ECONSTOR
Make Your Publications Visible.

A Service of
ZBW
Leibniz-Informationszentrum Wirtschaft
Leibniz Information Centre for Economics

Acemoglu, Daron; Autor, David H.; Dorn, David; Hanson, Gordon H.; Price, Brendan

Working Paper

Import Competition and the Great U.S. Employment Sag of the 2000s

CESifo Working Paper, No. 5366

Provided in Cooperation with:
Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Acemoglu, Daron; Autor, David H.; Dorn, David; Hanson, Gordon H.; Price, Brendan (2015) : Import Competition and the Great U.S. Employment Sag of the 2000s, CESifo Working Paper, No. 5366, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:
https://hdl.handle.net/10419/110869

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

WWW.ECONSTOR.EU

Mitglied der Leibniz-Gemeinschaft

The international platform of Ludwig-Maximilians University's Center for Economic Studies and the Ifo Institute

CESifo Working Papers

www.cesifo.org/wp

Import Competition and the Great U.S. Employment Sag of the 2000s

Daron Acemoglu
David Autor
David Dorn
Gordon H. Hanson
Brendan Price

CESIFO WORKING PAPER NO. 5366
CATEGORY 4: LABOR MARKETS
MAY 2015

An electronic version of the paper may be downloaded
- *from the SSRN website: www.SSRN.com*
- *from the RePEc website: www.RePEc.org*
- *from the CESifo website: www.CESifo-group.org/wp*

ISSN 2364-1428

CESifo
Center for Economic Studies & Ifo Institute

CESifo *Working Paper No. 5366*

Import Competition and the Great U.S. Employment Sag of the 2000s

Abstract

Even before the Great Recession, U.S. employment growth was unimpressive. Between 2000 and 2007, the economy gave back the considerable employment gains achieved during the 1990s, with a historic contraction in manufacturing employment being a prime contributor to the slump. We estimate that import competition from China, which surged after 2000, was a major force behind both recent reductions in U.S. manufacturing employment and—through input-output linkages and other general equilibrium channels—weak overall U.S. job growth. Our central estimates suggest job losses from rising Chinese import competition over 1999 through 2011 in the range of 2.0 to 2.4 million.

JEL-Code: F160, J210.

Keywords: trade flows, labor demand.

Daron Acemoglu
MIT Department of Economics
USA - Cambridge MA 02142-1347
daron@mit.edu

*David Autor**
MIT Department of Economics
USA - Cambridge MA 02142
dautor@mit.edu

David Dorn
University of Zurich
Zurich / Switzerland
david.dorn@econ.uzh.ch

Gordon H. Hanson
Department of Economics
University of California, San Diego
USA - La Jolla, CA 92093-0508
gohanson@ucsd.edu

Brendan Price
MIT Department of Economics
USA - Cambridge MA 02142
bmprice@mit.edu

*corresponding author

May 2015
We thank David Card, Alexandre Mas, Alireza Tahbaz-Salehi, and numerous participants at the NBER Labor Markets in the Great Recession conference for questions and suggestions that improved the paper. We are grateful to Christina Patterson for excellent research assistance. Dorn acknowledges funding from the Spanish Ministry of Science and Innovation (ECO2010-16726 and JCI2011-09709). Autor and Hanson acknowledge funding from the National Science Foundation (grant SES-1227334). Price acknowledges financial support from the Hewlett Foundation. Autor, Acemoglu and Price acknowledge support from the Alfred P. Sloan Foundation (grant 2011-10-12).

1 Introduction

During the last decade of the twentieth century—christened the "Roaring Nineties" by Krueger and Solow (2002)—the U.S. labor market exhibited a vigor not seen since the 1960s. Between 1991 and 2000, the employment-to-population ratio rose by 1.5 percentage points among men, and by more than 3 percentage points among women. Following five years of rapid wage growth accompanied by minimal inflation, the national unemployment rate in the year 2000 reached a nadir of 4.0 percent, its lowest level since 1969. Just one year later, the U.S. labor market commenced what Moffitt (2012) terms a "historic turnaround" in which the gains of the prior decade were undone. Between 2001 and 2007, male employment rates lost all of their ground attained between 1991 and 2000. The rapid increase of female employment rates halted simultaneously.[1] The growth rate of employment averaged only 0.9 percent between 2000 and 2007—that is, during the seven years *before* the onset of the Great Recession—versus 2.6 percent between 1991 and 2000 (Figure 1).[2]

This pre-Great Recession U.S. employment "sag" of the 2000s is widely recognized but poorly understood.[3] It coincides with a significant increase in import competition from China. Between 1990 and 2011, the share of world manufacturing exports originating in China increased from 2 percent to 16 percent (Hanson, 2012). China's export surge is the outcome of deep economic reforms in the 1980s and 1990s, which were reinforced by the country's accession to the World Trade Organization in 2001 (Naughton, 2007). The country's share in U.S. manufacturing imports has shown an equally meteoric rise from 4.5 percent in 1991 to 10.9 percent in 2001 before surging to 23.1 percent in 2011. Simultaneously, after staying relatively constant during the 1990s, U.S. manufacturing employment declined by 18.7 percent between 2000 and 2007 (Figure 1).[4]

In this paper, we explore how much of the U.S. employment sag of the 2000s can be attributed to rising import competition from China. Our methodology builds on recent work by Autor, Dorn and Hanson (2013, 2014), as well as related papers by Bloom, Draca and Van Reenen (2015), Pierce and Schott (2015), and Autor, Dorn, Hanson and Song (2014). Akin to Pierce and Schott (2015),

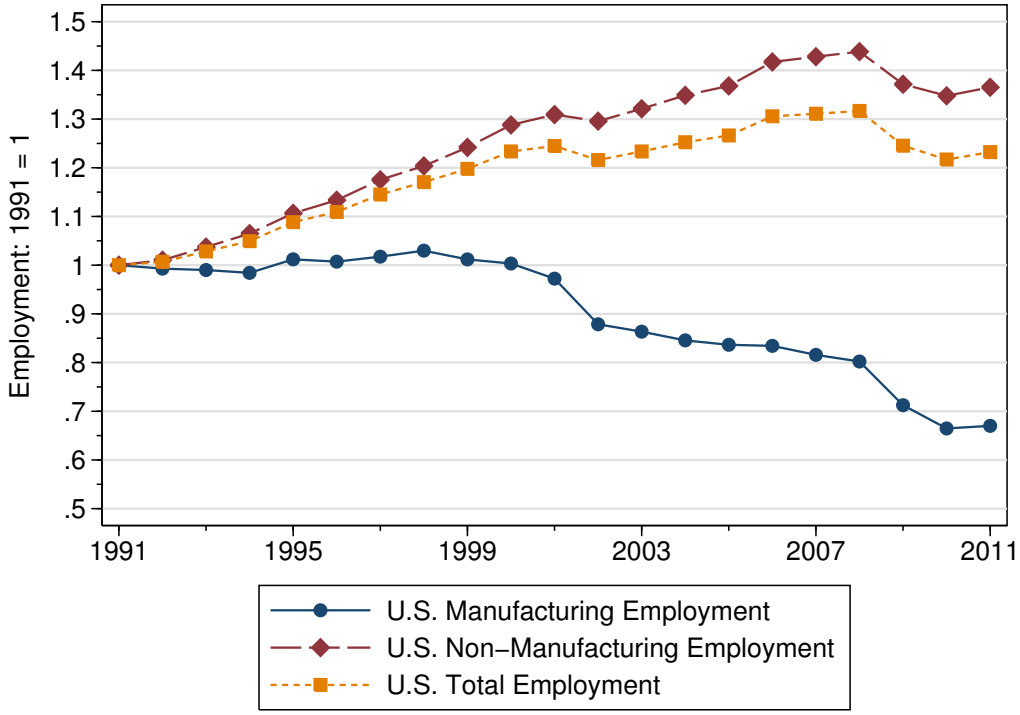
[1] See http://www.bls.gov/ilc/#laborforce for data on the size and the employment rate of the working-age population.

[2] The employment series plotted in Figure 1, as well as the employment statistics provided later in this section, are derived from the County Business Patterns. As detailed below, the County Business Patterns covers all U.S. employment except for self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees.

[3] Moffitt (2012) studies potential causes for the sag including wage levels, age structure, family structure, taxes, transfers, minimum wage policies, and population health. Only declining male wage rates are found to have substantial explanatory power. Yet, this explanation leaves unanswered the question of *why* male wages fell. The concurrence of falling wages and falling employment-to-population ratios suggests an inward shift in labor demand.

[4] Using County Business Patterns data, we calculate that U.S. manufacturing employment was 17.0 million in 1991, 17.1 million in 2000, 13.9 million in 2007, and 11.4 million in 2011.

Figure 1: Changes in U.S. Manufacturing and Non-Manufacturing Employment, 1991-2011.



Note.—Employment is computed in the County Business Patterns. Employment counts are normalized to unity in 1991.

we begin our analysis with industry-level empirical specifications.[5] This approach enables us to estimate the *direct* effect of exposure to Chinese import competition on industry employment at the U.S. national level. Our direct industry-level employment estimates come from comparing changes in employment across four-digit manufacturing industries from 1991 to 2011 as a function of industry exposure to Chinese import competition. The first part of our paper shows that there is a sizable and robust negative effect of growing Chinese imports on U.S. manufacturing employment.

Quantitatively, our *direct* estimates imply that had import penetration from China not grown after 1999, there would have been 560 thousand fewer manufacturing jobs lost through the year 2011. Actual U.S. manufacturing employment declined from 17.2 million workers in 1999 to 11.4 million in 2011, making the counterfactual job loss from the direct effect of greater Chinese import penetration amount to approximately 10 percent of the realized job decline in manufacturing.

These direct effects do not, however, correspond to the full general equilibrium impact of grow-

[5]NAFTA also contributed to changes in U.S. trade over our sample period. See McLaren and Hakobyan (2012) on NAFTA's impacts on U.S. employment patterns. More broadly, Ebenstein et al. (2014) examine the impact of trade in the form of offshoring on the wages of U.S. workers, finding that workers switching out of manufacturing experience relatively large wage declines.

ing Chinese imports on U.S. employment, which also encompasses several indirect channels through which rising exposure to import competition may impact employment levels. One source of indirect effects, also studied by Pierce and Schott (2015), is industry *input-output linkages*. These linkages can create both positive and negative changes in U.S. industry labor demand, generating a net employment change that is ambiguous in sign. If an industry contracts because of Chinese competition, it may reduce both its demand for intermediate inputs produced in the United States and its supply of inputs to other domestic industries. An industry may thus be negatively affected by trade shocks either to its domestic suppliers or to its domestic buyers. The sign of the "downstream effect"—through which import exposure propagates downstream from a supplying industry to its customers—is theoretically ambiguous: while trade competition may reduce the domestic supply of certain inputs, such reductions may be offset by the increased supply of imported inputs.[6] By contrast, the "upstream effect"—whereby import exposure within an industry propagates upstream to its suppliers—should have unambiguously contractionary consequences for the upstream industry.[7]

We use the U.S. input-output table for 1992 to estimate the effects of upstream and downstream import exposure for both manufacturing and non-manufacturing industries. Our initial measure of the upstream (respectively, downstream) effect for an industry, which sums over the *direct* import exposure experienced by all other industries using as weights their share in the total output demands of (respectively, their input supplies to) the industry in question, captures this notion.[8] Estimates from this exercise indicate sizable negative upstream effects while, consistent with the anticipated ambiguity of downstream effects, the downstream magnitudes are imprecisely estimated and unstable in sign. Our preferred measure of indirect trade shocks further accounts not only for shocks to an industry's immediate buyers or suppliers, but also for the full set of input-output relationships among all connected industries (e.g., shocks to an industry's buyers, its buyers' buyers, etc). Applying this direct plus full input-output measure of exposure increases our estimates of trade-induced job losses for 1999 to 2011 to 985 thousand workers in manufacturing alone, and to 1.98 million workers in the entire economy. Thus, inter-industry linkages magnify the employment effects of trade shocks, doubling the size of the impact within manufacturing and producing an equally large employment effect outside of manufacturing.

[6]Trade shocks to an industry's suppliers will have negative effects on that industry if, due to specific investments, existing supply relationships are more productive or are able to provide highly customized inputs as generally presumed in the industrial organization literature on vertical integration (e.g., Williamson, 1975; Hart and Moore, 1990).

[7]An earlier version of this paper (Acemoglu et al. 2014a) reversed the terminology of upstream and downstream effects. We have adopted the present terminology for consistency with common usage in the literature on input-output effects.

[8]See Long and Plosser (1983) and Acemoglu et al. (2012) for the reasoning behind this value share definition, which also corresponds to the relevant entries in the input-output tables. A detailed derivation is provided in Appendix B.

Our second empirical strategy, which focuses on local labor markets, is motivated by the fact that analysis at the level of national industries fails to capture two other potentially important and opposing general equilibrium channels. One such additional channel is a *reallocation effect* from growing trade with China, which works through the movement of factors of production from declining sectors to new opportunities, and potentially counteracts any negative direct or industry linkage effects. In both Heckscher-Ohlin and Ricardo-Viner models of international trade, stronger import competition for one sector reduces the relative price of its final good and induces the reallocation of labor and capital to sectors whose relative prices have increased (Feenstra, 2003). Under fully inelastic labor supply, no labor market frictions, and other neoclassical assumptions which ensure that the aggregate economy is always at full employment, reallocation effects would, by definition, exactly offset direct, upstream and downstream effects so as to restore full employment. However, with imperfections in labor and other markets, there is no guarantee that reallocation effects will be sufficient to restore employment to the same level that would have emerged in the absence of trade growth from China.

An additional general equilibrium channel operates through *aggregate demand effects*, multiplying the negative direct and indirect effects of import growth from China. Through familiar Keynesian-type multipliers, domestic consumption and investment may be depressed, extending employment losses to sectors not otherwise exposed to import competition. A negative effect of increased import competition on aggregate demand necessarily requires that employment reallocation in response to a negative trade shock is incomplete, such that aggregate earnings decline and this decline is multiplied throughout the economy via demand linkages.

We jointly estimate reallocation and aggregate demand effects (in net) at the level of local labor markets by exploiting the impact of trade shocks within U.S. commuting zones (CZs). If the reallocation mechanism is operative, then when an industry contracts in a CZ as a result of Chinese competition, some other industry in the same labor market should expand. Some component of aggregate demand effects should also take place within local labor markets, as shown by Mian and Sufi (2014) in the context of the recent U.S. housing bust: if increased trade exposure lowers aggregate employment in a location, reduced earnings will decrease spending on non-traded local goods and services, magnifying the impact throughout the local economy. Because aggregate demand effects also have a national component, which our approach does not capture, focusing on local labor markets is likely to provide a lower bound on the sum of reallocation and aggregate demand effects.[9]

[9] Of course, reallocation effects may also have a national component due to the movement of labor across regions. As we discuss in Section 2, in practice there appears to be little response of local labor supply to location-specific increases in import competition from China (Autor, Dorn, and Hanson, 2013; Autor, Dorn, Hanson, and Song, 2014),

Empirically, our second strategy examines changes in employment in CZs that have different levels of exposure to Chinese competition by virtue of differences in their initial pattern of industrial specialization, a strategy also used by Autor, Dorn, and Hanson (2013). The reallocation effect should result in a greater expansion of employment in non-exposed industries—meaning non-tradable industries as well as tradable industries not significantly exposed to trade with China. Surprisingly, we find no robust evidence for this effect: the estimated impact of import competition on employment in non-exposed industries is very modest in magnitude and statistically indistinguishable from zero. The reallocation of employment into non-exposed industries appears to be swamped by the adverse effect of the aggregate demand channel, which presumably inhibits labor reabsorption.

Our estimates of local general equilibrium effects imply that import growth from China between 1999 and 2011 led to an employment reduction of 2.4 million workers, inclusive of employment changes within non-exposed sectors. Consistent with the idea that import competition may have negative general equilibrium effects on local employment, this figure exceeds our national-industry-level estimate of the direct and indirect disemployment effects of rising import exposure mentioned above. As noted below, neither the CZ-level nor the national estimate fully incorporates all of the adjustment channels encompassed by the other. The national-industry estimates exclude reallocation and aggregate demand effects, whereas the CZ estimates exclude the national component of these two effects, as well as the non-local component of input-output linkage effects. Because the CZ-level estimates suggest that general equilibrium forces magnify rather than offset the effects of import competition, we view our industry-level estimates of employment reduction as providing a conservative lower bound.

