Other Countries Induced by Increased US Imports from China

Let $\Delta X_{C.U}$ be the increase in China's exports to the United States over a given period. Let λ_{MC} be China's marginal propensity to spend additional export earnings on additional imports. Let μ_{Ci} be the share of country *i* in China's imports. Let μ_{iU} be the share of the United States in the imports of country *i*. Then the additional US exports to other countries induced by an increase in US imports from China will be:

$$A.1)\ \Delta X_U^{ind} = \lambda_{MC} \times \Delta X_{C.U} \sum_{i \neq U} \mu_{Ci} \times \mu_{iU}$$

For each country *i* the product of the two parameters μ following the summation sign can be thought of as the "reflection ratio" for US exports with regard to increases in China's imports. For example, if Japan has a share of 14 percent in China's imports, and if the United States has a share of 12 percent in Japan's imports, then an increase of $1 billion in China's worldwide imports will induce an increase of $140 million in Japan's exports, and as Japan spends the additional export earnings on imports, the United States will experience an increase of 0.12 x $140 million = 16.8 million in its exports to Japan. The summation of these reflection ratios gives the overall US reflection ratio from increases in China's overall imports.

Table A.1 shows these trade shares and reflection ratios for the 43 largest trading partners of China in 2007, accounting for about 90 percent of China's imports. The summation indicates an overall reflection ratio of 8.53 percent for the United States, such that a $1 billion rise in China's imports induces a rise of $85.3 million in US exports to China's trading partners.

Table A.1
Reflection Ratio for Trading Partners of China in 2007

Trading Partner	China Import (Million $)	MCshr (%)	USctryshr (%)	ReflRatio (%)
Japan	133,903	14.01	11.62	1.628
Korea, Republic of	104,045	10.88	10.49	1.142
Taiwan Prov.of China	100,986	10.56	13.10	1.384
United States	69,998	7.32	0	0.000
Germany	45,422	4.75	4.51	0.214
Malaysia	28,737	3.01	10.84	0.326
Australia	25,758	2.69	12.83	0.346
Philippines	23,129	2.42	14.13	0.342
Thailand	22,652	2.37	6.82	0.162
Russian Federation	19,630	2.05	4.76	0.098
Brazil	18,342	1.92	15.50	0.297
Saudi Arabia	17,546	1.84	13.48	0.247
Singapore	17,520	1.83	12.48	0.229

EU ex 9	15,101	1.58	5.38	0.085
India	14,659	1.53	7.97	0.122
France	13,365	1.40	4.34	0.061
Iran, I.R. of	13,330	1.39	0.34	0.005
Angola	12,885	1.35	8.71	0.117
China,P.R.: Hong Kong	12,824	1.34	4.88	0.065
Indonesia	12,380	1.29	6.47	0.084
Canada	10,975	1.15	54.11	0.621
Chile	10,239	1.07	16.52	0.177
Italy	10,217	1.07	2.92	0.031
United Kingdom	7,784	0.81	7.40	0.060
Oman	6,719	0.70	5.78	0.041
South Africa	6,608	0.69	7.19	0.050
Kazakhstan	6,419	0.67	4.96	0.033
Argentina	6,313	0.66	12.00	0.079
Switzerland	5,872	0.61	5.81	0.036
Belgium	4,971	0.52	5.55	0.029
Netherlands	4,935	0.52	7.30	0.038
Spain	4,430	0.46	2.97	0.014
Peru	4,297	0.45	17.91	0.081
Sweden	4,153	0.43	3.11	0.013
Sudan	4,114	0.43	1.76	0.008
Finland	3,798	0.40	2.24	0.009
Mexico	3,260	0.34	49.53	0.169
Vietnam	3,214	0.34	2.71	0.009
United Arab Emirates	3,007	0.31	6.57	0.021
Congo, Republic of	2,828	0.30	1.84	0.005
Austria	2,465	0.26	2.22	0.006
Ireland	1,925	0.20	11.17	0.022
Yemen, Republic of	1,748	0.18	7.63	0.014
New Zealand	1,537	0.16	9.69	0.016
Subtotal	844,039	88.29		8.533
ROW	111,961	11.71		
Total	956,000	100.00		

Source: Calculated from IMF (2018c), Census(2019)

Appendix B

Regional Cross-Section Exposure Approach: Re-estimating and Updating ADH

Our principal estimates of the China shock are the results from counterfactual 4 (table 2 above) using the Input-Output Labor-Accounting (IOLA) method. However, because of the salience of the Autor, Dorn, Hanson (2013) estimates, this section presents a special examination, reformulation, and updating of those results.

Commuting Zone versus Industry -- A key feature of ADH is that its unit of observation is geographical: the commuting zone. This choice is well-suited to address a central focus of their paper: the disruptive impact of the China shock at the local level for communities with activity focused on manufactures imported from China. However, when used to arrive at aggregate estimates for US manufacturing jobs the geographical approach is subject to aggregation bias that overstates the impact for the US as a whole over time. The method applies a fixed set of industry weights in the base period (either 1990 for 1990-2000, or 2000 for 2000-2007) for the explanatory variable of exposure to imports from China. If there is a geographical shift in production of the goods that compete with China, toward other (for example, lower-wage) regions, the result will be to overestimate the decline in manufacturing employment associated with greater exposure to Chinese goods by not giving enough weight to the regions that benefitted from the shift.

In their subsequent paper with Acemoglu and Pierce (AADHP), the ADH authors implicitly recognize possible problems with the geographical cross-section approach by switching to the industrial sector as their unit of observation. AADHP examine the impact of the China shock on employment growth at the level of aggregate US employment in each of 392 manufacturing sectors, not the growth of manufacturing employment in 722 commuting zones. As shown in table 4 above, for the concept most directly comparable (direct job impact in manufacturing), this shift substantially reduces the estimate job losses (from a “conservative” 982,00 jobs for the period 2000-07 in ADH to 560,000 jobs for the period 1999-2011 in AADHP).