Our analysis of the aggregate employment consequences of import competition builds on the recent work of Autor, Dorn and Hanson (2013, 2014) by expanding their CZ-level analysis to include analysis at the level of national industries, a dimension they do not consider, and by characterizing the alternative mechanisms—reallocation versus changes in aggregate demand—through which trade induces employment decline at the local level. Our national-industry approach is similar in spirit to Bloom et al. (2015) and Pierce and Schott (2015). Pierce and Schott, in particular, explore how China's 2001 WTO accession affected U.S. manufacturing employment. Our paper, while complementary to theirs, differs in two respects. The first is in terms of identification strategy. Whereas Pierce and Schott seek to identify the growth in China trade that resulted from the post-

leading us to view reallocation effects as being primarily local in nature. Another complicating factor is that, in the presence of labor and product market imperfections, the decline of an industry in the local labor market may lead to the expansion of some tradable industries in other labor markets, making the local reallocation effects a lower bound on the aggregate reallocation effects.

2001 removal of uncertainty surrounding China's most-favored-nation access to the U.S. market, our identification strategy captures China's trade growth due to broader productivity-driven changes in its export supply. Further, our paper expands the analysis to include the transmission of trade shocks to non-manufacturing sectors and the estimation of employment effects resulting from reallocation across sectors and changes in aggregate demand.

We begin in Section 2 by outlining the conceptual framework that motivates our empirical analysis. Section 3 describes our empirical approach to estimating the effects of exposure to trade shocks and briefly discusses the data. Section 4 gives our primary OLS and 2SLS estimates of the impact of trade shocks on employment, and also considers additional labor market outcomes. Section 5 expands the analysis to include intersectoral linkages. Section 6 presents estimation results for data on local labor markets. Section 7 concludes. The Appendix contains the derivation of our upstream and downstream import exposure measures from a simple general equilibrium model with input-output linkages and also contains additional empirical results and robustness checks.

2 Conceptual Framework

We start with a brief outline of the conceptual framework that motivates our empirical work. Consider a simple decomposition of the total national employment impact of increased Chinese trade exposure:[10]

$$\begin{aligned}\text{National employment impact} = {} & \text{Direct impact on exposed industries} \\ & + \text{Indirect impact on linked industries} \\ & + \text{Aggregate reallocation effects} \\ & + \text{Aggregate demand effects}\end{aligned}$$

Here, the direct impact is the reduction in employment in industries whose outputs compete with imports from China. Added to this direct effect is an indirect effect arising because other industries linked to the impacted industry through the input-output matrix are also likely to see changes in output.[11] For example, the chemical and fertilizer mining industry—which is in non-manufacturing—sells 74% of its output to the manufacturing sector. Its largest single manufacturing customer is industrial organic chemicals not elsewhere classified, which accounts for 15% percent of its sales.

[10] We follow the standard practice in such decompositions and fold the "covariance" terms into the "main effects" (so that the magnitudes are not independent of the order in which these different terms are evaluated).

[11] See, among others, Long and Plosser (1983) and Acemoglu et al. (2012) on the propagation of shocks through the input-output network of the economy.

Similarly, the iron and ferroalloy ores industry sells 83% of its output to the manufacturing sector, two thirds of which goes to the blast furnace and steel mill industry. Accordingly, a shock to the demand for a given domestic manufactured good is likely to indirectly impact demand for, and reduce employment in, industries, whether in manufacturing or non-manufacturing, that supply inputs to the affected industry. We refer to these linkages as *upstream effects,* by which industries exposed to import competition indirectly affect industries that are located upstream of them in input-output space.[12]

Conversely, a trade shock to the suppliers of a given industry (e.g., the suppliers of tires to the automobile industry) may also affect the industries that are its customers. The direction of this effect is generally ambiguous. On the one hand, from the perspective of purchasing industries, the trade shock expands input supply and puts downward pressure on input prices, and thus may tend to expand employment in the industries that consume these inputs (Goldberg et al. 2010).[13] On the other hand, the trade shock may destroy existing long-term relationships for specialized inputs as domestic input suppliers are driven out of business, creating a force towards contraction in the industries that were their customers. We refer to such linkages as downstream effects, since they propagate from an import-exposed industry to industries located downstream in the production chain. We estimate these effects on linked industries using the input-output matrix of the U.S. economy as described below.

We begin our empirical analysis with industry-level regressions that estimate the direct impact of import competition on employment in exposed industries (Section 4), and subsequently add the indirect employment impacts arising from input-output linkages between industries (Section 5). The industry-level analysis thus captures the first two components of the aggregate national employment effect, the direct impact on exposed industries plus the indirect impact on linked industries. The industry-level regressions do not, however, encompass the third and the fourth components of the national employment effect: the *reallocation effect*, which captures the potential increase in employment from the expansion of other industries to absorb the factors of production freed by contracting industries, and the *aggregate demand effect*, which corresponds to the impact of Keynesian-type multipliers operating through local or national shifts in consumption and investment.[14]

[12]Unfortunately, the terminology of upstream and downstream effects is open to confusion, since upstream effects—that is, effects that propagate upstream—work through the import exposure experienced by downstream industries, and similarly for downstream effects.

[13]Consistent with this reasoning, De Loecker et al. (2014) find substantial negative domestic product price effects from trade liberalization in India, and Goldberg et al. (2010) document that greater availability of imported intermediate inputs is associated with more rapid introduction of new product varieties by domestic firms, also in the Indian context.

[14]It is in theory possible for the aggregate demand effect to be positive; for instance, aggregate demand may increase because the aggregate price level declines as a result of the lower costs of imported products from China. We view this

To obtain estimates of the magnitudes of these two additional effects, we turn in Section 6 to local labor market analysis, focusing on the employment impact of increased import competition from China at the commuting zone level. The total employment effect observed in a local labor market can be decomposed as:

$$\begin{aligned}\text{Local employment impact} &= \text{Direct impact on exposed industries}\\ &\quad + \text{Local impact on linked industries}\\ &\quad + \text{Local reallocation effects} + \text{Local demand effects}\end{aligned}$$

We hypothesize that the direct impact at the local level, when scaled appropriately by the size of the industry in the local labor market, is comparable to the direct impact estimated at the national level. The other three effects could potentially differ between the local and the aggregate levels. For instance, even though linked industries tend to co-locate (e.g., Ellison, Glaeser and Kerr, 2010), only part of the input-output linkages will be within the same local labor market, and the local impact on linked industries may thus be much smaller than the aggregate effect.

What makes our local labor market analysis informative is that local reallocation and local demand effects are linked to their aggregate counterparts. Consider the reallocation effects first. Local labor markets are a plausible unit of analysis for the study of this channel. As a local labor market experiences a loss of jobs when local industries contract in response to rising import competition, there should be an adjustment of quantities *within the same labor market*, despite the fact that prices are, at least in part, determined in the national or the international equilibrium. If the extent of worker migration between local labor markets in response to these labor market shocks is modest, as suggested by the evidence in Autor, Dorn and Hanson (2013), Notowidigdo (2013), and Autor, Dorn, Hanson and Song (2014), this adjustment will take the form of reallocation from declining industries to others within this locale.[15]

An important component of aggregate demand effects also plausibly takes place within local labor markets. Mian and Sufi (2014) show that during the Great Recession, U.S. counties suffering large wealth losses because of particularly severe declines in housing values also saw large declines in employment, consistent with local transmission of shocks to aggregate demand. Components of

positive channel as second-order and in general presume that the aggregate demand effect, working in the standard Keynesian fashion, amplifies the potential negative direct impact of trade shocks. This is consistent with the results from our local labor market, which indicate that the sum of reallocation and demand effects is negative.

[15] Complementing this U.S.-based evidence, Balsvik, Jensen and Salvanes (2014) and Dix-Carneiro and Kovak (2015) document weak labor mobility responses to trade-induced employment shocks in Norway and Brazil, respectively. As discussed in footnote 9, there are some components of reallocation that might take place outside the local labor market.

the aggregate demand effect that operate at the national level will not be captured by our analysis, however, as they will be common across locations. Our empirical strategy seeks to identify the combined impact of reallocation and aggregate demand effects by quantifying how trade-induced shocks impact a commuting zone's employment in *non-exposed industries*—defined as industries that are not exposed to imports from China either through direct product market competition or through inter-industry purchases of intermediate inputs.

Overall, this discussion suggests that our local labor market strategy will provide an informative alternative estimate of the aggregate employment impact of greater import competition from China, though this is likely to be an underestimate of the aggregate effects because it ignores part of the impact on linked industries and also excludes demand effects that have no counterpart at the local level. In what follows, we will separately compute the implied aggregate effects consisting of the sum of the direct impact and the impact on linked industries from our national-industry-level analysis, and the total employment impact from the local analysis.

3 Empirical Approach

Sweeping economic reforms initiated in the 1980s and extended in the 1990s permitted China to experience rapid industrial productivity growth (Naughton, 2007; Hsieh and Ossa, 2011; Zhu, 2012), rural to urban migration flows in excess of 150 million workers (Li et al. 2012), and massive capital accumulation (Brandt, Van Biesebroeck, and Zhang, 2012), which together caused manufacturing to expand at a breathtaking pace. What did this growth mean for U.S. employment inside and outside manufacturing? We seek to capture the changes in U.S. industry employment induced by shifts in China's competitive position and the subsequent increase in its exports, accounting for input-output linkages between industries and other indirect channels of transmission. We subsequently consider how these labor demand shifts can be aggregated to national totals.

3.1 Industry Trade Shocks

Our baseline measure of trade exposure is the change in the import penetration ratio for a U.S. manufacturing industry over the period 1991 to 2011, defined as

$$\Delta IP_{j\tau} = \frac{\Delta M_{j,\tau}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}}, \tag{1}$$

where for U.S. industry j, $\Delta M_{j,\tau}^{UC}$ is the change in imports from China over the period 1991 to 2011 (which in most of our analysis we divide into two subperiods, 1991 to 1999 and 1999 to 2011) and $Y_{j,91}+M_{j,91}-E_{j,91}$ is initial absorption (measured as industry shipments, $Y_{j,91}$, plus industry imports, $M_{j,91}$, minus industry exports, $E_{j,91}$). We choose 1991 as the initial year as it is the earliest period for which we have the requisite disaggregated bilateral trade data for a large number of country pairs that we can match to U.S. manufacturing industries.[16] The quantity in (1) can be motivated by tracing export supply shocks in China—due, e.g., to productivity growth—through to demand for U.S. output in the markets in which the United States and China compete. Supply-driven changes in China's exports will tend to reduce demand for and employment in U.S. industries.

One concern about (1) as a measure of trade exposure is that observed changes in the import penetration ratio may in part reflect domestic shocks to U.S. industries that affect U.S. import demand. Even if the dominant factors driving China's export growth are internal supply shocks, U.S. industry import demand shocks may still contaminate bilateral trade flows. To capture this supply-driven component in U.S. imports from China, we instrument for trade exposure in (1) with the variable

$$\Delta IPO_{j\tau} = \frac{\Delta M_{j,\tau}^{OC}}{Y_{j,88} + M_{j,88} - X_{j,88}} \tag{2}$$

where $\Delta M_{j,\tau}^{OC}$ is the growth in imports from China in industry j during the period τ (in this case 1991 to 2011 or some subperiod thereof) in eight other high-income countries excluding the United States.[17] The denominator in (2) is initial absorption in the industry in 1988. The motivation for the instrument in (2) is that high-income economies are similarly exposed to growth in imports from China that is driven by supply shocks in the country. The identifying assumption is that industry import demand shocks are uncorrelated across high-income economies, and that there are no strong increasing returns to scale in Chinese manufacturing (which might imply that U.S. demand shocks will increase efficiency in the affected Chinese industries and induce them to export more to other high-income countries).[18]

Figure A1 (in Appendix A) plots the value in (1) against the value in (2) for all U.S. manufacturing industries at the four-digit level, as defined below, which is equivalent to the first-stage

[16] Our empirical approach requires data not just on U.S. trade with China but also on China's trade with other partners. Specifically, we require trade data reported under Harmonized System (HS) product codes in order to match with U.S. SIC industries. The year 1991 is the earliest in which many countries began using the HS classification.

[17] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, which represent all high-income countries for which we can obtain disaggregated bilateral trade data at the Harmonized System level back to 1991.

[18] See Autor, Dorn and Hanson (2013) and Autor, Dorn, Hanson and Song (2014) for further discussion of threats to identification using this instrumentation approach.

regression in our subsequent estimation without detailed controls. The coefficient is 0.98 and the t-statistic and R-squared are 7.0 and 0.62 respectively, indicating the strong predictive power of import growth in other high-income countries for U.S. import growth from China.[19]

A potential concern about our analysis is that we largely ignore U.S. exports to China, focusing primarily on trade flows in the opposite direction. This is for the simple reason that our instrument, by construction, has little predictive power for U.S. exports to China. Nevertheless, to the extent that our instrument is valid, our estimates will correctly identify the direct and indirect effects of increased import competition from China (this is in particular because there is no reason for trade to balance at the *industry or region level*, so we do not need to simultaneously treat exports to China in our analysis). We also take comfort from the fact that imports from China are much larger—approximately five times as large—as manufacturing exports from the United States to China (Figure 2).[20]

3.2 Data Sources

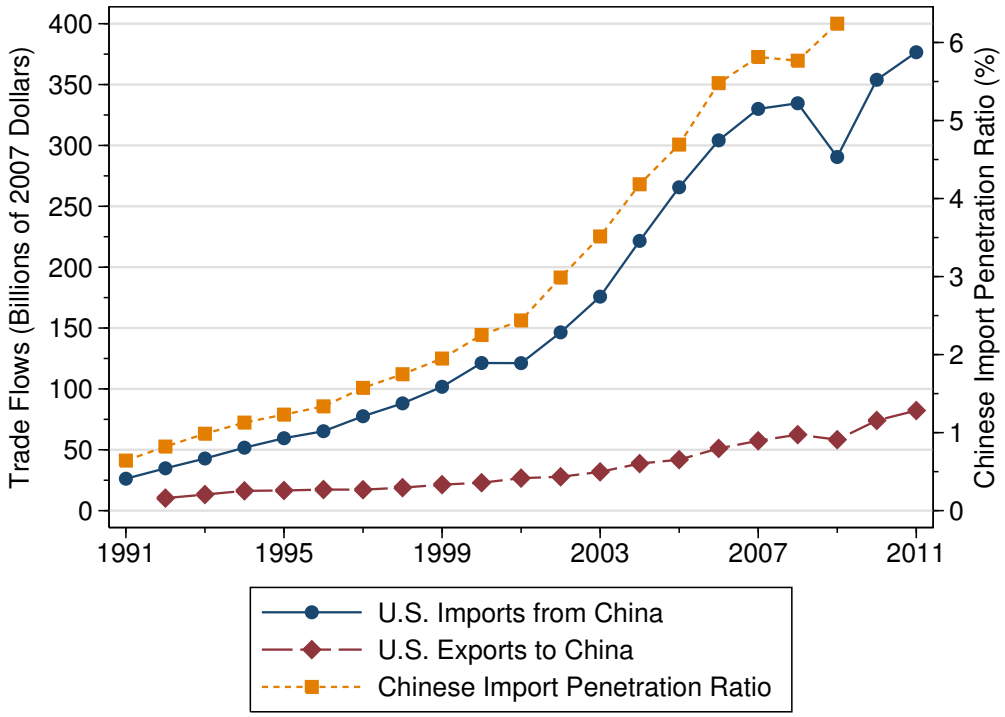
Data on international trade for 1991 to 2011 are from the UN Comtrade Database,[21] which gives bilateral imports for six-digit HS products. To concord these data to four-digit SIC industries, we first apply the crosswalk in Pierce and Schott (2012), which assigns 10-digit HS products to four-digit SIC industries (at which level each HS product maps into a single SIC industry), and aggregate up to the level of six-digit HS products and four-digit SIC industries (at which level some HS products map into multiple SIC industries). To perform this aggregation, we use data on U.S. import values at the 10-digit HS level, averaged over 1995 to 2005. The crosswalk assigns HS codes to all but a small number of SIC industries. We therefore slightly aggregate the four-digit SIC industries so that each of the resulting 397 manufacturing industries matches to at least one trade code, and none is immune to trade competition by construction. To ensure compatibility with the additional data sources below, we also aggregate together a few additional industries such that our final data

[19] Modeling the China trade shock as in equation (1) does not exclude the role of global production chains. During the 1990s and 2000s, approximately half of China's manufacturing exports were produced by export processing plants, which import parts and components from abroad and assemble these inputs into final export goods (Feenstra and Hanson, 2005). Our instrumental variable strategy does not require China to be the sole producer of the goods it ships abroad; rather, we require that the growth of its gross manufacturing exports is driven largely by factors internal to China (as opposed to shocks originating in the United States), as would be the case if, plausibly, the recent expansion of global production chains involving China is primarily the result of its hugely expanded manufacturing capacity.

[20] A second rationale for our import focus is data constraints. Much of U.S. exports to China are in the form of indirect exports via third countries or embodied services of intellectual property, management expertise, or other activities involving skilled labor. These indirect and service exports are difficult to measure because the direct exporter may be a foreign affiliate of a U.S. multinational or because they occur via a chain of transactions involving third countries. As such exports tend to be intensive in highly skilled labor, they may have only modest direct impacts on the employment of production workers—though their indirect impacts are difficult to gauge with available data.

[21] See http://comtrade.un.org/db/default.aspx.

Figure 2: Bilateral U.S.-China Trade Flows and Chinese Import Penetration, 1991-2011.



Note.—Trade data are taken from the UN Comtrade Database. Imports and exports are deflated to 2007 U.S.$ using the Personal Consumption Expenditure price index. Chinese import penetration is constructed by dividing U.S. manufacturing imports from China by U.S. domestic manufacturing absorption, defined as U.S. domestic manufacturing output plus imports less exports. Export data are available only from 1992 onwards. The import penetration ratio series ends in 2009 because computing the denominator requires use of the NBER-CES Manufacturing Industry Database, which ends in 2009.

contains 392 manufacturing industries. All import amounts are inflated to 2007 U.S. dollars using the Personal Consumption Expenditure deflator.

Our main source of data on U.S. employment is the County Business Patterns (CBP) for the years 1991, 1999, 2007 and 2011. CBP is an annual data series that provides information on employment, firm size distribution, and payroll by county and industry. It covers all U.S. employment except self-employed individuals, employees of private households, railroad employees, agricultural production employees, and most government employees.[22]

To supplement the employment and establishment count measures available from the CBP, we utilize the NBER-CES Manufacturing Industry Database for the years 1971 through 2009 (the latter

[22]CBP data is extracted from the Business Register, a file of all known U.S. companies that is maintained by the U.S. Census Bureau; see http://www.census.gov/econ/cbp/index.html. To preserve confidentiality, CBP information on employment by industry is sometimes reported as an interval instead of an exact count. We compute employment in these cells using the fixed-point imputation strategy developed by Autor, Dorn and Hanson (2013).

being the latest year available).[23] These data allow us to explore labor market outcomes not reported in the CBP, as well as to perform a falsification exercise not possible in the CBP. We additionally draw on the NBER-CES data to compute measures of the production structure in each industry, subsequently used as controls, including: production workers as a share of total employment, the log average wage, the ratio of capital to value added, computer investment as a share of total investment, and high-tech equipment as a share of total investment. Additionally, we create industry pre-trend controls for the years 1976 through 1991, including the changes in industry log average wages and in the industry share of total U.S. employment.

A final data source used in our analysis is the 1992 input-output table for the U.S. economy (from the U.S. Bureau of Economic Analysis), which we use to trace upstream and downstream demand linkages between industries both inside and outside of U.S. manufacturing.[24] We discuss our application of input-output tables in more detail below.

4 Estimates of the Direct Impact of Trade Exposure on Employment

We begin by estimating the direct effect of trade exposure on employment over the period 1991 through 2011 using aggregate, industry-level regressions.

4.1 Baseline Results for National Industries

Our initial specification is of the following form:

$$\Delta L_{j\tau} = \alpha_\tau + \beta_1 \Delta IP_{j\tau} + \gamma X_{j0} + e_{j\tau}, \tag{3}$$

where $\Delta L_{j\tau}$ is 100 times the annual log change in employment in industry j over time period τ; $\Delta IP_{j\tau}$ is 100 times the annual change in import penetration from China in industry j over period τ as defined in (1); X_{j0} is a set of industry-specific start of period controls (specified later); α_τ is a period-specific constant; and $e_{j\tau}$ is an error term. We fit this equation separately for stacked first differences covering the two subperiods 1991-1999 and 1999-2011, where in some specifications we shorten the second subperiod to 1999-2007 in order to evaluate employment impacts prior to the onset of the Great Recession. Variables specified in changes (denoted by Δ) are annualized since

[23] The NBER-CES database contains annual industry-level data from 1958-2009 on output, employment, payroll and other input costs, investment, capital stocks, TFP, and various industry-specific price indexes (Becker, Gray, and Marvakov, 2013). Data and documentation are at http://www.nber.org/data/nberces5809.html.

[24] These data are at http://www.bea.gov/industry/io_benchmark.htm.

equation (3) is estimated on periods of varying lengths. The elements in the vector of controls X_{j0}, when included, are each normalized with mean zero so that the constant term in (3) reflects the change in the outcome variable conditional only on the variable of interest, $\Delta IP_{j\tau}$. Most outcome variables are measured at the level of 392 four-digit manufacturing industries, while later models also estimate spillovers to 87 non-manufacturing industries. Regression estimates are weighted by start-of-period industry employment, and standard errors are clustered at the three-digit industry level to allow for arbitrary error correlations within larger industries over time.[25]

Table 1 summarizes the import exposure and employment variables used in initial estimates of equation (3). The employment-weighted mean industry saw Chinese import exposure rise by 0.5 percentage points per year between 1991 and 2011, with more rapid penetration during 1999 through 2007 than during 1991 through 1999: 0.8 versus 0.3 percentage points, respectively. Growth from 2007 to 2011, at 0.3 percentage points per year, indicates a marked slowdown in import expansion in the late 2000s. The slowdown during that period is the combined effect of a steep decline in U.S. trade in 2008 and 2009 and an equally dramatic recovery in 2010 (Levchenko, Lewis, and Tesar, 2010), which together left import penetration rates modestly higher.[26]

Table 1

Industry-Level Changes in Chinese Import Exposure and U.S. Manufacturing Employment.

		1991-2011				1991-1999	1999-2011	1999-2007	2007-2011
	N	Mean/SD	Median	Min	Max	Mean/SD	Mean/SD	Mean/SD	Mean/SD
100 x Annual Δ in U.S. Exposure to Chinese Imports	392	0.50	0.14	-0.02	10.93	0.27	0.66	0.84	0.30
		(0.94)				(0.75)	(1.33)	(1.61)	(1.68)
Instrument for Δ in U.S. Exposure to Chinese Imports	392	0.44	0.15	-0.52	8.59	0.18	0.60	0.60	0.62
		(0.76)				(0.44)	(1.07)	(1.07)	(1.32)
100 x Annual Log Δ in Emp. (Manufacturing Industries)	392	-2.71	-2.05	-38.32	4.62	-0.30	-4.32	-3.62	-5.73
		(3.07)				(3.49)	(3.85)	(4.15)	(5.02)
100 x Annual Log Δ in Emp. (Non-Manufacturing Industries)	87	1.33	1.02	-5.73	5.75	2.46	0.57	1.54	-1.37
		(1.46)				(2.38)	(1.56)	(1.59)	(2.83)

Note.—For each manufacturing industry, the change in U.S. exposure to Chinese imports is computed by dividing 100 x the annualized increase in the value of U.S. imports over the indicated period by 1991 U.S. market volume in that industry. The instrument is constructed by dividing 100 x the annualized increase in imports from China in a set of comparison countries by 1988 U.S. market volume in the industry. The quantities used in these computations are deflated to constant dollars using the Personal Consumption Expenditures price index. Employment changes are computed in the County Business Patterns. All observations are weighted by 1991 industry employment.

Changes in import penetration are highly right-skewed across manufacturing industries, with

[25]There are 135 three-digit manufacturing industry clusters encompassing the 392 four-digit industries. Because our non-manufacturing data have already been extensively aggregated to 87 industries for concordance with the BEA input-output table, we treat each of the 87 non-manufacturing industries as a single cluster.

[26]Explanations for the excess sensitivity of trade flows during the Great Recession include the role of shocks to the credit market and trade finance (Amiti and Weinstein, 2011; Chor and Manova, 2012), and to global production networks (Levchenko et al. 2010). Other explanations dwell on the large drop in durable good spending during the crisis (Eaton et al., 2013).

the mean increase exceeding the median by a factor of 3.5. We find a similar pattern of import penetration change and skewness in the other high-income countries used to construct the import penetration instrument, where this skewness reflects China's strong comparative advantage in labor-intensive industries. Table 1 also shows that the manufacturing decline accelerated throughout the sample: the average industry contracted by 0.3 log points per year between 1991 and 1999, by 3.6 log points per year between 1999 and 2007, and by 5.7 log points per year in the final period 2007 to 2011. The within-industry growth rate of non-manufacturing employment also slowed across the three subperiods of our sample, but the deceleration was not nearly as pronounced as in manufacturing.

Table 2 presents a simple stacked first-difference model for the two time periods 1991-1999 and 1999-2011, with the change in import penetration and a dummy for each time period as the only regressors. Alongside these estimates, we also present results from stacking the time periods 1991-1999 and 1999-2007, and from fitting the model separately for the three subperiods 1991-1999, 1999-2011, and 1999-2007. These additional specifications permit inspection of results before and after the commencement of the 2000s U.S. employment sag, and allow for comparison of the results for the 2000s with and without including the Great Recession years. We also present results for the single long difference, 1991-2011, for comparison against the stacked first differences.

Table 2

Effect of Import Exposure on Log Employment in U.S. Manufacturing Industries: OLS and 2SLS Estimates.

	Stacked Differences (N = 784)				Separately By Period (N = 392)			
		1991-2011		1991-2007	1991-1999	1999-2011	1999-2007	1991-2011
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
100 x Annual Δ in U.S.		-0.81***	-1.30***	-1.24***	-2.30**	-1.16***	-1.12***	-1.49***
Exposure to Chinese Imports		(0.16)	(0.41)	(0.37)	(1.12)	(0.37)	(0.34)	(0.47)
1{1991-1999}	-0.30	-0.08	0.05	0.04				
	(0.37)	(0.36)	(0.36)	(0.36)				
1{1999-2011}	-4.32***	-3.79***	-3.46***					
	(0.37)	(0.33)	(0.33)					
1{1999-2007}				-2.58***				
				(0.38)				
Constant					0.32	-3.55***	-2.68***	-1.96***
					(0.43)	(0.34)	(0.39)	(0.27)
Estimation Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

Note.—Columns (1)-(4) report results from stacking log employment changes and changes in U.S. exposure to Chinese imports over the periods 1991-1999 and either 1999-2011 or 1999-2007, as indicated (N = 784 = 392 4-digit manufacturing industries x 2 periods). Columns (5)-(8) report results from regressing the employment change over the indicated period on the change in U.S. exposure to Chinese imports over the same period (N = 392). Employment changes are computed in the County Business Patterns and are expressed as 100 x annual log changes. In 2SLS specifications, the change in U.S. import exposure is instrumented as described in the text. In all specifications, observations are weighted by 1991 employment. Standard errors in parentheses are clustered on 135 3-digit industries in all specifications.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

In column 1, which excludes the import penetration variable, the time dummies reflect the (employment-weighted) mean annual within-industry change in employment in each period. Column 2 adds the observed import exposure measure without instrumentation. This variable is negative and highly significant, consistent with the hypothesis that rising import penetration lowers domestic industry employment. Nevertheless, as noted above, this OLS point estimate could be biased because growth in import penetration is driven partly by changes in domestic supply and demand. Column 3 mitigates this simultaneity bias by instrumenting the observed changes in industry import penetration with contemporaneous changes in other-country China imports as specified in equation (2) above. The estimate in column 3 implies that a one percentage point rise in industry import penetration reduces domestic industry employment by 1.3 percentage points (t-ratio of 3.2). Column 4, which stacks the periods 1991-1999 and 1999-2007, shows that the coefficient of import penetration is very similar if we restrict attention to the years preceding the Great Recession.

The remaining columns of Table 2 present bivariate estimates of this relationship separately by subperiod. The coefficient on trade exposure is negative and statistically significant in all time periods, and is largest in absolute value for 1991 to 1999 and smallest for 1999 to 2007. Even though

the sensitivity of employment to import penetration is greater before 2000, the much faster growth in China's imports after 2000 produces an overall impact of trade on employment that, as we discuss below, is considerably larger in the latter period. The sensitivity of employment to trade from 1999 to 2011 is similar to the estimate for 1999 to 2007, despite the onset of the global financial crisis in 2007 and the associated dislocation of worldwide trade patterns.[27]

A simple long-difference model for the change in manufacturing employment over the full 1991 through 2011 period (column 8) also supports a negative relationship between import penetration and U.S. manufacturing employment. The coefficient estimates in column 3, for the stacked first differences, and column 8, for the long time difference, are quite similar, reflecting strong persistence in the growth in China's import penetration within industries. Replacing stacked first differences with the long difference may remove cyclical variation in the data, accounting for the mildly larger coefficient estimates in the latter case.

Returning to the results in column 3 of Table 2, we evaluate the economic magnitude of these estimates by constructing counterfactual changes in employment that would have occurred absent increases in Chinese import competition. Using equation (3), we write the difference between actual and counterfactual manufacturing employment in year t as

$$\Delta L_t^{cf} = \sum_j L_{jt} \left[1 - e^{-\hat{\beta}_1 \Delta \widetilde{IP}_{jt}} \right], \tag{4}$$

where $\hat{\beta}_1$ is the 2SLS coefficient estimate from (3) and $\Delta \widetilde{IP}_{jt}$ is the increase in import penetration from China that we attribute to China's improving competitive position in industry j between 1991 (or 1999) and year t. Following Autor, Dorn and Hanson (2013), we estimate $\Delta \widetilde{IP}_{jt}$ by multiplying the observed increase in import penetration ΔIP_{jt} with the partial R-squared from the first-stage regression of (1) on the instrument in (2), which has a value of 0.56 in our baseline specification in column 3 in Table 2. When our instrument is valid and there is no measurement error, this partial R-squared adjusted $\Delta \widetilde{IP}_{jt}$ variable is a consistent estimate of the contribution of Chinese import supply shocks to changes in import penetration. In constructing the counterfactuals, we further assume that all other factors, including observed covariates and unobserved shocks captured by the error term in (3), would be unaffected by the artificially imposed reduction in the growth of import penetration from China.

[27] In the United States, imports plus exports divided by GDP fell by a stunning 22% from the first quarter of 2008 to the first quarter of 2009. However, imports fully recovered in 2010 and continued to grow in 2011. The exaggerated cyclical swings in trade surrounding the Great Recession thus mix with the continued secular growth in China's exports to the United States over the period.

We collect these counterfactual estimates in Table 8, where we compare employment estimates across three different estimation strategies. The first row of Table 8 reports counterfactual employment differences implied by the estimates in Table 2, where we evaluate changes for 1991 to 1999, 1999 to 2011, and the entire 1991 to 2011 period. Using coefficient estimates from column 3, we calculate that had import penetration from China remained unchanged between 1991 and 2011, manufacturing employment would have fallen by 837 thousand fewer jobs over the full 1991 to 2011 span, and by 560 thousand fewer jobs during the employment sag era of 1999 to 2011. Observed manufacturing employment changes over these time periods were minus 5.6 million workers (11.4 million - 17.0 million) and minus 5.8 million workers (11.4 million - 17.2 million), respectively. The larger quantity for the second period is indicative of the modest growth in manufacturing employment of 200 thousand workers that occurred between 1991 and 1999. By shutting down China's import growth, the contraction of U.S. manufacturing employment suggested by our estimates would have been 14.9 percentage points smaller over 1991 to 2011, and 9.7 percentage points smaller for the period after 1999. It is also worth noting that counterfactual reductions in employment for the period 1991-2007—based on the specification in column 4 of Table 2—amount to 853 thousand, quite similar to our estimates for 1991-2011.