Instrumental Variable Issues -- A central issue in the ADH estimates is that they use imports from China into eight other advanced economies to create an instrumental variable for US import exposure to China. [27] They state: “… both US employment and imports may be positively correlated with unobserved shocks.”[28] The logic is apparently as follows. Suppose there is a demand shock that shifts US demand in the direction of goods that China tends to export to the United States. Then a reduction in US employment in such an industry in the presence of a shock to supply capability from China will be smaller than it would have been if there were no relative rise in demand for that product category. That is, the shift in demand toward that category

[27] ADH (2013, p. 2131). The other advanced economies are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.
[28] ADH (2013, pp. 2128-29).

provides additional jobs for workers in the sector who would otherwise have been displaced by the extra imports from China.

As it turns out, however, it is empirically not the case that such a shift in demand occurred. As shown in Appendix C, table C.1, there was actually a slight shift of demand *away* from goods relatively more important for imports from China, from 1990 to 2000. In particular, apparel accounted for 37 percent of imports from China in 1990 and 18 percent in 2000. US demand for apparel as a percent of total demand for manufactures fell by 1 percentage point during this period (from 8 percent to 7 percent). Applying the average China import weight of the two benchmark years, the shift in demand away from apparel imposed an adverse shock of 0.29 percentage point on demand for imports from China.[29] The largest positive shocks in demand were increases of about 3 percentage points each in computers and motor vehicles, but the presence of these sectors in imports from China was too small (only 5 percent for computers and 0.1 percent for motor vehicles) to obtain much of a boost from this demand shift.

A second issue regarding the IV estimates concerns the ADH (and later AADHP) approach of obtaining a conservative (or in AADHP, main) estimate by shrinking the estimated coefficient by the ratio of explained to total variance. This approach is not standard in IV estimates. The authors cite no prior literature applying it. The underlying logic of IV is that it is already supposed to be the best estimate of the exogenous influence of the explanatory variable, a better estimate than OLS using the raw explanatory variable. Shrinking down the IV estimate would seem to violate this premise.

Normalizing by Working Age Population versus Employment --Still another ADH effort to avoid endogeneity gives rise to an additional problem. Rather than use the change in manufacturing employment as a fraction of the employment base in each zone as their dependent variable, ADH use change in manufacturing employment as a fraction of the working age population (WAP) in the zone. They are concerned about using manufacturing employment in the denominator on both sides of the equation, considering that their right-hand side variable is the rise in exposure to imports from China per worker. However, it is not persuasive that using "workers" in the denominator on both sides would cause endogeneity. Studies of the response of agricultural yields to fertilizer, for example, will appropriately examine how many additional bushels of wheat per acre cultivated can be obtained from an additional ton of fertilizer per acre cultivated, and would be mistaken to substitute (for example) total farm size (including unplanted grazing area) in the right-hand side denominator in a pursuit of removing endogeneity. Moreover, there appears to be considerable noise in the ADH database regarding the implicit estimate of WAP (which is never explicitly reported).[30]

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[29] Use of the average for weighting is analogous to application of a Fisher ideal weight rather than a base period Laspeyres weight or an end period Paasche index weight.

[30] Contrary to what one might expect, one cannot obtain the ADH WAP simply by dividing the seeming number of manufacturing workers by the variable for the ratio of manufacturing workers to WAP. The variable "l_no_workers_totcbp" is the total number of workers employed in the zone in the initial year of the period (variable 16 or v16). The variable "l_shind_manuf_cbp" (v17) is the initial fraction of workers in the zone that is employed in manufacturing. The variable "l_sh_empl_mfg" (v24) is the initial share of working age population

Replication – Table B.1 reports the results of two tests using the database published online by ADH. The tests are for the change in manufacturing employment as a percent of working-age population (WAP) from 1990 to 2000, as the dependent variable; and change in the commuting zone's exposure to imports from China, divided by the initial total number of workers, as the independent variable. All regressions weight by the total population of each of the 722 commuting zones.

Table B.1

Change in Manufacturing Employment as Percent of Working Age Population
as a Function of Increase in Exposure to China Imports (1990 to 2000)

Regression	Coefficient	Statistic[31]	InstrVar
1	-0.888	-4.9 (z)	Yes
2	-0.237	-1.9 (t)	No

ADH: Autor-Dorn-Hanson database
InstrVar: instrumental variable using 2-stage least squares
Regressions are weighted by commuting zone population

The first regression successfully replicates the estimate of ADH (p. 2135). They report that in the decade 1990-2000, an increase of $1,000 (at 2007 prices, deflating by the PCE) per base-period worker in exposure to imports from China reduced the percent of working-age-population employed in manufacturing by 0.89 percentage point. Regression 2 uses the same left-hand side but directly uses the US import exposure data rather than the instrumental variable.[32]

The extremely large reduction in the absolute size of the coefficient on exposure to imports from China when using OLS rather than IV sharply contradicts the estimates in Appendix C showing that there was, if anything, a small demand shift *against* imports from China in the period 1990-2000. As a consequence, one should have expected use of the IV rather than OLS to *reduce* slightly rather than increase sharply the negative impact of China exposure on change in manufacturing employment. The implication is that the IV approach chosen by ADH exaggerates the labor shock. There is still a large exaggeration even if the replication estimate "1" in table B.1 is cut by half under the ADH argument that a "conservative' variant should be shrunk that much to capture only the exogenous effect of increased Chinese supply.