4.2 Comparison to Other Estimates in the Literature

How do our estimates of the direct effect of import competition on manufacturing employment compare with those found the literature? There are few estimates to consider, as the majority of work on the labor market implications of globalization addresses not the *absolute* employment effects of trade, but its impact on relative wages and relative employment levels by skill (e.g., Harrison, McLaren, and McMillan, 2011). Trade impacts on *absolute* employment levels are a less common object of study, perhaps reflecting modeling conventions that impose inelastic labor supply and full employment.

In an influential treatment of trade impacts on U.S. manufacturing, Bernard, Jensen, and Schott (2006) estimate that import penetration from low-income countries—with China being the largest member of this group by far—accounts for 14% of the total decline in manufacturing employment of 675 thousand workers that occurred between 1977 and 1997.[28] Their specification differs from ours, making a direct comparison of the two sets of results difficult to perform. They regress the change

[28] In related work, Artuç, Chaudhuri, and McLaren (2010) evaluate how costs to workers of moving between sectors dampen the employment response to changes in trade barriers, and Muendler and Becker (2010) and Harrison and McMillan (2011) estimate the responsiveness of employment in multinational companies to changes in foreign wages. This work tends to emphasize the elasticity of employment with respect to changes in trade barriers or foreign production costs, rather than producing estimates of aggregate impacts of foreign competition on employment.

in log employment at the level of the manufacturing *plant* (rather than industry) on the initial *level* (rather than change) of the *share* of low income countries in industry imports (rather than the import penetration rate). Despite these differences, Bernard et al. find a relatively high sensitivity of employment to import competition. But over their period of study, the annual increase in import penetration from low income countries in U.S. manufacturing was only 0.09 percentage points,[29] whereas over our sample period the annual increase in import penetration from China alone was 0.50 percentage points (Table 1). Had their much lower level of import growth obtained over our sample period, the reduction in manufacturing job loss implied by our coefficient estimates would have been only one-fifth as large.[30] One reason why Bernard et al.'s analysis may produce higher estimates of the impact of imports on employment than ours is that they study plant-level data as compared to our industry-level regressions. Aggregating across plants within an industry is preferable in this instance because it avoids confounding aggregate effects with within-industry reallocation, which take place as some workers may exit declining plants to take jobs with establishments in their same sector (consistent with the results in Autor, Dorn, Hanson and Song, 2014).

Pierce and Schott (2015) use a difference-in-difference strategy to test whether after 2001 manufacturing employment fell by more in industries that were more exposed to China's WTO accession. They measure this potential increase in exposure to China trade using the difference between the U.S. MFN (most favored nation) tariff and the U.S. non-MFN tariff—to which China was potentially subject prior to becoming a WTO member and whose level was substantially higher than the MFN duty. Pierce and Schott thus identify the growth in China trade after 2001 using the notional reduction in U.S. trade barriers confronting China. A complication with this approach is that the U.S. granted China MFN status on a renewable basis in 1980, two decades prior the country joining the WTO. The U.S. non-MFN tariff is only a meaningful predictor of China's pre-2001 trade to the extent that there was genuine risk the U.S. government would choose not to renew China's MFN privileges, an eventuality that Congress discussed annually but that never materialized. Pierce and Schott estimate that China's WTO accession reduced post-2001 manufacturing employment by 15.1 log points in exposed industries relative to non-exposed industries.[31] Our estimates, which identify the impact of growth in China's imports based on the common component of the country's export expansion across high-income markets, imply that had there been no increase in import pen-

[29] This figure comes from information provided in Table 2 of Bernard et al. (2006).

[30] This ratio is based on the calculation, $\left(1 - e^{-1.30\times.56\times.09}\right) / \left(1 - e^{-1.30\times.56\times.50}\right) = 0.21$, where the value -1.30 is the coefficient from column 3 of Table 2 and the value .56 discounts observed changes in import penetration by the partial R-squared of the first stage.

[31] This estimate is from column 3 of Table 1 of their paper, which we view as closest in spirit to the specifications in our paper.

etration from China after 1999, the 2011 level of employment would have been 4.9 percent higher (.560m/11.4m) than it otherwise would have been. Comparing our results in Table 2 to Bernard et al. (2006) and to Pierce and Schott (2015) thus suggests that our estimates for the direct industry-level employment effects of China trade are relatively modest.

4.3 Controlling for Industry Confounds and Pre-trends

A challenge for our analysis is that industries subject to greater import competition may be exposed to other economic shocks that are correlated with China trade. We begin to address this concern in Table 3 by incorporating controls for potential industry confounds. We additionally offer a set of falsification tests.

We consider three groups of control variables. First, we probe the robustness of our results by including dummies for ten one-digit manufacturing sectors. Since our regressions are in first differences, the inclusion of these dummies amounts to allowing for differential trends across these one-digit sectors. Regressions including these dummies therefore identify the industry-level impacts of trade exposure while purging common trends within the one-digit sectors and using only variation in import growth across industries with relatively similar skill intensities.

Technological progress within manufacturing has been most rapid in recent decades in computer and skill-intensive sectors (Doms, Dunne, and Troske, 1997; Autor, Katz, and Krueger, 1998). To capture the extent to which industries are exposed to technical change, we next add a second set of control variables, drawn from the NBER-CES database, measuring the intensity of their use of production labor and capital. These variables, summarized in Table A1, include the share of production workers in total employment, the log of the average wage, the ratio of capital to value added (all measured in 1991), as well as computer and high-tech equipment investment in 1990, each expressed as a share of total 1990 investment.

U.S. manufacturing as a share of employment has been declining since the 1950s, and the number of manufacturing employees has also trended downward since the 1980s. This long-standing secular trend highlights a concern that the correlation we document between rising industry trade penetration and contemporaneous, within-industry declines in manufacturing employment during 1991 through 2011 could potentially pre-date the recent rise in import exposure. In that case, our estimates would likely overstate the impact of trade exposure in the current period. We therefore finally add measures of pre-trends in industry employment and earnings in Table 3, specifically the change in the industry's share of total U.S. employment, and the change in the log of the industry average wage, both measured over the interval 1976 to 1991 (Table A1).

The first seven columns of Table 3 permute among combinations of these three groups of industry controls: the one-digit sector dummies, industry-level controls for production structure, and industry-level controls for pre-trends. Column 1 replicates results from column 3 of Table 2 to serve as a benchmark. Among the additional groups of covariates, only the one-digit sector dummies have a substantial impact on the point estimates, reducing the (instrumented) estimates by about 40 percent.[32] Though the inclusion of the sectoral dummies is an important robustness check for our results, there are two reasons why these specifications may underestimate the impact of Chinese import competition. First, trade exposure at the four-digit industry level is likely to be measured with error, and the inclusion of the one-digit sector dummies will then cause significantly greater attenuation of our estimates of the impact of Chinese import growth. Second, if there is a significant increase in imports in some industries within a one-digit sector (say, in women's dresses within textiles), then employers in other similar industries within this broad sector (say, women's blouses and shirts, also within textiles) may anticipate greater competition both from the substitutes already being imported from China and also from future waves of Chinese imports, and thus will be more likely to downsize and close existing plants and less likely to open new plants. By contrast, neither the production nor the pre-trend variables have an important effect on the magnitude or precision of the coefficient of interest. As a further robustness test, column 8 includes a full set of dummies for the 392 four-digit manufacturing industries in our data. These variables serve as industry-specific trends in our stacked first-difference specification, so the effect of import competition on industry employment in this specification is identified by changes in the *growth rates* of industry employment and import penetration in 1999-2011 relative to 1991-1999. Remarkably, relative to specifications that include one-digit sector dummies, the addition of an exhaustive set of industry-specific trends only modestly reduces the point estimate and precision of the coefficient of interest, thus highlighting the robustness of the relationship. In summary, while our preferred industry-level model from column 3 of Table 2 allows for an impact of Chinese trade competition on employment both within and across broad manufacturing subsectors, the estimates in Table 3 document that a sizable negative employment effects remains even when focusing only on the within-subsector or within-industry, over-time variation in trade exposure.

[32] Quantitatively, the specification in column 2 of Table 3 implies that had import penetration from China remained unchanged between 1991 and 2011, manufacturing employment would have fallen by 463 thousand jobs over the full 1991 to 2011 span, and by 307 thousand jobs between 1999 and 2011, which are about 45% lower than our baseline numbers.

Table 3

2SLS Estimates of Import Effects on Log Employment Including Industry-Level Controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
100 x Annual Δ in U.S.	-1.30***	-0.75***	-1.10***	-1.33***	-0.80***	-0.76***	-0.74***	-0.60**
Exposure to Chinese Imports	(0.41)	(0.22)	(0.35)	(0.43)	(0.25)	(0.22)	(0.23)	(0.29)
1{1991-1999}	0.05	-0.09	0.00	0.06	-0.08	-0.09	-0.10	
	(0.36)	(0.32)	(0.37)	(0.36)	(0.30)	(0.32)	(0.30)	
1{1999-2011}	-3.46***	-3.82***	-3.59***	-3.44***	-3.79***	-3.82***	-3.83***	-3.79***
	(0.33)	(0.27)	(0.35)	(0.32)	(0.28)	(0.26)	(0.27)	(0.45)
1-Digit Mfg Sector Controls	No	Yes	No	No	Yes	Yes	Yes	No
Production Controls	No	No	Yes	No	Yes	No	Yes	No
Pretrend Controls	No	No	No	Yes	No	Yes	Yes	No
Industry Fixed Effects	No	No	No	No	No	No	No	Yes

Note.—Each column reports results from stacking log employment changes and changes in U.S. exposure to Chinese imports over the periods 1991-1999 and 1999-2011 (N = 784 = 392 4-digit manufacturing industries x 2 periods). The dependent variable is 100 x the annual log change in each industry's employment in the County Business Patterns (CBP) over the relevant period. The regressor is 100 x the annual change in U.S. exposure to Chinese imports over the same period; it is instrumented as described in the text. Sector controls are dummies for 10 1-digit manufacturing sectors. Production controls for each industry include production workers as a share of total employment, the log average wage, and the ratio of capital to value added (in 1991); and computer investment as a share of total investment and high-tech equipment as a share of total investment (in 1990). Pretrend controls are changes in the log average wage and in the industry's share of total employment over 1976-1991. In the final column, we include a full set of 4-digit industry fixed effects. Covariates are demeaned to facilitate interpretation of the time effects. Observations are weighted by 1991 employment. Standard errors in parentheses are clustered on 135 3-digit industries.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

As a falsification exercise, Table 4 reports results from a regression of changes in industry employment in earlier decades on the instrumented change in industry import exposure between 1991 and 2011. It would be problematic for our identification strategy if future growth in Chinese import exposure predicted industry employment declines in the era prior to China's trade opening.[33] Panel A performs this exercise without additional covariates, while panel B controls for ten one-digit sector dummies. In both panels, the estimated relationship between our China trade exposure measure and industry employment is statistically insignificant and close to zero in both the 1970s (1971-1981) and 1980s (1981-1991). The point estimate only becomes economically large and statistically significant after 1990. This pattern of results is consistent with the hypothesis that the within-industry correlation between rising import penetration and declining manufacturing employment in the 1990s and 2000s emanates from contemporaneous trade shocks rather than long-standing factors driving

[33] To carry the analysis back to 1971, we employ the NBER-CES data, which covers a longer time horizon than the County Business Patterns data used in our main estimates. A disadvantage is that the NBER-CES database is currently only updated through 2009, two years less than the CBP. To improve comparability, we use the NBER data in *all* columns of Table 4, including for the post-1990 period (unlike in Tables 2 and 3, where we use CBP data). These estimates also differ from those in Tables 2 and 3 in that the import exposure variable (and its instrument) corresponds to the long 1991-2011 change in all columns.

industry decline.

Table 4

2SLS Estimates of Import Effects on Log Employment over 1971-2009.

	1971-1981	1981-1991	1991-1999	1999-2009	1991-2009
	(1)	(2)	(3)	(4)	(5)
	A. Excluding 1-Digit Mfg Sector Controls				
100 x Annual Δ in U.S. Exposure to Chinese	0.34	-0.40	-0.84*	-2.01***	-1.49***
Imports (computed over 1991-2011)	(0.33)	(0.28)	(0.45)	(0.66)	(0.51)
Constant	1.19***	-0.68**	0.35	-3.97***	-2.05***
	(0.30)	(0.34)	(0.46)	(0.43)	(0.29)
	B. Including 1-Digit Mfg Sector Controls				
100 x Annual Δ in U.S. Exposure to Chinese	0.20	0.03	-0.57*	-0.91***	-0.76***
Imports (computed over 1991-2011)	(0.26)	(0.26)	(0.31)	(0.31)	(0.23)
Constant	-0.05	-0.08	0.52	-0.98**	-0.32
	(0.32)	(0.74)	(0.63)	(0.45)	(0.48)

Note.—N = 384 4-digit manufacturing industries (we exclude 8 industries for which post-1996 employment data are unavailable in the NBER-CES Manufacturing Industry Database). The dependent variable in each specification is 100 x the annual log employment change over the indicated period, as computed in the NBER-CES data. The regressor in each specification is 100 x the annual change in U.S. exposure to Chinese imports over 1991-2011, instrumented as described in the text. Panel A includes no additional controls. Panel B includes dummies for 10 1-digit manufacturing sectors. Observations are weighted by 1991 employment. Standard errors in parentheses are clustered on 135 3-digit industries.

* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$

4.4 Additional Employment and Establishment-Level Outcomes

We have so far focused on the effects of trade exposure on industry employment, which is but one margin along which industries adjust. Others include the wage bill, establishment size, establishment shutdown, and production versus non-production employment and earnings. Using a combination of CBP and NBER-CES data, we explore these outcomes in Table 5.

Table 5

2SLS Estimates of Import Effects on Additional Labor Market Outcomes.

	Emp.	Num Estabs.	Emp Per Estab.	Real Wage Bill	Real Wage	Prod. Emp.	Non-Prod. Emp.	Real Prod. Wage	Real Non-Prod. Wage
	CBP	CBP	CBP	CBP	CBP	NBER	NBER	NBER	NBER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					A. 2SLS Estimates				
100 x Annual Δ in U.S.	-0.75***	-0.23***	-0.52***	-0.67***	0.08	-0.99***	-0.78***	0.24**	-0.05
Exposure to Chinese Imports	(0.22)	(0.09)	(0.17)	(0.21)	(0.06)	(0.31)	(0.29)	(0.11)	(0.09)
1{1991-1999}	-0.09	0.48**	-0.57**	1.53***	1.63***	0.33	-0.20	1.13***	1.81***
	(0.32)	(0.19)	(0.26)	(0.30)	(0.08)	(0.38)	(0.34)	(0.06)	(0.09)
1{1999-2011} or 1{1999-2009}	-3.82***	-1.51***	-2.31***	-3.42***	0.40***	-4.84***	-3.63***	0.22	0.32***
	(0.27)	(0.19)	(0.18)	(0.30)	(0.10)	(0.37)	(0.31)	(0.14)	(0.11)
1-Digit Mfg Sector Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
					B. Dependent Variable Means by Time Period				
1{1991-1999}	-0.30	0.41**	-0.71***	1.35***	1.65***	0.06	-0.40	1.19***	1.80***
	(0.32)	(0.19)	(0.26)	(0.31)	(0.07)	(0.38)	(0.33)	(0.06)	(0.08)
1{1999-2011} or 1{1999-2009}	-4.32***	-1.67***	-2.66***	-3.87***	0.46***	-5.38***	-4.06***	0.35**	0.30**
	(0.25)	(0.17)	(0.17)	(0.29)	(0.08)	(0.34)	(0.32)	(0.14)	(0.13)

Note.—In the table heading, CBP and NBER indicate the dataset used to compute the indicated outcome (CBP = County Business Patterns, NBER = NBER-CES Manufacturing Industry Database). Each column stacks changes in the indicated outcome and changes in U.S. exposure to Chinese imports over the periods 1991-1999 and either 1999-2011 (for CBP outcomes) or 1999-2009 (for NBER-CES outcomes). In columns (1)-(5), N = 784 = 392 4-digit manufacturing industries x 2 periods. In columns (6)-(9), we exclude 8 industries for which post-1996 data are unavailable in the NBER-CES, yielding N = 768 = 384 industries x 2 periods. In each column, the dependent variable is 100 x the annual log change in the indicated quantity. Panel A reports 2SLS estimates including the annual change in U.S. exposure to Chinese imports over the relevant period; it is instrumented as described in the text. Panel B reports OLS estimates from a regression including only time effects and sector controls. All specifications include dummies for 10 1-digit manufacturing sectors, which are demeaned to facilitate interpretation of the time effects. Observations are weighted by 1991 employment in the relevant dataset. Standard errors in parentheses are clustered on 135 3-digit industries.

* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$

Given our findings on how import penetration affects employment in Tables 2 and 3, many of the results in Table 5 are in line with expectations. Stronger import competition reduces the count of establishments (column 2), average employment per establishment (column 3), and total industry wage payments (column 4). Production employment (column 6) declines slightly more than non-production employment (column 7), indicating a larger sensitivity to Chinese import competition on the part of lower skilled labor, a result consistent with China's strong comparative advantage in labor-intensive sectors.

The table also contains some informative surprises. Trade exposure predicts a *rise* in real industry log wages for production workers (column 8)—that is, the real production worker wage bill divided by the production worker headcount. The impact on non-production worker wages (column 9) is

negative but small and not statistically significant. Joining these two effects produces the positive but insignificant coefficient estimate for average real wages (column 5). The results for production workers that combine strongly negative employment effects and mildly positive average wage effects are suggestive of trade-induced changes in the composition of employment. Less highly paid workers may be those more likely to be laid off within the subgroup of production employees, leading to an upward shift in wages among those still employed as a result of unobserved changes in composition. This interpretation is consistent with Autor, Dorn, Hanson, and Song's (2014) finding that the earnings of lower wage workers are most adversely affected by greater import competition.[34]

5 Accounting for Sectoral Linkages

We now expand the scope of the inquiry to encompass the effects of trade shocks on employment in both manufacturing and non-manufacturing industries working through input-output linkages. In Appendix B, we present a simple model of Cobb-Douglas production that yields expressions for changes in industry employment resulting from upstream and downstream import exposure. Here we discuss the empirical implementation of these upstream and downstream effects.

To study these inter-industry linkages, we envisage an economy along the lines of that studied by Long and Plosser (1983) and Acemoglu et al. (2012), where each industry uses with different intensities the output of other industries as inputs. We apply this methodology to the Bureau of Economic Analysis' input-output table for 1992. We choose the 1992 input-output table since it largely predates the China trade shock and hence measures linkages that are unlikely to be endogenous to the subsequent shock.

To estimate the upstream effect—the exposure to import competition that propagates upstream from an industry's buyers—we calculate the following quantity for each industry j,

$$\Delta IP^U_{j\tau} = \sum_g w^U_{gj} \Delta IP_{g\tau}, \tag{5}$$

[34]Complementing these results, Table A2 reports the impact of Chinese import competition on industry output, measured as the value of shipments. In panel A, we find that import exposure has an economically and statistically significant negative effect on nominal shipments (column 1), but when we decompose this effect into changes in real shipments and changes in the shipments price deflator (columns 2 and 3), we find no effect on real shipments. This surprising pattern turns out to be driven by computer-producing industries, which experienced rapid growth in real value added, precipitous declines in output prices, and substantial increases in Chinese import penetration during our sample period. In panel B, where we exclude 28 computer-producing industries corresponding to NAICS 334, we find comparable effects on nominal shipments, but these effects are now driven primarily by relative declines in real shipments in trade-exposed industries, rather than by relative declines in output prices. We view these results as consistent with a mounting body of evidence that computer-producing industries have an outsized influence on measured output and productivity in the manufacturing sector (Houseman, Bartik, and Sturgeon 2015; Acemoglu et al. 2014b).

which is equal to the weighted average change in import penetration during time interval τ across all industries, indexed by g, that purchase from industry j. These weights w_{gj}^{D} are defined as

$$w_{gj}^{U} = \frac{\mu_{gj}^{U}}{\sum_{g'} \mu_{g'j}^{U}}, \tag{6}$$

where μ_{gj}^{U} is the 1992 "use" value in the BEA input-output matrix for the value of industry j's output purchased by industry g, such that the weight in (6) is the share of industry j's total sales that are used as inputs by industry g. Thus, (5) is a weighted average of the trade shocks faced by the purchasers' of j's output.[35] When industry j's purchasers suffer a negative trade shock, they are likely to reduce demand for j's output. The theoretical justification for these expressions is provided in Appendix B using a simple model of input-output linkages.

Similarly, to compute the downstream effect $\Delta IP_{j\tau}^{D}$ experienced by each industry j—that is, the exposure to import competition that propagates downstream from j's suppliers—we make the same calculation after reversing the j and g indexes in the numerator of (6).[36] We instrument both the upstream and downstream exposure measures analogously to our main import shock measure: using contemporaneous changes in China imports in eight other high-income countries to calculate *predicted* upstream and downstream exposure for each industry, where these predictions serve as instruments for the measured domestic values. Concretely, we construct these instruments by replacing the term $\Delta IP_{g\tau}$ with $\Delta IPO_{g\tau}$ in equation (5), while retaining the same weights.

Equation (5) accounts for the direct (first-order) effect on output demand of an industry j stemming from trade-induced changes in demand from its immediate buyers. But it ignores further indirect effects on industry j's demand stemming from changes in demand from its buyers' buyers, and so on. To account for the full chain of linked downstream and upstream demands, we replace $\Delta IP_{j\tau}^{U}$ and $\Delta IP_{j\tau}^{D}$ (and their instruments) with the full chain of implied responses from the input-output matrix, which is given by the Leontief inverse of the matrix of upstream and downstream linkages (see, e.g., Acemoglu et al. 2012). The details of this computation are given in Appendix B.

Upstream and downstream exposure measures are summarized in Table A3. As expected, the

[35] We use the BEA "make" table to assign commodities to the industries that produce them. The summation in the denominator of equation (6) runs over not only manufacturing industries, but also non-manufacturing industries as well as final demand. Since our *direct* shock variable only reflects manufacturing trade, all upstream effects experienced by a sector emanate by definition from shocks to their manufacturing purchasers (that is, $\Delta IP_{g\tau}$ is defined to equal zero for non-manufacturing industries and for final demand). These shocks affect both manufacturing and non-manufacturing industries to the degree that they supply inputs to manufacturing industries g that are directly shocked.

[36] When we construct weights for the downstream effect, the summation in the denominator again runs over industry j's total sales. Analogously to the case of upstream effects, downstream effects emanate from trade shocks to these industries' suppliers in manufacturing (though, as just noted, both manufacturers and non-manufacturers may have suppliers in manufacturing).

indirect exposure measures are substantially smaller in magnitude, and have far less cross-industry variation, than the direct exposure measures. In the average manufacturing industry, direct trade exposure is five times as large as the first-order downstream exposure measure and over three times as large as the first-order upstream exposure measure. Incorporating higher-order linkages significantly increases the magnitude of the upstream and downstream exposure measures. The full indirect upstream exposure measure (given by the Leontief inverse) is approximately half as large as the direct exposure measure, while the full indirect downstream exposure measure is about one-third as large as the direct exposure measure.

The two panels of Table 6 present instrumental variables estimates of the effects of import exposure on industry employment, akin to those in Table 3 column 1 (without the one-digit sector dummies) and column 2 (with the one-digit sector dummies), here augmented with the upstream and downstream import exposure measures. The upper panel of Table 6 employs the first-order upstream and downstream measures, $\Delta IP^U_{j\tau}$ and $\Delta IP^D_{j\tau}$, while the lower panel uses the full Leontief exposure measures. We present results with and without the one-digit sector dummies introduced earlier.[37]

[37] We do not include the industry production and pre-trend controls used in Table 3 since these were shown to have little effect conditional on sector dummies but still absorb degrees of freedom, which is problematic in a setting with multiple instrumented endogenous variables that are themselves correlated.

Table 6

2SLS Estimates of Import Effects on Employment Incorporating Input-Output Linkages.

	Manufacturing Inds. (N = 784)			Non-Mfg. Inds. (N = 174)		Pooling Mfg. and Non-Mfg. Inds. (N = 958)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					A. First-Order Input-Output Linkages					
Direct Import Exposure	-1.17***	-1.28***	-0.72***			-1.14***	-1.11**	-0.69***	-1.07***	
	(0.42)	(0.49)	(0.22)			(0.42)	(0.48)	(0.22)	(0.38)	
Upstream Import Exposure	-2.21*	-2.44**	-1.03**	-6.63**	-6.88**	-2.70**	-2.64**	-1.72**	-3.06***	
	(1.14)	(1.13)	(0.45)	(2.79)	(2.97)	(1.26)	(1.32)	(0.75)	(1.09)	
Downstream Import Exposure		2.31			-5.80		-0.67			
		(2.66)			(7.43)		(3.69)			
Combined Import Exposure (Direct + Upstream)										-1.35***
										(0.38)
					B. Full (Higher-Order) Input-Output Linkages					
Direct Import Exposure	-1.20***	-1.30***	-0.72***			-1.18***	-1.14**	-0.71***	-1.12***	
	(0.42)	(0.49)	(0.22)			(0.42)	(0.48)	(0.22)	(0.38)	
Upstream Import Exposure	-1.64*	-1.78**	-0.85**	-3.19	-3.17	-1.90**	-1.86**	-1.29**	-2.10***	
	(0.84)	(0.82)	(0.37)	(2.14)	(2.27)	(0.86)	(0.91)	(0.59)	(0.75)	
Downstream Import Exposure		1.74			-4.26		-0.68			
		(2.10)			(5.94)		(2.95)			
Combined Import Exposure (Direct + Upstream)										-1.32***
										(0.37)
Sector x Period Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1-Digit Mfg Sector Controls	No	No	Yes	No	No	No	No	Yes	No	No
Exclude 2007-2011	No	No	No	No	No	No	No	No	Yes	No

Note.—The sample consists of 392 manufacturing industries (columns 1-3), 87 non-manufacturing industries (4-5), or both sets of industries pooled (6-10). Each column stacks changes in log employment and changes in import exposure over the periods 1991-1999 and either 1999-2011 (columns 1-8, 10) or 1999-2007 (9). The dependent variable is 100 x the annual log change in employment, as computed in the County Business Patterns. The direct import exposure of industry i equals 100 x the annual change in U.S. exposure to Chinese imports. In panel A, upstream (respectively, downstream) import exposure for a given industry is a weighted average of the direct import exposure experienced by its customers (suppliers), as identified by the Bureau of Economic Analysis's 1992 input-output table. In panel B, we use the Leontief inverse of the input-output matrix to incorporate higher-order linkages. Direct, upstream, and downstream measures of import exposure are instrumented using changes in comparison countries' exposure to Chinese imports. See text for details. In column (10), combined import exposure is defined as the sum of the direct and upstream exposure measures used in the other columns; we include separate instruments for the direct and upstream components of the combined measures. Columns (1)-(5) include dummies for each time period. Columns (6)-(10) include sector (manufacturing/non-manufacturing) x period interactions. Where indicated, we include dummies for 10 1-digit manufacturing sectors (which equal zero for non-manufacturing industries). Observations are weighted by 1991 industry employment, and standard errors in parentheses are clustered on 3-digit industry (with each non-manufacturing industry constituting its own cluster).

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

Columns 1 through 3 of Table 6 consider the impact of upstream and downstream linkages on employment in the 392 manufacturing industries; columns 4 and 5 consider these impacts on employment in the 87 non-manufacturing industries; and columns 6-10 present results for manufacturing

and non-manufacturing pooled. All regressions employ the stacked first differences specification: columns 1 through 8 and 10 cover the time periods 1991 to 1999 and 1999 to 2011, while column 9 shortens the second period to 1999 - 2007. Downstream import effects are not statistically significant in any specification, and are unstable in sign, showing up as positive in the manufacturing only specification (column 2) and negative in the non-manufacturing and pooled specifications (columns 5 and 7).[38] This imprecision may be due to the fact that the downstream effects combine the offsetting effects of reduced domestic input supply (due to U.S.-based suppliers curtailing shipments in the face of increased import competition) and increased foreign input supply. Given the instability of effects working through downstream linkages, we focus our attention on the upstream effects, which are, in contrast, quite stable across specifications and are qualitatively similar for manufacturing and non-manufacturing sectors.

Consistent with our reasoning above, growth in an industry's upstream trade exposure is found to reduce industry employment. For manufacturing industries alone, the coefficient of the upstream linkage effect is quite large without the one-digit sector dummies in the regression (column 2), and of similar magnitude to the direct trade shock coefficient as well as more precisely estimated when the one-digit sector dummies are added in column 3. For non-manufacturing industries, upstream linkages are also negative and statistically significant (columns 4 and 5), and larger in magnitude than the estimates for manufacturing. Pooling manufacturing and non-manufacturing, coefficients on upstream linkages are negative and statistically significant either without (columns 6 and 7) or with (column 8) the one-digit sector dummies included in the regression.[39] Results for the period 1991-2007 (column 9) are quantitatively similar.

Finally, in the last specification in Panel B (column 10), we regress changes in industry employment on the *sum* of the direct and upstream exposure measures, which is the form suggested by our theoretical model in Appendix B. As expected, the estimated coefficient on the combined shock lies between the coefficients on the direct and upstream effects in column 6.[40]

Comparing across the two panels of Table 6, which employ the first-order (panel A) and full

[38] Additionally, the downstream effect in manufacturing reverses sign (while remaining insignificant) when the upstream variable is omitted. Observe that there is no 'direct' trade exposure effect in non-manufacturing since our trade measures are confined to manufactured goods.

[39] The non-manufacturing estimates do not include sector dummies (unlike the manufacturing estimates) since our non-manufacturing industry scheme is already highly aggregated and, moreover, does not collapse down readily to a one- or two-digit sector scheme since we had to extensively aggregate four-digit SIC industries for concordance with the input-output tables used by the BEA.

[40] We cannot reject the hypothesis that the coefficient on this combined variable is the same as the separate coefficients on the direct and the upstream exposure measures in column 2. The implied quantitative magnitudes (reported below) are also very similar regardless of whether we use this combined measure or separate measures for direct and indirect upstream effects.

(panel B) upstream and downstream measures, we detect a similar pattern of coefficient estimates. In all cases, the coefficients on the full exposure measures are smaller in magnitude than those on the first-order exposure measures, though they are also more precisely estimated. Of course, the full exposure measures are considerably larger in magnitude than the first-order exposure measures, so the smaller coefficients do not imply smaller quantitative effects.

Accounting for upstream linkages substantially increases the impact of trade shocks on employment. Using estimates from the regression that pools manufacturing and non-manufacturing together (column 6, the specification without one-digit sector dummies), we evaluate the counterfactual change in employment analogous to the exercise in equation (4), with the results again shown in Table 8. This new exercise combines the employment impacts of trade shocks working through direct effects and indirect effects associated with upstream linkages.[41] Had import competition from China remained unchanged between 1991 and 2011, according to our estimates from panel A (using only first-order upstream effects), there would have been 1.33 million additional workers employed in manufacturing and 805 thousand additional workers employed in non-manufacturing, for a total employment differential of 2.14 million workers. Examining just the 1999 to 2011 period, the corresponding counterfactual employment additions are 928 thousand in manufacturing and 653 thousand in non-manufacturing, for a total of 1.58 million additional workers employed. Accounting for the full set of direct and indirect upstream effects shown in our preferred specification (panel B, column 6), we obtain employment estimates that are larger again: 1.41 million workers in manufacturing, 1.22 million in non-manufacturing, and 2.62 million overall for 1991 through 2011; and 985 thousand workers in manufacturing, 994 thousand in non-manufacturing, and 1.98 million overall for 1999 through 2011. These combined direct and indirect effects of increased Chinese imports are substantially larger than the direct effects alone (837 thousand workers for 1991 to 2011, and 560 thousand workers for 1999 to 2011). Thus, accounting for upstream linkages inside and outside of manufacturing more than triples the estimated direct employment effects for manufacturing alone.[42]

These estimated magnitudes do not, however, include the full general equilibrium impact of trade exposure as they fail to capture aggregate reallocation and demand effects as outlined above. We

[41] Consistent with the analysis of Section 4, these counterfactuals assume that 56% of the observed growth in direct and indirect import exposure is attributable to the Chinese supply shock.