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employed in manufacturing. But WAP cannot be calculated from v16 x v17 /v24. Manufacturing employment in v17 refers to County Business Pattern (CBP) data (Census, 2018), which include workers of all ages. In contrast, v24 (which is the basis for the dependent variable v82) only refers to manufacturing workers of working age population, and is obtained from IPUMS (Ruggles et al, 2018), which has sectoral definitions that differ from CBP.

[31] Robust *t* and *z* statistics with 48 state clusters.

[32] The right-hand side is thus change in the commuting zone's weighted exposure to imports from China (based on its manufacturing industry composition compared to the profile of imports from China) from 1990 to 2000, normalized by commuting zone employment in 1990.

New Estimates for 2000-2016 --It is useful to examine a revised test for the direct impact of imports from China, and apply it to the period 2000-16. We use the same underlying databases as ADH and, like them, in this test we base the estimates on observations at the commuting zone level. A key difference is that we use ordinary-least-squares rather than instrumental variables. The approach here addresses the possible endogeneity question by applying a two-year lag for the independent variable. The regression test is of the form:

$$B.1) \Delta z_w = \alpha + \beta \Delta E_{-2}$$

The dependent variable, Δz_w is the change in manufacturing employment as a percent of working age population from "2000 to 2016", using 2000-01 and 2015-16 averages.[33] The independent variable, ΔE_{-2} is the change in per-worker commuting-zone exposure to imports from China from a lagged base of 1998-99 to 2013-14. The import exposure data are in thousands of 2007 dollars, deflating with the PCE index. The worker base used to normalize the right-hand-side variable is the number of workers in the commuting zone in 2007, approximately the midpoint of the period.[34]

As an alternative specification, the left-hand side refers to the change in manufacturing employment as a percent of employment (rather than working-age population), or Δz_e. The concern in ADH about having the denominator be the same (employment) on both the left- and right-hand sides is moot because the normalizing denominator on the right-hand side is for 2007 whereas the employment denominators on the left-side are averages for 2000-01 and 2015-16. Table B.2 shows the resulting estimates for the two specifications.

Table B.2

2000 to 2016 Change in Manufacturing Employment as a Function of
Change in Per-worker Exposure to Imports from China: 2000 to 2016

	% WAP	%EMP
Constant	-2.43 (-11.6)	-3.33 (-10.1)
Coefficient on Change in Import exposure[a]	-0.3237 (-6.3)	-0.4006 (-3.9)
R^2	0.186	0.112
Observations	722	722

[33] Except for WAP in the base period, which applies 2000 alone given IPUMS data limitations.

[34] Note that the County Business Patterns data on employment in the commuting zone database exclude most government workers, and as a consequence the aggregate employment in the database (like that in the ADH database) understates total employment by about 15 percent. Thus, in 2007 total US employment was 138.0 million; the total in the commuting zone database was 117.2 million. Most of the difference was from excluded government workers. There was a total of 22.2 million government workers in 2007 (FRED, 2018b). Note that the commuting zone database also excludes Alaska and Hawaii.

a. Thousands of 2007 dollars per commuting zone employment in 2007. WAP: working-age population; EMP: total employment

Robust t-statistics in parentheses. Regressions weight by commuting zone population in 2007.

In the first column, the estimate shows that from 2000 to 2016, manufacturing employment as a percent of working-age population fell by 2.43 percentage points plus an additional decline of 0.3237 percentage point for each thousand dollars (2007 prices) increase in per-worker exposure to imports from China. The second column shows the corresponding results when the dependent variable is change in manufacturing employment as a percent of total employment. Although the constant term as well as the coefficient on China-import exposure are both larger in this case, they apply to a smaller base (employment rather than WAP, and County Business Pattern employment rather than total employment).

The most relevant summary coefficient for comparison in the ADH study is their preferred estimate of -0.596 for the period 1990-2007 (p. 2137). By implication, the estimates in table B.2 confirm the expectation that the use of the instrumental variable in the ADH estimates causes a much larger impact coefficient.[35]

Table B.3 translates the estimates of table B.2 into estimated manufacturing jobs displaced by the direct effect of rising imports from China. The table shows two periods: 2000 to 2007, and 2000 to 2016. For comparison, the table also includes the ADH preferred estimate for 2000 to 2007, as well as the implied corresponding number for 2000 to 2016 (discussed above).[36]

Table B.3

Number of Manufacturing Jobs Lost to Direct Impact of Imports from China (1,000)

Period	ADH:	This Study: R1 (WAP)	R2 (Empl)
2000-07	2,044 [981]	1,126	824
2000-16	{2,860 [1,375]} e	1,656	1,202

Source: Author's calculations

ADH: Autor-Dorn-Hanson (2013). { … }e: imputed ADH estimate for 2000-16. […]: applying ADH shrinkage factor 0.48 associated with exogeneity argument

R1: this appendix, first regression, table B.2 R2: second regression, table B.2

[35] The directly comparable coefficient here is -0.3237, only 54 percent as large an impact as the ADH coefficient of -0.589. Although the coefficient in our preferred "percent employment" variant (final column) is larger at -0.4006, it applies to a considerably smaller base (employment rather than working age population).

[36] The base magnitudes for the calculations in the R1 and R2 columns are as follows. Working age population: 2000 = 181.0 million; 2007 = 197.2 million; 2016 = 207.4 million. Total employment in the County Business Patterns database: 2000 = 114.2 million; 2007 = 117.2 million; 2016 = 121.6 million. Change in total imports from China per total County Business Patterns employment in 2007: $1.756 thousand from 2000 to 2007 $2.467 thousand from 2000 to 2016. Thus, for 2000-2016, using R1, manufacturing jobs lost =– 0.3237 x 2.467 = –0.7986 percentage point applied to 207.4 million; using R2, = –0.4006 x 2.467 percentage point = 0.9883 percentage point applied to 121.6 million.

The main implication of the findings in table B.3 is that correction of the ADH estimates for possible IV bias and for more appropriate (employment) weighting substantially reduces their estimates of manufacturing job losses from the China shock. In the most direct comparison, for 2000-07 the estimate "preferred" by ADH is that 2.04 million manufacturing jobs were lost, whereas the lagged OLS, employment-weighted test in the final column places this estimate at only 824,000 jobs.

We remain skeptical of using the cross-section geographical approach to assess the impact of the China shock. As a consequence, we consider even the estimates of the final column of table B.3 to be mainly of methodological use rather than the most meaningful empirical estimate. Our preferred estimates are those of Counterfactual 4 reported in table 2 of the main text.

Finally, an important additional pattern in table B.3 is that all of the estimates show a smaller total decline by 2016 than would have been inferred from simple extrapolation of the decline in 2000-07. This slowdown reflects the fact that the absolute increase in imports from China was smaller in 2007-16 than in 2000-07. In 2007 dollars (deflating by the PCE index), US imports from China amounted to $117 billion in 2000, $323 billion in 2007, and $406 billion in 2016. The increase from 2007 to 2016 was only $83 billion, just 40 percent as large as the increase of $206 billion from 2000 to 2007. The emergence of an aggressive retaliatory trade confrontation with China in the 2016 presidential campaign and a trade war by mid-2018 may thus be seen as a substantially delayed reaction to the timing of the actual impact. This phenomenon is consistent with the fact that by 2016, China's overall external surplus (current account) was only 1.8 percent of GDP, far below the 9.9 percent of GDP reached in 2007 (IMF, 2018b). Similarly, whereas China had persistently intervened in exchange markets to curb the pace at which its currency appreciated in the period 2000-13, in 2014 and after it stopped intervening except in the opposite direction – to keep the currency from falling.[37]

[37] Thus, whereas China's external reserves rose from $169 billion in 2000 to $3.85 trillion in 2013, they were approximately unchanged in 2014 and fell to $3.23 trillion by 2017 (IMF, 2018a).

Appendix C

Influence of Changing Demand Composition on Imports from China

As discussed in Appendix B, ADH argue that the use of an instrumental variable for exposure to imports from China is necessary to address possible simultaneity caused by a shock to demand composition. A positive correlation between increased imports from China and an upward shift in demand for the type of goods produced by China would understate the adverse employment effect from the China supply shock alone, because the demand shift would create additional domestic jobs in the China-exposed sectors that mask the negative job impact from the China supply influence alone.

Table C.1 tests whether this concern is warranted. Using the same breakdown of manufacturing industries as applied in table 1 in the main text, the table shows the percentage distribution of domestic demand across manufacturing sectors in 1990 and 2000. Domestic demand is measured as Consumption plus Investment plus Government in the input-output tables for 1990 and for 2000 (BEA, 2018d,e).

The column reporting the change in these sectoral shares shows sizable swings in just a few sectors: computers and electronic products (+3 percentage points, from 1990 to 2000), motor vehicles (+3.35 percentage points), food and beverages (-3.83 percentage points), apparel and leather products (-1.05 percentage points), petroleum and coal products (-1.33 percentage points), and chemical products (+1.1 percentage points). The table also shows the share of each sector in imports from China in 1990 and in 2000. The final column uses the average of these shares for 1990 and 2000 to obtain a weighted average of the change in sectoral demand. For example, the average share of apparel in imports from China was 0.274, and multiplying this weight by the change of -3.83 percentage points for the share of apparel in total demand for manufactures yields a negative shock from demand shift for imports from China in that sector, amounting to -0.2861 percentage point. When these weighted shocks are summed over all manufacturing sectors, the result is a small net negative demand shock, amounting to -0.1283 percentage point.

Table C.1
Impact of Sectoral Domestic Demand Shock on Imports from China

Sector		SIC	Demand 1990		Demand 2000		Change	Share in MChina		Shift
			$ mn	%	$ mn	%	%	1990	2000	%
			A	B	C	D	E	F	G	H
321	Wood products	24	5,510	0.45	9,775	0.50	0.05	0.010	0.011	0.0005
327	Nonmetallic mineral products	32	4,528	0.37	7,476	0.38	0.01	0.017	0.026	0.0002
331	Primary metals	33	776	0.06	4,128	0.21	0.15	0.009	0.019	0.0021
332	Fabricated metal products	34	15,590	1.28	20,084	1.02	-0.26	0.030	0.038	-0.0087
333	Machinery	b	114,738	9.41	177,848	9.05	-0.36	0.043	0.064	-0.0193
334	Computer and electronic products	357	141,521	11.61	287,074	14.61	3.00	0.014	0.087	0.1512
335	Electrical equip.,appliances, and components	36	34,519	2.83	52,368	2.67	-0.17	0.158	0.239	-0.0330
3361MV	Motor vehicles, bodies and trailers, and parts	37	195,222	16.01	380,417	19.36	3.35	0.003	0.011	0.0241
3364OT	Other transportation equipment	37	51,491	4.22	70,170	3.57	-0.65	0.005	0.009	-0.0045
337	Furniture and related products	25	39,224	3.22	68,367	3.48	0.26	0.010	0.049	0.0078
339	Miscellaneous manufacturing	39	58,465	4.80	100,330	5.11	0.31	0.189	0.166	0.0551
311FT	Food and beverage and tobacco products	20,21	267,900	21.97	356,462	18.14	-3.83	0.011	0.006	-0.0320
313TT	Textile mills and textile product mills	22	21,148	1.73	22,124	1.13	-0.61	0.022	0.007	-0.0088
315AL	Apparel and leather and allied products	23,31	98,150	8.05	137,657	7.01	-1.05	0.369	0.178	-0.2862
322	Paper products	26	10,917	0.90	16,346	0.83	-0.06	0.007	0.010	-0.0005
323	Printing and related support activities	27	2,088	0.17	4,140	0.21	0.04	0.004	0.007	0.0002
324	Petroleum and coal products	29	72,070	5.91	90,005	4.58	-1.33	0.000	0.001	-0.0008
325	Chemical products	28	72,369	5.94	138,249	7.04	1.10	0.021	0.017	0.0206
326	Plastics and rubber products	30	12,938	1.06	21,991	1.12	0.06	0.078	0.054	0.0038
			1,219,164	100	1,965,011	100		1	1	-0.1284