[42] The specification in column 8, which controls for ten one-digit manufacturing sector dummies, implies somewhat smaller employment effects. According to our estimates from panel B (accounting for the full set of direct and upstream effects), had import competition from China remained unchanged between 1991 and 2011, there would have been 857 thousand additional workers employed in manufacturing and 821 thousand additional workers employed outside of manufacturing, for a total employment gain of 1.68 million workers. For the 1999 to 2011 period, the corresponding counterfactual employment additions are 597 thousand in manufacturing and 670 thousand in non-manufacturing, yielding total employment gains of 1.27 million. These numbers are about 35% smaller than our baseline estimates incorporating the indirect upstream effects.

turn to local labor market analysis to obtain estimates of these additional adjustment mechanisms.

6 Local General Equilibrium Effects of Trade on Employment

Our industry-level analysis, which compares changes in relative employment among industries with differing levels of trade exposure, is not well-suited to identifying the reallocation and demand effects discussed in the Introduction and Section 2. In this section, we attempt to quantify the reallocation and aggregate demand effects by applying an alternative strategy that focuses on the implications of rising import competition from China for employment in local labor markets

6.1 Empirical Approach

To exposit the logic of our approach, consider a simplified setting in which each commuting zone (CZ) houses up to three sectors that have no input-output linkages: toys, footwear, and construction.[43] Toys and footwear experience an increase in imports from China, so we label these sectors as *exposed*. Construction does not experience this shock and we label it *non-exposed*. If a particular CZ has many workers employed in toys prior to the rise of import competition from China, it will experience significant worker displacement as this sector contracts.[44] Due to the reallocation effect, we would expect displaced workers to gain employment in another sector. This sector is unlikely to be footwear, however, since it is simultaneously facing rising import competition. In this simple setting, labor within the commuting zone should therefore reallocate towards construction. Estimating by how much employment in construction expands in this CZ as toys and footwear decline can help us to assess the positive general equilibrium effects resulting from reallocation.

Employment in construction may be affected by a second channel as well: the potentially negative Keynesian aggregate demand multiplier, stemming from reductions in local economic activity. In our simple example, the initial reduction in employment in exposed industries will reduce local incomes and, via this channel, may depress local demand for new home construction or renovation, further depressing employment.[45] The net effect of these reallocation and aggregate demand effects on employment in construction may be positive or negative.

[43] The choice of construction as the non-traded sector is motivated in part by Charles, Hurst, and Notowidigdo (2013), who find that the 2000-2007 housing boom helped local labor markets absorb workers displaced from manufacturing.

[44] This discussion also makes it clear that empirically, it is appropriate to combine the shocks of all of the local industries using weights related to their local employment shares, which is the strategy employed here and in Autor, Dorn and Hanson (2013).

[45] It is possible for trade-induced price declines to simultaneously contribute to aggregate demand by spurring additional consumption or investment as discussed in footnote 14.

Now suppose that the third industry in this economy is not construction but chemicals, which unlike construction, is tradable within the United States across local labor markets and, as it happens, has not been subject to significant increases in import competition from China. To make progress in this case, suppose that our local labor markets can be thought of as small open economies within the United States, so that prices of tradables are determined at the U.S. level (or on world markets). This does not change the reallocation effect, but it may alter the aggregate demand effect. Even if aggregate demand for non-tradables in the local labor market is depressed, there might be an increase in local employment in chemicals, the output of which is then sold to residents in other CZs. This is simply a reflection of the fact that the component of the negative aggregate demand effect working at the national level will not be easily identified from variation across local labor markets. An implication of this observation is that our strategy will tend to underestimate the aggregate demand effect, to the degree it operates nationally rather than locally.

6.2 Estimates

The local labor market analysis is based on 722 CZs that cover the entire U.S. mainland. These CZs are clusters of counties with strong internal commuting ties (see Tolbert and Sizer, 1996, and Autor and Dorn, 2013).

We begin by estimating stacked first-difference models for changes in CZ employment-to-population rates of the following form:

$$\Delta E_{i\tau} = \alpha_\tau + \beta \Delta IP_{i\tau}^{CZ} + \gamma X_{i0} + e_{i\tau} \tag{7}$$

Here, the dependent variable $\Delta E_{i\tau}$ is equal to 100 times the annual change in the ratio of employment to working-age population in CZ i over time period τ; X_{i0} is a set of CZ-by-sector start-of-period controls (specified later); α_τ is a time effect; and $e_{i\tau}$ is an error term.[46] The key explanatory variable in this model is $\Delta IP_{i\tau}^{CZ}$, which measures a CZ's annual change in exposure to Chinese imports over period τ. The coefficient β reveals the impact of import exposure on overall employment rates, combining employment shifts in both trade-exposed and non-exposed industries. We define a CZ's change in import exposure as a local employment-weighted average of changes in import exposure:

$$\Delta IP_{i\tau}^{CZ} = \sum_j \frac{L_{ij\tau}}{L_{i\tau}} \Delta IP_{j\tau}. \tag{8}$$

[46]Throughout this section, local employment is derived from the County Business Patterns, and local working-age population (ages 15-64) is derived from the Census Population Estimates.

In (8), $\Delta IP_{j\tau}$ is the measure of Chinese import competition used in our industry-level analysis, and $L_{ij\tau}/L_{i\tau}$ is industry j's start-of-period share of total employment in CZ i.[47] The variation in $\Delta IP_{i\tau}^{CZ}$ across local labor markets stems entirely from variation in local industry employment structure at the start of period τ. As with our industry-level estimates, a concern is that realized U.S. imports from China in (8) may be correlated with industry import demand shocks. We again instrument for growth in Chinese imports to the U.S. using the contemporaneous growth of Chinese imports in eight other developed countries as specified in (2).[48] Table A4 summarizes CZ-level changes in exposure to Chinese imports and in employment-to-population rates.

To gauge the differential impact of import exposure on different types of industries within local labor markets, we decompose employment changes into three broad sectoral groupings. Specifically, we interact the CZ's change in import exposure with indicator variables for exposed industries, non-exposed tradable industries, and other non-exposed industries:

$$\begin{aligned}\Delta E_{ik\tau} = \quad & \alpha_{k\tau} + \beta_1 \Delta IP_{i\tau}^{CZ} \times 1\,[\text{Exposed}_k] + \beta_2 \Delta IP_{i\tau}^{CZ} \times 1\,[\text{Non-Exposed Tradable}_k] \\ & + \beta_3 \Delta IP_{i\tau}^{CZ} \times (1 - 1\,[\text{Exposed}_k] - 1\,[\text{Non-Exposed Tradable}_k]) + \gamma X_{ik0} + e_{ik\tau}.\end{aligned} \tag{9}$$

In these regressions, $\Delta E_{ik\tau}$ is the change in employment of sector k in CZ i, expressed in percentage points of working-age population. While the specification in (9) is similar to that in Autor, Dorn, and Hanson (2013), it differs importantly by separating the employment effects of import competition in CZs according to sector import exposure and tradability. To compute $\Delta E_{ik\tau}$, we assign each industry to one of the three mutually exclusive sectors: exposed industries, non-exposed tradable industries, and other non-exposed industries. First, we define the exposed sector to encompass all manufacturing industries for which predicted import exposure rose by at least 2 percentage points between 1991 and 2011, as well as all industries (both within and outside of manufacturing) for which the predicted full upstream import exposure measure increased by at least 4 percentage points over 1991-2011.[49] Relative to an exposure definition based only on own-industry import exposure, incorporating upstream linkages expands the exposed sector to include additional manufacturing

[47] This is similar to Autor, Dorn, and Hanson (2013) and Autor, Dorn, Hanson and Song (2014), except that for consistency with our industry-level analysis, we normalize industry-level imports by initial U.S. market volume instead of initial employment.

[48] Our expression for *non*-U.S. exposure to Chinese imports, which serves as an instrument for $\Delta IP_{i\tau}^{CZ}$, differs from the expression in equation (8) in that in place of realized changes in U.S. import exposure ($\Delta IP_{j\tau}$), we use the analogous expression based on realized imports from China to other high-income markets ($\Delta IPO_{j\tau}$). In addition, we use 1988 employment counts for the construction of the instrument to reduce the error covariance between the dependent and independent variables.

[49] Predicted import exposure is computed from first-stage estimates of equation (3) over the single long period 1991-2011.

industries, as well as industries outside of manufacturing that sell a sizable portion of their outputs to import-exposed manufacturing firms. For example, the latter group includes forestry, wholesale trade, miscellaneous repair services, and chemical and fertilizer mining.[50] All other industries are designated as non-exposed. Following our simple example of construction versus chemicals as non-exposed industries, we next subdivide the non-exposed sector into tradables and non-tradables. In our nomenclature, tradable industries are those that produce tradable goods or commodities, and specifically comprise the manufacturing, agriculture, forestry, fishing, and mining sectors. We classify all other sectors, including services, as non-tradable, though this approach is admittedly imperfect since some services are also traded.[51]

Table 7 presents our estimates. The first set of specifications in columns 1 through 3 pool employment across all sectors to determine the impact of import exposure in local labor markets on overall employment. Column 1 considers the relationship between CZ import exposure and changes in CZ employment-to-population rates without additional controls. The strongly negative and statistically significant point estimate in this column indicates that a one percentage point increase in the average import penetration of local industries reduces the employment rate among a CZ's working-age population by 1.64 percentage points. We refine the estimates and explore robustness in the next pair of columns by controlling for the initial manufacturing employment share in a local labor market (column 2) and for nine Census divisions (column 3). By controlling for local manufacturing intensity, we allow for differential employment trends in the manufacturing and non-manufacturing sectors, as we do in our industry-level estimates of Table 6. The controls for Census divisions allow for heterogeneity in regional time trends. Adding these covariates has a modest impact on the trade coefficient, which remains sizable and statistically significant at -1.70 in column 3.

[50] Despite this broad definition of the exposed sector, our regression analysis in this section will only partially capture the indirect effects working through input-output linkages we directly estimated previously. While pairs of industries linked through input-output relationships tend to co-locate (e.g., Ellison et al. 2010), many firms purchase and sell inputs beyond the boundaries of their commuting zone, and thus any local strategy will exclude a potentially sizable fraction of these indirect effects.

[51] The exposed sector consists of 293 industries (285 in manufacturing and 8 outside of manufacturing), which together comprised 20.2 percent of 1991 U.S. employment. The non-exposed tradable sector consists of 113 industries (107 in manufacturing, 6 outside of manufacturing), comprising 6.7 percent of 1991 employment. Finally, the non-exposed non-tradable sector consists of 73 industries (all outside manufacturing) accounting for 73.1 percent of 1991 employment.

Table 7

2SLS Estimates of Import Effects on Commuting Zone Employment-to-Population Ratios.

	Overall Employment 1991-2011			Sectoral Employment 1991-2011			Overall 1991-2007	Sectoral 1991-2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commuting Zone Import Exposure	-1.64***	-1.95***	-1.70**				-1.89***	
	(0.46)	(0.62)	(0.78)				(0.65)	
Commuting Zone Import Exposure x 1{Exposed Sector}				-1.95***	-2.14***	-1.68***		-1.66***
				(0.16)	(0.30)	(0.24)		(0.19)
Commuting Zone Import Exposure x 1{Non-Exposed Tradable Sector}				-0.01	0.04	-0.00		-0.05
				(0.06)	(0.11)	(0.11)		(0.10)
Commuting Zone Import Exposure x 1{Non-Exposed Non-Tradable Sector}				0.33	0.15	-0.01		-0.18
				(0.39)	(0.44)	(0.57)		(0.55)
Sector x Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector x Mfg Emp Share at Baseline	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Sector x Census Division Dummies	No	No	Yes	No	No	Yes	Yes	Yes
N	1444	1444	1444	4332	4332	4332	1444	4332

Note.—Each column reports results from stacking changes in commuting zone employment rates and exposure to Chinese imports over the periods 1991-1999 and either 1999-2011 (columns 1-6) or 1999-2007 (7-8). In columns (1), (2), (3), and (7), the dependent variable is 100 x the annual change in the ratio of total employment to working-age population (N = 1444 = 722 commuting zones x 2 periods). In the other columns, the dependent variable is 100 x the annual change in the ratio of sectoral employment to working-age population, with industries partitioned into three sectors: industries exposed to trade competition, non-exposed industries that produce tradable goods, and all remaining non-exposed industries (N = 4332 = 722 commuting zones x 3 sectors x 2 periods). See text for details. Commuting zone import exposure is an employment-weighted average of annualized changes in exposure to Chinese within local industries; it is instrumented as described in the text. Employment is computed in the County Business Patterns; population data come from the Census Population Estimates. The manufacturing share of baseline commuting zone employment is computed in 1991 (for the 1991-1999 period) or 1999 (for the 1999-2011 and 1999-2007 periods). Census division dummies control for 9 Census divisions. Observations are weighted by 1991 commuting zone population. Standard errors in parentheses are clustered on commuting zone.

* $p < 0.10$
** $p < 0.05$
*** $p < 0.01$

The regressions of columns 4 through 6 disaggregate the overall employment effects of columns 1 through 3 into their sectoral components. Consistent with the results of the industry analysis, column 4 shows a strongly negative and statistically significant effect of import exposure on local labor market employment in trade-exposed industries. The point estimate indicates that a one percentage point increase in local import exposure reduces the share of a CZ's working-age population employed in exposed industries by 1.95 percentage points. Between 1999 and 2011, mean CZ import exposure rose by 1.21 percentage points, while employment in exposed industries declined by 3.64 percentage points of working-age population. The estimate in column 4 thus implies that 1.32 percentage points (or 36 percent) of this fall can be explained by rising Chinese import competition.[52]

[52] As above, this calculation discounts the growth of imports by the partial R-squared of 0.56 of the first stage regression: $1.32 = 0.56 \times 1.21 \times 1.95$.

As our conceptual discussion anticipates, the estimate in column 4 also shows some offsetting employment growth in non-exposed industries, corresponding to the net impact of local reallocation and Keynesian demand effects. However, the offsetting employment effect is substantially smaller than the employment reduction in exposed industries and is never statistically significant. These estimates suggest that employment gains through the sectoral reallocation effect are largely offset by negative aggregate demand effects. In parallel with our specifications examining overall employment impacts, we refine the estimates in the next pair of columns by controlling for initial local labor market manufacturing intensity (column 5) and Census divisions (column 6), with the coefficients on these controls allowed to vary by sector. Adding these covariates only modestly changes the estimated negative impact of import exposure on employment in exposed industries, while the small and imprecise estimates for offsetting employment gains decline to almost zero. The final columns replicate the specifications from columns 3 and 6 over the stacked periods 1991-1999 and 1999-2007. The results are similar to those for the full sample period and suggest negative effects of trade competition on employment in exposed industries, combined with small and insignificant effects in non-exposed sectors.

While our estimates suggest the presence of strong aggregate demand effects that limit employment gains in the non-exposed sectors of trade-exposed local labor markets, we would anticipate that these local demand effects primarily impact employment in the non-traded sector rather than the non-exposed tradable sector. Our results however provide scant evidence for differential employment impacts in the two non-exposed sectors. In columns 4 and 5, the point estimates for non-tradables exceed the point estimate for non-exposed tradables; in columns 6 and 8, the relationship is reversed.