Demand = Consumption + Investment + Government
MChina = imports from China
Note: H = E x (F+G)/2
Source: calculated from BEA (2018d,e) and UN (2018)

Appendix D

Notes on the Database Used in Appendix B[38]

Timetable summary

The new tests conducted in this study examine the period from 2000 through 2016. The manufacturing employment and working age population data used for the dependent variable are averages for 2000-2001 as the base period and 2015-2016 as the terminal period. The lagged independent variable for per-worker exposure to imports from China are correspondingly averages for 1998-1999 for the base period and 2013-2014 for the terminal period.

Period	US Import from China	Other Variables
1	1998-1999	2000-2001
2	2013-2014	2015-2016

Matching trade data to SIC industries

Data on US imports from China for 1998-1999 and 2013-2014 come from the UN Comtrade Database[39]. UN Comtrade is the pseudonym for United Nations International Trade Statistics Database, the largest depository of international trade data. We collect data on US imports from China at the level of all HS1992 commodity codes.[40] We retain import data only at six-digit HS commodity code, and concord them to four-digit SIC industries using the crosswalk file provided by Dorn[41]. The crosswalk, or correspondence, from HS to manufacturing sectors is created by aggregating four-digit SIC codes to 397 manufacturing industries using an average of US import values at the ten-digit HS level over the period 1995-2005[42]. In order to keep our data compatible with ADH's[43], we keep only manufacturing imports, and adjust the dollar value to 2007 US$ using the Personal Consumption Expenditure deflator (FRED, 2018a). We then compute the average import value for each industry for both periods 1 and 2. We use lagged import values to address potential simultaneity bias in contemporaneous data for imports from China and manufacturing employment.

Matching working age population and population to commuting zone (CZ)

Data on working age population come from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2018), a database that collects, preserves and harmonizes U.S. census microdata. The 2000 sample includes 5% of the U.S. population, while 2015 and 2016 samples, collected from the American Community Surveys (ACS), include 1% of the U.S. population[44].

[38] Prepared by David Xu.
[39] Data available at https://comtrade.un.org/data/
[40] HS refers to Harmonized Commodity Description and Coding System.
[41] Crosswalk files ([D4], [C2]) available at https://www.ddorn.net/data.htm
[42] ADH online data appendix, P2.
[43] ADH paper, publicly published data
[44] Both data sets are available at https://usa.ipums.org/usa/index.shtml

Our working age population consists of all individuals who were between age 16 and 64 and resided within U.S. mainland. We use crosswalk files provided by Dorn[45] to map working age population data from PUMA (Public Use Microdata Area, the smallest identifiable geographic unit in the IPUMS database) to CZs. Commuting zones (CZs) are reasonable geographic units for labor market analysis as they cover all metropolitan and nonmetropolitan areas in the U.S. (Tolbert and Sizer, 1996). The detailed matching strategy is described in the appendix of Dorn (2009). CZ working age populations are obtained by the Census sampling weight multiplied with a mapping weight from PUMA to CZ[46]. We then compute the average working age population for each CZ for period 2[47].

Data on 2007 population come from the ACS, whose sample includes 1% of the U.S. population. Similarly, we use the crosswalk files provided by Dorn to map population data from PUMA to CZs[48]. 2007 CZ populations are weighted by the Census sampling weight multiplied with a mapping weight from PUMA to CZ. The data for 2007 CZ population are used to create population weights for our regressions.

Measuring the industry structure of local labor markets

Data on industry-level employment at local labor markets come from the County Business Patterns (CBP) database[49]. CBP is an annual series that provides subnational economic data by industry, including the number of establishments, employment, and payroll at the county level. The CBP raw data is processed using ADH's data cleaner files[50]. For year 2015 and 2016, necessary changes were made due to Census's substantial change to counties[51]. The CBP 2007 and CBP 2015/2016 report employment by industry for 6-digit NAICS codes respectively, at 2002 NAICS and 2012 NAICS. We concord CBP data for 2007, 2015 and 2016 to 1997 NAICS six-digit codes[52] before mapping the CBP data from NAICS to SIC codes, using crosswalk files provided by Dorn[53]. The employment data are then aggregated to the CZ level from the county level using crosswalk files provided by Dorn[54]. Consequently, we obtain industry-CZ level employment data for year 2000, 2001, 2007, 2015 and 2016. We further aggregate the employment data by CZ and average the data to create CZ level employment data for both periods 1 and 2. CZ level employments are the denominators of our dependent variables, whose construction is shown below.

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[45] Crosswalk files ([E5], [E6]) available at https://www.ddorn.net/data.htm

[46] According to IPUMS, the Census sampling weight is "[the number of] persons in the U.S. population represented by a given person in an IPUMS sample".

[47] Due to data limitations for year 2001, we use only 2000 working age population data for period 1 (2000-2001).

[48] Crosswalk file ([E5]) available at https://www.ddorn.net/data.htm

[49] The CBP data are available at https://www.census.gov/programs-surveys/cbp/data/datasets.html

[50] Data cleaner files ([F3], [F6]), available at https://www.ddorn.net/data.htm

[51] Relevant information is available at https://www.census.gov/geo/reference/county-changes.html. County code 12-086 is changed to 12-025 due to renaming issue of county "Dade County" to "Miami-Dade County". County code 08-014 is changed to 08-001 due to the creation of Broomfield county in 2001.

[52] Concordance data available at https://www.census.gov/eos/www/naics/concordances/concordances.html. Concordance file also available in Stata format in our data.

[53] Crosswalk file ([C1]) available at https://www.ddorn.net/data.htm

[54] Crosswalk file ([E7]) available at https://www.ddorn.net/data.htm

Data on CZ level manufacturing employment[55] come from IPUMS, for year 2000, 2015 and 2016.[56] From IPUMS data, we select samples who are between the ages of 16 and 64, and were employed the previous year. We concord IPUMS data from ind1990 industry code[57] to SIC codes[58]. We then map the employment data from PUMA to CZs, following the same method discussed above. We retain only employment data in manufacturing industries based on SIC codes.[59] We further aggregate manufacturing employment data by CZ and average the data (for period 2) to create CZ level manufacturing data for both periods.

Change in per-Worker Exposure to Imports from China

Our measure of the change in exposure to imports from China, per worker, for each CZ i is calculated as shown in equation (D.1). This calculation follows from ADH's formula to measure change in Chinese import exposure per worker[60].

$$\Delta IPW_i = \frac{\Delta M_i}{Emp_{i,07}} = \frac{M_{i,2} - M_{i,1}}{Emp_{i,07}} \qquad (D.1)$$

For each CZ, our change in import exposure is the difference between the average import in two periods normalized by CZ level employment in 2007. The imports are allocated to each CZ based on its share of national industry employment in 2007. Alternatively, this is mathematically represented in equation (D.2). The imports of each CZ i at each period t is weighted by imports from China at the national industry level import multiplied by the share of CZ's employment in national employment for each industry j.

$$M_{ijt} = M_{jt} \times \frac{L_{ij,07}}{L_{j,07}}, \qquad M_{it} = \sum_j M_{ijt} \qquad (D.2)$$

Change in Manufacturing Share

We create two variables to measure the impact of exposure to imports from China on local labor markets. For each CZ i, these are: change in manufacturing share of employment; and change in manufacturing employment as a share of working age population. Both variables are represented in equations (D.3a) and (D.3b), where MFG denotes manufacturing employment, Emp denotes employment and WAP denotes working age population.

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[55] To be more precise, it is working-age manufacturing employment data.
[56] Due to data limitation for year 2001, we use only 2000 manufacturing employment data for period 1 (2000-2001).
[57] According to IPUMS, ind1990 classifies industries from all years since 1950 into the 1990 Census Bureau industrial classification scheme. It offers researchers a consistent long-term classification of industries
[58] Crosswalk file ([C8]) available at https://www.ddorn.net/data.htm
[59] All industries between 2011 and 3999 in SIC 4 digit code. Detail information about SIC industry classification is available at https://www.ddorn.net/data.htm ([C9])
[60] Equation (3) in ADH paper, P2128

$$\Delta MFG_{i,wap} = \Delta\left(\frac{MFG}{WAP}\right)_i = \left(\frac{MFG}{WAP}\right)_{i,t=2} - \left(\frac{MFG}{WAP}\right)_{i,t=1} \qquad (D.3a)$$
$$\Delta MFG_{i,emp} = \Delta\left(\frac{MFG}{Emp}\right)_i = \left(\frac{MFG}{Emp}\right)_{i,t=2} - \left(\frac{MFG}{Emp}\right)_{i,t=1} \qquad (D.3b)$$

The consideration of change in manufacturing share of working age population follows from ADH, who wanted to avoid using employment data on both sides of regression[61].

[61] ADH paper, P2128 footnote 18

Appendix E
Sectoral Labor Coefficients (2016)

			Output	Employment	1000 workers
Sector	I-O Code	Description	$ bn	thous.	per $ bn
1	111CA	Farms	375.3	820	2.18
2	113FF	Forestry, fishing	52.9	597	11.29
3	211	Oil and gas extraction	230.5	175	0.76
4	212	Mining, except oil and gas	91.2	180	1.97
5	213	Support activities for mining	60.3	256	4.25
6	22	Utilities	477.3	554	1.16
7	23	Construction	1478	6883	4.66
8	321	Wood products	104.6	391	3.74
9	327	Nonmetallic mineral products	124.6	407	3.27
10	331	Primary metals	205.8	374	1.82
11	332	Fabricated metal products	338	1420	4.20
12	333	Machinery	351.1	1073	3.06
13	334	Computer and electronic products	340.8	1048	3.08
14	335	Electrical equp., appliances	124.3	382	3.07
15	3361MV	Motor vehicles, parts	694.8	945	1.36
16	3364OT	Other transportation equip.	310	681	2.20
17	337	Furniture	74.1	391	5.28
18	339	Miscellaneous manufacturing	168	592	3.52
19	311FT	Food, beverage, tobacco	936.8	1798	1.92
20	313TT	Textile mills & products	52.3	230	4.40
21	315AL	Apparel, leather products	23.2	159	6.85
22	322	Paper products	178.9	370	2.07
23	323	Printing	84.1	448	5.33
24	324	Petroleum and coal products	432.3	111	0.26
25	325	Chemical products	796.4	813	1.02
26	326	Plastics and rubber products	232.8	702	3.02
27	42	Wholesale trade	1817.7	5899	3.25
28	441	Motor vehicle and parts dealers	303.9	1996	6.57
29	445	Food and beverage stores	233.2	3110	13.34
30	452	General merchandise stores	230.4	3222	13.98
31	4A0	Other retail	953	7636	8.01
32	481	Air transportation	195.3	478	2.45