Why does reallocation fail to accord more clearly with the simple reasoning outlined in Section 6.1? It is conceivable that the small increase in employment in non-tradable sectors detected in columns 4 and 5 (though not in column 6) may be related to the rapid rise in the U.S. aggregate trade deficit during our sample period, a substantial part of which reflects a growing trade imbalance with China (Figure 2). In response to import competition, an open economy normally reallocates resources out of some tradable industries into others, at least under balanced trade. If, however, the trade shock is accompanied by a rise in the trade deficit, then the reallocation from exposed tradables into non-exposed tradables may be delayed, shifting employment into non-tradables instead—that is, the deficit may fuel increasing expenditure in the domestic economy, part of which falls on non-tradable consumption. While this reasoning is not inconsistent with a *long-run* reallocation towards non-exposed tradables, the large and growing U.S. trade deficit during the period under study may have significantly slowed down such a reallocation. This reasoning is, unfortunately, silent on

why a rising U.S. trade deficit coincided with China's growing import penetration. It nevertheless underscores that shifts in global imbalances may complicate the simple adjustment mechanism we posit.

Quantitatively, the estimates in column 6 of Table 7 encompass four impacts of Chinese trade competition on local labor market employment: direct employment effects in exposed industries, indirect employment effects via local input-output linkages between industries, local reallocation effects, and local aggregate demand effects. As summarized in Table 8, the coefficient estimates imply that had import competition from China not increased after 1999, trade-exposed industries in local labor markets would have avoided the loss of 2.35 million jobs. Comparing this quantity to the outcome of our national-industry analysis, it is modestly larger than the employment effect derived from Table 6B reported above, which incorporated both the direct and the upstream effects of import competition and tallied employment reductions in trade-exposed manufacturing and non-manufacturing industries at 1.98 million jobs. The fact that employment effects on exposed industries in CZs are slightly larger than the direct and indirect effects of import competition in national industries is suggestive of negative local aggregate demand spillovers. Such spillovers imply that multipliers operating at the local level suppress demand in non-exposed industries as well, inducing further employment declines in trade-exposed industries.

Our estimates imply near zero, though imprecisely estimated, employment effects of trade exposure on non-exposed industries. Absent further increases in import penetration from China after 1999, the results summarized in Table 8 show that non-exposed industries would have shed 18 thousand fewer jobs. Combining figures from exposed and non-exposed industries, the overall local impact is 2.37 million jobs whose loss would have been averted absent further increases in Chinese import competition after 1999. With the numerous caveats acknowledged, our conceptual framework in Section 2 suggests that this estimate is a lower bound on the aggregate total impact of increased import competition from China on national employment. In particular, this estimate does not include the components of industry interlinkage effects and aggregate demand effects that work at the national level. This lower bound estimate is relatively close to the jobs lost based on our industry-level analysis in Table 6B (shown in Table 8), which combines direct competition effects and inter-industry linkages with non-manufacturing sectors. Recall that Table 6B's industry-level estimate of the jobs lost does not include reallocation and aggregate demand effects. Since our analysis in this section indicates that employment losses due to negative aggregate demand effects dominate employment gains due to reallocation effects, our industry-level estimates of employment

reduction should indeed be lower bounds.[53]

[53] In particular, recall that the industry-level numbers could underestimate the net employment losses due to aggregate demand effects or overestimate these losses due to reallocation effects. But if reallocation effects are modest and swamped by demand effects at the local level, as suggested by the Table 7 estimates, we would also expect the demand effects to dominate at the aggregate level—especially since these demand effects are themselves underestimated at the local level.

Table 8

Implied Employment Changes Induced by Changes in Exposure to Chinese Imports.

Specification	Unit of Analysis	Description	Affected Sector(s)	Implied Employment Changes (000s) 1991-1999	1999-2011	1991-2011	1991-2007
Table 2, Columns 3/4	Industry	Direct effect of import exposure	Manufacturing	-277	-560	-837	-853
Table 6A, Columns 6/9	Industry	Direct and "first-order" upstream effects	Total	-556	-1581	-2137	-2218
		of import exposure	Manufacturing	-404	-928	-1332	-1414
			Non-manufacturing	-152	-653	-805	-804
Table 6B, Columns 6/9	Industry	Direct and "full" (higher-order)	Total	-645	-1979	-2624	-2669
		upstream effects of import exposure	Manufacturing	-421	-985	-1406	-1475
			Non-manufacturing	-224	-994	-1218	-1194
Table 7, Column 6/9	Commuting Zone	Effect of local import exposure on	Total	-743	-2367	-3110	-3031
		employment in the commuting zone,	Exposed industries	-737	-2348	-3086	-2663
		controlling for baseline manufacturing	Non-exposed tradables	0	-1	-1	-79
		share and for Census divisions	Other non-exposed	-5	-17	-23	-289

Note.—Reported quantities represent the change in employment attributed to instrumented changes in import exposure in each of our preferred specifications. Negative values indicate that import exposure is estimated to have reduced employment. For the industry-level analyses, we first use the estimated coefficients to predict the changes in each industry's log employment induced by changes in import exposure over the periods 1991-1999 and 1999-2011. Concretely, we multiply the coefficient of interest by the observed change in import exposure, then multiply this product by .56 (the partial R-squared from our baseline first-stage regression). We then use each industry's observed end-of-period employment to convert these estimates from logs into levels. Upstream effects are handled similarly. For the commuting-zone analyses, we first use observed changes in imports per worker—again discounted by .56—to predict the trade-induced change in each commuting zone's employment-to-population ratio within the indicated sectors over the periods 1991-1999 and 1999-2011. We then multiply by end-of-period commuting zone working-age population to compute the implied changes in each sector's employment in each commuting zone. Summing these sectoral estimates across commuting zones yields nationwide estimates. See the text for definitions of the exposed, non-exposed tradable, and non-exposed non-tradable sectors. For both industry-level and commuting-zone-level analyses, predictions for 1991-2011 equal the sum of the predictions for the two subperiods. Predicted employment changes for the period 1991-2007 are computed similarly, using coefficients from models estimated over the stacked periods 1991-1999 and 1999-2007.

7 Concluding Discussion

In the years leading up to the Great Recession, overall U.S. employment growth was slow and manufacturing employment experienced a steep contraction. In this paper, we investigate the contribution of the rise in import competition from China to this employment "sag".

We begin by estimating the direct effect of trade competition on employment in manufacturing industries that are differentially exposed to growing Chinese import penetration, and then expand the analysis to include multiple general equilibrium channels through which trade exposure may affect employment: other sectors might be impacted because they are related to the affected sectors through input-output linkages; employment may reallocate away from trade-exposed industries toward non-exposed industries; and Keynesian-type aggregate demand spillovers may significantly magnify the direct competition effect.

In our analysis of U.S. national industries, we estimate upstream and downstream trade effects for both manufacturing and non-manufacturing sectors. We expect upstream effects to contribute to further job losses, while the impact of downstream effects is ambiguous. Consistent with these expectations, we find large negative employment responses when an industry's customers are exposed to trade competition and unstable effects when an industry's suppliers are exposed to trade competition.

As a complementary strategy, we assess the impact of Chinese trade on U.S. commuting zones to jointly estimate reallocation and aggregate demand effects at the local level. Theoretically, if an industry contracts in a local labor market because of Chinese competition, then, barring substantial interregional migration, some other industry in the same labor market should expand. In addition, part of any aggregate demand spillovers will also accrue to the local labor market. Our estimates show sizable job losses in exposed industries, and few if any offsetting job gains in non-exposed industries, a pattern that is consistent with substantial job loss due to aggregate demand spillovers.

Our results are a first step in quantifying the employment impact of increasing import competition on the U.S. labor market. Several questions remain unanswered that could be addressed in future work. Using plant-level data to achieve a finer distinction between tradable and non-tradable industries would enable both a sharper test of the implications of local general equilibrium interactions, and a separate quantification of reallocation and aggregate demand effects. We should in particular see employment declines in non-tradables due to local aggregate demand spillovers, but no differential decline in tradables except through geographically-concentrated input-output linkages. This perspective could elucidate how local and national labor markets respond to growing import

competition, in particular allowing us to determine to which degree shocks propagate locally or at the national level.

We finally note that, though our paper has focused on the contribution of rising international competition to the U.S. "employment sag" of the 2000s, we have had comparatively less to say about the impact of trade during the Great Recession. As shown in Figure 2, U.S. imports from China dropped sharply in 2009. This might imply that exporters to the United States—China in particular—absorbed part of the demand shock accompanying the Great Recession that would otherwise have further reduced U.S. employment (albeit from a notionally higher base). While this hypothesis is intuitive, additional exploration of U.S. manufacturing data suggests otherwise. We find that U.S. manufacturing industries that were heavily exposed to Chinese import competition during the 1999 to 2007 period continued to see rapid, differential employment declines during 2007 to 2011, despite the fact that there was almost no correlation between industry-level changes in trade exposure during 1999 to 2007 and changes in trade exposure during 2007 to 2011.[54] This pattern suggests that the trade shocks of the prior decade cast a long shadow over U.S. manufacturing, even when trade pressure eased temporarily. One explanation for this long shadow is that U.S. manufacturers recognized that the loss in comparative advantage in the sectors that China had penetrated in the prior decade was largely permanent whereas the lull in trading activity was temporary. Indeed, as shown in Figure 2, U.S. imports from China *more than* made up all of their ground lost in 2009 by the following year, and then rose further from there. Thus, trade pressure appears to have contributed to the U.S. employment sag not just before, but also *during* the Great Recession, despite the temporary drop off of international trading activity during this period. Though much evidence suggests that rising labor costs in China augur a reduction in trade pressure in the years ahead (Li et al. 2012), our analysis suggests that this particular Chinese export has yet to reach U.S. shores.

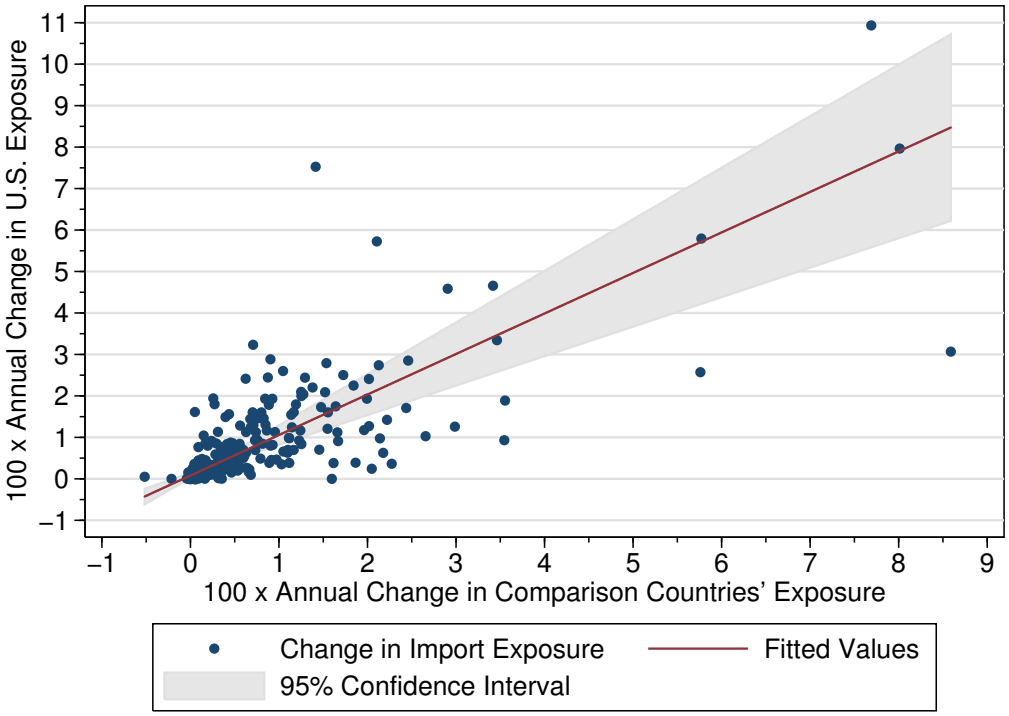
[54] When we regress 100 x the annual log change in manufacturing industry employment between 2007 and 2011 on changes in Chinese import competition between 2007 and 2011 and between 1999 and 2007 (expressed as percentage points of 1991 U.S. market volume), we find

$$\widehat{\Delta L}_{j,07-11} = -\underset{(0.52)}{5.02} - \underset{(0.40)}{1.06} \times \Delta IP_{j,99-07} + \underset{(0.67)}{0.59} \times \Delta IP_{j,07-11}.$$

This substantial impact of Chinese import competition between 1999 and 2007 on 2007-2011 employment growth suggests a pattern of delayed declines in employment in affected industries. We obtain similar results if we control for ten one-digit sector dummies.

Appendix A: Additional Results

Figure A.1: First-Stage Regression, 1991-2011.



Note.—Each point represents a 4-digit manufacturing industry (N = 392). The change in U.S. exposure to Chinese imports is defined as the change in U.S. imports from China divided by 1991 U.S. market volume; the change in the comparison countries' exposure to Chinese imports is defined as the change in these countries' imports from China divided by 1988 U.S. market volume. Lines are fitted by OLS regression, weighting by each industry's 1991 employment in the County Business Patterns. The 95% confidence interval is based on standard errors clustered on 135 3-digit industries. The slope coefficient is .98 with standard error .14; the regression has an R-squared of .62.

Table A1

Industry-Level Control Variables.

	Mean	SD	Min	Max
Production Workers' Share of Employment, 1991	68.43	15.50	18.72	97.62
Ratio of Capital to Value Added, 1991	0.92	0.55	0.19	3.52
Log Real Wage (2007 U.S.$), 1991	10.54	0.29	9.78	11.09
Computer Investment As Share of Total, 1990	6.56	6.07	0.00	43.48
High-Tech Equipment As Share of Total Investment, 1990	8.24	4.84	1.20	18.25
Change in Industry Share of Total Employment, 1976-1991	-0.03	0.07	-0.42	0.07
Change in Log Real Wage, 1976-1991	3.57	9.94	-32.01	48.06

Note.—N = 392 4-digit manufacturing industries. Observations are weighted by industry employment in 1991, as measured in the County Business Patterns. Production workers' share, the ratio of capital to value added, log real wage, and the changes in industry employment share and in log real wage are computed using the NBER-CES Manufacturing Industry Database; total employment in 1976 and 1991 is computed from the Current Employment Statistics. The remaining control variables are taken from Autor, Dorn, Hanson, and Song (2014). Share variables are expressed in percentage points.

Table A2

Estimates of Import Effects on Log Gross Output and Log Price Deflators.

	Nominal Shipments (1)	Real Shipments (2)	Shipments Deflator (3)
	A. All Manufacturing Industries (N = 768)		
100 x Annual Δ in U.S.	-1.08***	-0.17	-0.91**
Exposure to Chinese Imports	(0.32)	(0.44)	(0.42)
1-Digit Mfg Sector Controls	Yes	Yes	Yes
	B. Exclude Computer Industries (N = 712)		
100 x Annual Δ in U.S.	-1.00**	-0.86**	-0.14*
Exposure to Chinese Imports	(0.47)	(0.41)	(0.08)
1-Digit Mfg Sector Controls	Yes	Yes	Yes

Note.—Each column stacks changes in the indicated outcome and changes in U.S. exposure to Chinese imports over the periods 1991-1999 and 1999-2009. In panel A, the sample consists of 384 4-digit manufacturing industries for which data are consistently available in the NBER-CES Manufacturing Industry Database (N = 768 = 384 industries x 2 periods). In panel B, we exclude 28 computer-producing industries corresponding to NAICS 334 (N = 712 = 356 industries x 2 periods). The dependent variable in each column is 100 x the annual log change in the indicated outcome, as computed in the NBER-CES. The change in U.S. exposure to Chinese imports is instrumented as described in the text. All specifications include time effects as well as controls for 10 1-digit manufacturing sectors. Observations are weighted by 1991 employment in the NBER-CES. Standard errors in parentheses are clustered on 3-digit industries.

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

Table A3

Direct, Upstream, and Downstream Import Exposure, 1991-2011.