Appendix E, Continued

			Output	Employment	1000 workers
Sector	I-O Code	Description	$ bn	thous.	per $ bn
33	482	Rail transportation	74.9	190	2.54
34	483	Water transportation	46.9	66	1.41
35	484	Truck transportation	326.5	1474	4.51
36	485	Transit, ground passenger trns.	67.8	491	7.24
37	486	Pipeline transportation	44.4	49	1.10
38	487OS	Other transportation	221.7	1344	6.06
39	493	Warehousing and storage	126.6	928	7.33
40	511	Publishing except internet	334.8	874	2.61
41	512	Motion pics., sound recording	146.7	448	3.05
42	513	Broadcasting, telecommunic.	854.8	1073	1.26
43	514	Data process., internet pub., oth. Inf.	323	422	1.31
44	521CI	Banks, credit intermed.	848.9	2627	3.09
45	523	Securities, investment	548.9	921	1.68
46	524	Insurance, related	1077.8	2594	2.41
47	525	Funds, trusts, other financial vehicles	152.2	10	0.07
48	HS	Housing	2047.8	1069.99	0.52
49	ORE	Other real estate	1192.4	527.01	0.44
50	532RL	Rental, leasing	333.1	575	1.73
51	5411	Legal services	340.7	1140	3.35
52	5415	Computer systems design	408.3	1987	4.87
53	5412OP	Misc. profess., scientific, tech. svcs	1350.8	5804	4.30
54	55	Management of companies	535.5	2234	4.17
55	561	Administrative and support services	863.8	8643	10.01
56	562	Waste management	94.1	402	4.27
57	61	Educational services (a)	349	3608	10.34
58	621	Ambulatory health care services	1019.5	7099	6.96
59	622	Hospitals	850.2	5009	5.89
60	623	Nursing and residential care facilities	240.7	3375	14.02

Appendix E, Concluded

			Output	Employment	1000 workers
Sector	I-O Code	Description	$ bn	thous.	per $ bn
61	624	Social assistance	196.6	3722	18.93
62	711AS	Perform. Arts, sports, museums	177.7	641	3.61
63	713	Amusements, gambling, recreational	142.4	1640	11.52
64	721	Accommodation	266.6	1951	7.32
65	722	Food services and drinking places	776.8	11469	14.76
66	81	Other services, except government	674.4	7061	10.47
67	GFGD	Federal government (defense)	614.2	2152	3.50
68	GFGN	Federal government (nondefense)	404.4	2207	5.46
69	GFE	Federal government enterprises	93.8	702	7.48
70	GSLG	State, local government (b)	2201.1	18345	8.33
71	GSLE	State, local government enterprises	334.4	1179	3.53

a. Except by state and local governments
b. Including educational services

Source: Calculated from BEA (2018b, c)

Appendix F

Data Description for Intermediate Inputs Imported from China

Import data at the level of the North American Industry Classification System (NAICS) for 2016 are drawn from Schott (2019) for total imports and imports from China. These data are allocated to the 405 input-output categories in the Bureau of Economic Analysis input-output data using the concordance provided by the BEA (2019a). The ratio of imports from China to total imports in each of the 405 categories provides the China-share parameter ϕ_i.

The BEA (2019d) data for imported intermediate goods at the level of 405 input-output sectors (estimated for 2012) then provide the basis for examining imported intermediate inputs from China. The China share for (row) supplying sector *i*, namely ϕ_i, is multiplied by the total imports of good *i* used as intermediate inputs into (column) using sector *j* to obtain the estimate of imports of Chinese goods in sector *i* used as intermediate inputs into sector *j*, or m_{ij}^C. The estimated total of imports of manufactures from China in 2016 used as intermediate inputs into US production amounted to $140.7 billion.

Table F.1 shows the top 25 sectors for imported intermediate imports from China in 2016, out of the 234 manufacturing sectors in the 405 sector input-output table. These 25 sectors alone accounted for $83.5 billion in intermediate imports. Six of the top sectors were in the broad category 334 (computers and electronics equipment), and accounted for $31.9 billion in intermediate imports. The final column shows the China share in total imports from each sector. The weighted average share of China in supply of the top 25 intermediate imports amounted to 46 percent (and 52 percent in broad sector 334).

The sectoral parameter for sensitivity to imported intermediate inputs from China is then obtained by summing up all (row) supplying sector amounts used in (column) using-sector *j*, and dividing by gross output in using sector *j*. Gross output in each sector is reported in the "Total industry output" row along the bottom of the 405-sector "Use" table available for 2012 (BEA, 2019d). Table F.2 reports the 25 sectors with the highest sensitivity to imported inputs from China. Median sensitivity is 0.0073, or intermediate imports from China amounting to 0.73 percent of the using sector's gross output. Sensitivity at the 25th percentile is 0.0032; at the 75th percentile, 0.0145. The highest sensitivity is 0.0984, indicating that nearly 10 percent of gross output in "Nonupholstered wood household furniture manufacturing" comprises imported intermediate inputs from China.

Translation of the sensitivity parameters into downstream impacts on demand, gross output, and employment from the China shock is discussed in the main text. Table F.3 reports these impacts at the level of the 71-sector input-output table. Total downstream jobs gained from the availability of cheaper intermediate inputs amounted to an estimated 136,610 for 2000-2016. Of the total, 41,000 were in manufacturing. The largest impact was in administrative services (sector 561), reflecting the large employment base in that sector (8.6 million; see Appendix E).

Table F.1

Top 25 Intermediate Imports of Manufactures from China, 2016

Code	I-O category	Import ($ mn)	China share
334220	Other communic. Equip.	8,490	0.56
334118	Telephone apparatus manufacturing	7,133	0.59
326190	Tire manufacturing	5,942	0.52
33441A	Electromedical apparatus mfg.	5,924	0.37
334210	Broadcast, wireless communic. Equip.	5,812	0.78
336390	Vehicle steering, suspension, brake	4,530	0.17
335120	Small electrical appliance	4,373	0.68
325190	Plastics material and resin manufacturing	3,944	0.15
314900	Apparel manufacturing	3,189	0.61
33291A	Ball and roller bearing manufacturing	3,010	0.23
332999	Farm machinery	2,998	0.45
334413	Printed circuit assembly	2,920	0.12
339990	Dog and cat food	2,630	0.56
335920	Wiring device manufacturing	2,537	0.42
314120	Other textile product mills	2,444	0.57
327200	Glass and glass product manufacturing	2,151	0.39
332500	Spring and wire product manufacturing	1,898	0.33
335312	Switchgear, switchboard apparatus	1,894	0.25
316000	Pulp mills	1,816	0.55
333415	Industrial & commercial fan & blower mfg.	1,786	0.32
332200	Plate work, fabricated structural product	1,773	0.53
327100	Clay product and refractory manufacturing	1,660	0.38
334300	Magnetic & optical media mfg.	1,649	0.41
337215	Office furniture, woodwork, millwork	1,608	0.46
336320	Vehicle transmission, power train	1,403	0.11
	25 sectors	83,512	0.46
	broad 334 category (6 of 25)	31,927	0.52

Source: Authors' calculations

Table F.2

Top 25 Sectoral Intensities of Imported Inputs from China

Code	I-O Category	Sensitivity
337121	Nonupholstered wood household furniture manufacturing	0.098
334220	Other communications equipment manufacturing	0.062
311700	Bread and bakery product manufacturing	0.052
336320	Motor vehicle transmission & power train parts mfg.	0.050
336500	Ship building and repairing	0.049
326220	Other rubber product manufacturing	0.048
334118	Telephone apparatus manufacturing	0.047
335999	Automobile manufacturing	0.046
336360	Motor vehicle metal stamping	0.042
336214	Motor vehicle gasoline engine & engine parts mfg.	0.042
314120	Other textile product mills	0.040
326210	Rubber and plastics hoses and belting manufacturing	0.039
336991	Military armored vehicle, tank, & tank component mfg.	0.037
335314	Storage battery manufacturing	0.036
337122	Institutional furniture manufacturing	0.036
316000	Pulp mills	0.034
335312	Switchgear and switchboard apparatus manufacturing	0.033
336112	Heavy duty truck manufacturing	0.032
333415	Industrial & commercial fan, blower, air purific. equip. mfg.	0.031
33399A	Fluid power process machinery	0.031
335224	Other major household appliance manufacturing	0.030
336120	Motor vehicle body manufacturing	0.030
335311	Motor and generator manufacturing	0.030
333314	Photographic and photocopying equipment manufacturing	0.030
336111	Light truck and utility vehicle manufacturing	0.029

Source: Authors' calculations

Table F.3
Downstream Impact of Intermediate Imports from China Shock, 2000-2016
($ million and 1000 jobs)

	Sector	Dem	Q	Empl		Sector	Dem	Q	Empl
1	111CA	201	558	1.22	37	486	12	47	0.05
2	113FF	27	155	1.75	38	487OS	124	339	2.06
3	211	172	397	0.30	39	493	76	191	1.40
4	212	91	237	0.47	40	511	97	126	0.33
5	213	103	120	0.51	41	512	7	99	0.30
6	22	53	494	0.57	42	513	1015	1370	1.72
7	23	1518	1668	7.77	43	514	178	333	0.43
8	321	113	320	1.20	44	521CI	41	382	1.18
9	327	127	346	1.13	45	523	47	203	0.34
10	331	214	1333	2.42	46	524	5	428	1.03
11	332	445	1283	5.39	47	525	27	32	0.00
12	333	1251	1691	5.17	48	HS	47	47	0.02
13	334	888	1431	4.40	49	ORE	163	1038	0.46
14	335	347	604	1.86	50	532RL	61	392	0.68
15	3361MV	1852	3031	4.12	51	5411	84	279	0.93
16	3364OT	573	810	1.78	52	5415	192	425	2.07
17	337	297	344	1.82	53	5412OP	561	1791	7.69
18	339	188	253	0.89	54	55	425	1091	4.55
19	311FT	721	1044	2.00	55	561	352	1131	11.32
20	313TT	133	266	1.17	56	562	114	192	0.82
21	315AL	73	113	0.77	57	61	86	100	1.03
22	322	177	472	0.98	58	621	233	242	1.69
23	323	90	137	0.73	59	622	283	284	1.67
24	324	61	318	0.08	60	623	182	182	2.56
25	325	835	2073	2.12	61	624	183	183	3.47
26	326	490	963	2.90	62	711AS	13	106	0.38
27	42	480	2064	6.70	63	713	67	71	0.82
28	441	72	107	0.70	64	721	167	232	1.70
29	445	65	68	0.90	65	722	205	371	5.48
30	452	181	191	2.68	66	81	489	718	7.51
31	4A0	257	400	3.20	67	GFGD	432	432	1.51
32	481	18	84	0.21	68	GFGN	124	124	0.68
33	482	25	125	0.32	69	GFE	14	68	0.51
34	483	8	27	0.04	70	GSLG	0	0	0.00
35	484	38	356	1.61	71	GSLE	0	29	0.10
36	485	4	33	0.24		Total	18295	36995	136.61

Table F.3, Continued

Sector	Dem	Q	Empl
Primary	2165	3629	12.59
Manufac.	8876	16834	40.94
Services	7254	16532	83.09

Dem: demand
Q: gross output
Empl: employment
Sectors: see Appendix E for descriptions

Source: Authors' calculations

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