	Manufacturing Industries (N = 392)				Non-Manufacturing Industries (N = 87)			
	Mean/SD	Median	Min	Max	Mean/SD	Median	Min	Max
Direct Import Exposure								
Direct Exposure	0.50	0.14	-0.02	10.93				
	(0.94)							
Instrument for Direct Exposure	0.44	0.15	-0.52	8.59				
	(0.76)							
First-Order Indirect Exposure								
Upstream Exposure	0.16	0.06	0.00	1.88	0.03	0.01	0.00	0.19
	(0.26)				(0.04)			
Instrument for Upstream Exposure	0.12	0.05	0.00	1.55	0.02	0.01	0.00	0.22
	(0.18)				(0.03)			
Downstream Exposure	0.10	0.07	0.00	0.83	0.03	0.02	0.00	0.24
	(0.11)				(0.04)			
Instrument for Downstream Exposure	0.09	0.07	-0.02	0.46	0.02	0.02	0.00	0.14
	(0.08)				(0.03)			
Full (Higher-Order) Indirect Exposure								
Upstream Exposure	0.24	0.09	0.00	1.98	0.06	0.03	0.00	0.67
	(0.35)				(0.07)			
Instrument for Upstream Exposure	0.19	0.10	0.00	1.61	0.05	0.02	0.00	0.65
	(0.25)				(0.06)			
Downstream Exposure	0.14	0.11	0.00	1.05	0.05	0.04	0.01	0.33
	(0.13)				(0.05)			
Instrument for Downstream Exposure	0.14	0.12	-0.01	0.61	0.05	0.04	0.01	0.21
	(0.10)				(0.04)			

Note.—The direct import shock to industry i is defined as the 100 x the annual change in U.S. exposure to Chinese imports in that industry over 1991-2011. The first-order measure of upstream (respectively, downstream) import exposure experienced by i is a weighted average of the direct import exposure experienced by its customers (suppliers) j, where the weight on industry j equals i's sales to (i's purchases from) j divided by i's total sales. The full upstream and downstream exposure measures are constructed using the Leontief inverse of the input-output matrix to incorporate higher-order linkages; see text for details. Instruments for the direct, upstream, and downstream exposure measures are constructed analogously, using changes in comparison countries' exposure to Chinese imports in own and linked industries. Observations are weighted by 1991 industry employment in the County Business Patterns.

Table A4

Changes in Commuting Zone Import Exposure and Employment-to-Population Ratios.

	1991-1999				1999-2011			
	Mean/SD	Median	Min	Max	Mean/SD	Median	Min	Max
Δ in Local Exposure to Chinese Imports								
100 x Annual Δ in Commuting Zone Exposure to Chinese Imports	0.05	0.04	0.00	0.95	0.10	0.09	0.00	0.69
	(0.05)				(0.07)			
Instrument for Δ in Commuting Zone Exposure to Chinese Imports	0.04	0.04	-0.06	0.53	0.13	0.12	-0.01	0.79
	(0.04)				(0.09)			
Δ in Employment/Working-Age Pop								
100 x Annual Δ in Overall Emp/Pop	0.73	0.73	-1.15	3.48	-0.52	-0.58	-2.16	2.63
	(0.39)				(0.40)			
100 x Annual Δ in Emp/Pop within Exposed Industries	-0.03	-0.04	-1.90	1.21	-0.30	-0.30	-1.55	0.64
	(0.16)				(0.17)			
100 x Annual Δ in Emp/Pop within Non-Exposed Tradable Industries	-0.04	-0.04	-0.70	1.47	-0.07	-0.08	-0.85	1.52
	(0.10)				(0.08)			
100 x Annual Δ in Emp/Pop within Other Non-Exposed Industries	0.80	0.82	-0.62	3.21	-0.14	-0.14	-1.82	1.34
	(0.32)				(0.32)			

Note.—N = 722 commuting zones. The annual change in commuting zone exposure to Chinese imports is a weighted average of changes in U.S. import exposure in 392 4-digit manufacturing industries, where the weights are start-of-period employment shares within the commuting zone. The instrument is constructed by replacing U.S. imports from China with imports from China by a set of comparison countries, and by using 1988 commuting-zone employment shares as weights; see text for details. Imports are deflated to constant dollars using the Personal Consumption Expenditures price index. In the second panel, each variable describes the annual change in 100 x total or sectoral employment divided by the commuting-zone population between the ages of 15 and 64. Exposed industries include manufacturing industries for which the predicted increase in Chinese import penetration exceeds 2 percentage points between 1991 and 2011, plus industries for which the predicted increase in the measure of full upstream import exposure (incorporating higher-order linkages) exceeds 4 percentage points over 1991-2011. Among non-exposed industries, we define agriculture, forestry, fishing, mining, and manufacturing industries as tradable and all other industries as non-tradable. Employment is computed in the County Business Patterns, and population is computed using the Census Population Estimates. Observations are weighted by total 1991 commuting-zone population.

Appendix B: Derivation of the Downstream and Upstream Effects

In this Appendix, we briefly outline the justification for the specifications we use for the upstream and downstream effects in Section 5 of the paper.

Setup

Consider a static perfectly competitive economy with n industries, and suppose that each industry $j = 1, ..., n$ has a Cobb-Douglas production function of the form

$$y_j = l_j^{\alpha_j^l} \prod_{i=1}^{n} x_{ji}^{a_{ji}}. \tag{1}$$

Here x_{ji} is the quantity of goods produced by industry i used as inputs by industry j. We assume that, for each j, $\alpha_j^l > 0$, and $a_{ji} \geq 0$ for all i, and that

$$\alpha_j^l + \sum_{i=1}^{n} a_{ji} = 1,$$

so that the production function of each industry exhibits constant returns to scale. (Physical capital can also be introduced without affecting the results, but we omit it to simplify the notation and the discussion.)

The output of each industry is used as input for other industries or consumed in the final good sector. In addition, there are also imports from abroad (say China), and we ignore exports for simplicity (and thus also ignored is the trade balance condition). The market clearing condition for industry j can then be written as

$$y_j = c_j + \sum_{k=1}^{n} x_{kj} - m_j, \tag{2}$$

where c_j is final consumption of the output of industry j, and m_j denotes total (real) imports.

The preference side of this economy is summarized by a representative household with a utility function

$$u(c_1, c_2, ..., c_n).$$

We focus on the *competitive equilibrium* of this economy.

Main result

First consider the unit cost function of sector j:

$$C(\mathbf{p}, w) = B_j w^{\alpha_j^l} \prod_{i=1}^{n} p_i^{a_{ji}}, \tag{3}$$

where $\mathbf{p}$ is the vector of prices, w is the wage rate, and

$$B_j = \left[\frac{1}{\alpha_j^l}\right]^{\alpha_j^l} \prod_{i=1}^{n} \left[\frac{1}{a_{ji}}\right]^{a_{ji}}$$

is a sector-specific constant.

Cost minimization of industry j (given competitive markets) implies that

$$a_{ji} = \frac{p_i x_{ji}}{p_j y_j}, \tag{4}$$

where p_j is the price of the output of industry j. This expression makes it clear that a_{ij}'s also correspond to the entries of the input-output matrix, which we denote by $\mathbf{A}$.

Next, given the constant returns to scale production function of each sector specified in (1), prices satisfy the zero profit conditions of the n sectors in the competitive equilibrium. In particular, the price of good j must be equal to the unit cost function of that sector, (3), and thus

$$p_j = B_j w^{\alpha_j^l} \prod_{i=1}^{n} p_i^{a_{ji}},$$

Taking logs, we have

$$\ln p_j = \ln B_j + \alpha_j^l \ln w + \sum_{i=1}^{n} a_{ji} \ln p_i \text{ for all } j \in \{1, .., n\}.$$

Let us choose $w = 1$ as the numeraire. Then, these equations define an n equation system in n prices

$$\ln \mathbf{p} = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{b},$$

where, as noted above, $\mathbf{A}$ is the input-output matrix of the economy, and $\mathbf{b}$ is the vector with entries given by $\ln B_i$ (and we are using the fact that $\ln w = 0$). This implies that prices in this economy are determined independently of imports (purely from the supply side). Consequently, there will only be quantity responses to imports.

But from consumer maximization, with unchanged prices relative consumption levels remain unchanged. How total consumption is impacted depends on whether there is trade balance or not. With trade balance, the economy would have to export some goods to make up for the increase in imports. Here for simplicity, we allow for a trade deficit and thus leave the entire consumption vector unchanged. With unchanged consumption levels, we must have from (2) combined with (4)

that

$$a_{ji} d(p_j y_j) = d(p_i x_{ji}). \tag{5}$$

For future reference, let us define nominal values (which are more useful for several of the expressions below) with tildes. For example,

$$\tilde{x}_{ji} \equiv p_i x_{ji},\ \tilde{y}_j \equiv p_j y_j, \text{ and } \tilde{m}_j \equiv p_j m_j.$$

Then (5) can be equivalently written as

$$a_{ji} d\tilde{y}_j = d\tilde{x}_{ji}. \tag{6}$$

Now totally differentiating the resource constraint, (2), for sector i, we obtain

$$dy_i = dc_i + \sum_{j=1}^{n} dx_{ji} - dm_i$$

which, using (6) and the fact that consumption levels are not changing, can be written as

$$\frac{d(p_i y_i)}{p_i y_i} = \sum_{j=1}^{n} a_{ji} \frac{d(p_j y_j)}{p_i y_i} - \frac{d(p_i m_i)}{p_i y_i}.$$

Writing this in matrix form, and noting that, because prices are constant, $\frac{d(p_i y_i)}{p_i y_i} = d \ln y_i$, we have

$$\begin{aligned} \mathbf{d} \ln \mathbf{y} &= \hat{\mathbf{A}}' \mathbf{d} \ln \mathbf{y} - \mathbf{\Lambda} \mathbf{d} \hat{\mathbf{m}} \\ &= -\left(\mathbf{I} - \hat{\mathbf{A}}'\right)^{-1} \mathbf{\Lambda} \mathbf{d} \hat{\mathbf{m}} \\ &= -\hat{\mathbf{H}}' \mathbf{\Lambda} \mathbf{d} \hat{\mathbf{m}} \end{aligned} \tag{7}$$

where $\hat{\mathbf{m}}$ is the vector with entries given by $p_i m_i$, $\hat{\mathbf{H}} = \left(\mathbf{I} - \hat{\mathbf{A}}\right)^{-1}$,

$$\hat{\mathbf{A}} = \begin{pmatrix} \hat{a}_{11} & \hat{a}_{12} & & \dots \\ \hat{a}_{21} & \hat{a}_{22} & & \\ & & \ddots & \\ & & & \\ & & & \hat{a}_{nn} \end{pmatrix},$$

with entries $\hat{a}_{ij} = \frac{p_j x_{ij}}{p_j y_j}$ (as opposed to a_{ij} which is equal to $\frac{p_j x_{ij}}{p_i y_i}$), and $\mathbf{\Lambda}$ is the matrix with $\frac{1}{\tilde{y}_j}$

on the diagonals and zero on the non-diagonals.[55] Intuitively, any import shock creates a direct negative effect on the directly impacted sector, which is captured by the matrix $\mathbf{\Lambda}$, and the indirect effects are summarized by the Leontief inverse matrix $\hat{\mathbf{H}}'$.

We can see from this expression that there will only be upstream effects (simply note that it is the transpose of the matrix $\hat{\mathbf{A}}$, $\hat{\mathbf{A}}'$, which matters in the Leontief inverse, thus corresponding to transmission only in the upstream direction). This is a consequence of the fact that there are no changes in prices and hence quantities will respond to changes in imports, but for each change in the quantity of a sector directly affected by imports from China, the quantities of inputs that it receives from its suppliers will have to adjust, causing upstream propagation.[56] In fact, the matrix $\hat{\mathbf{H}}'$ is exactly what we use in Section 5 for computing the full (Leontief inverse) upstream effects.

Equation (7) gives the output responses to import shocks. It is straightforward to derive from this the employment responses, which are our main focus. In particular, given the Cobb-Douglas form of the production function in (1), cost minimization for industry i implies that $wl_i = \alpha_i^l p_i y_i$. Since the wage is constant, employment in industry i is proportional to its nominal output, enabling us to work with an analog of (7) with employment on the left-hand side.

We next develop a more heuristic derivation of this result, which provides further intuition, shows how the full effects summarized by the Leontief inverse matrix $\hat{\mathbf{H}}'$ come about, and also explains why under more general conditions there might also be some downstream effects.

Heuristic Derivation

Let us first ignore the second- and higher-order input-output linkages, and focus on first-order impacts. Let us use the notation for nominal variables introduced above and begin by approximating the impact of the increase in imports in industry j on domestic production in the same industry as $d\tilde{y}_j \approx -d\tilde{m}_j$. (This is clearly an approximation, since as our derivation in the previous section showed, there will be higher-order effects on the output of sector j as captured by the Leontief inverse matrix $\hat{\mathbf{H}}'$.)

Note further that from (4), any reduction in the value of output of an industry translates into a proportionate reduction in all of the inputs, in particular,

$$\frac{d\tilde{x}_{ji}}{d\tilde{y}_j} = a_{ji} \tag{8}$$

[55] Note that since the largest eigenvalue of $\hat{\mathbf{A}}$ is less than one, $\mathbf{I} - \hat{\mathbf{A}}'$ is invertible.

[56] There would be further effects if we were to impose trade balance, because some sectors would have to expand in order to compensate for the increase in imports. In that case the matrix $\mathbf{\Lambda}$ would have non-zero off-diagonals.

for each industry i. Then from (8) we have

$$\frac{d\tilde{y}_i}{d\tilde{m}_j} \approx -\frac{d\tilde{y}_i}{d\tilde{y}_j} = -a_{ji}$$

for each industry $i \neq j$, and we have

$$\frac{d\tilde{y}_j}{d\tilde{m}_j} \approx -(1 + a_{jj})$$

for industry j itself, reflecting both direct import substitution and the resultant decline in j's demand for its own inputs. These two cases can be dealt with succinctly by defining $d_{ij} \equiv \mathbf{1}\{i = j\}$, so that for any industries i and j

$$\frac{d\tilde{y}_i}{d\tilde{m}_j} \approx -(d_{ij} + a_{ji}).$$

For small changes in m_j, a first-order Taylor approximation gives the total impact on domestic production in industry i as

$$d\tilde{y}_i \approx \frac{d\tilde{y}_i}{d\tilde{m}_j} \times d\tilde{m}_j \approx -(d_{ij} + a_{ji}) \times d\tilde{m}_j.$$

Now turning this into a proportional (log) effect by normalizing the impact on industry i relative to its domestic production, we obtain

$$\frac{d\tilde{y}_i}{\tilde{y}_i} \approx \frac{d\tilde{y}_i}{d\tilde{m}_j} \times d\tilde{m}_j \times \frac{1}{\tilde{y}_i} \approx -(d_{ij} + a_{ji}) \times d\tilde{m}_j \times \frac{1}{\tilde{y}_i}.$$

This expression shows how industry i is affected when a *single* industry j to which it sells inputs is exposed to import competition. We can next compute the total effect on industry i from the full vector of import changes by summing this expression across all of i's customer industries:

$$\begin{aligned}(d\ln\tilde{y}_i)_{\text{first order}} \approx \left(\sum_{j=1}^{n} \frac{d\tilde{y}_i}{d\tilde{m}_j} \times d\tilde{m}_j \times \frac{1}{\tilde{y}_i}\right)_{\text{first order}} &\approx -\sum_{j=1}^{n}(d_{ij} + a_{ji}) \times d\tilde{m}_j \times \frac{1}{\tilde{y}_i}. \\ &= -\sum_{j=1}^{n}(d_{ij} + \hat{a}_{ji}) \times d\tilde{m}_j \times \frac{1}{\tilde{y}_j}, \qquad (9)\end{aligned}$$

where $\hat{a}_{ij}$'s correspond to the entries of the matrix $\hat{\mathbf{A}}$ used in equation (7). Now using the same matrix notation as in that equation, this relationship can be written as

$$\mathbf{d}\ln\mathbf{y}_{\text{first order}} \approx -(\mathbf{I} + \hat{\mathbf{A}}')\mathbf{\Lambda}\mathbf{d}\hat{\mathbf{m}},$$

which clarifies that first-order effects take exactly the same form as the full effects we just derived, but with only the direct effect working through the transpose of the matrix $\hat{\mathbf{A}}$ included (hence the first-order designation rather than the full effects). This expression is what we use to compute first-order downstream effects in Section 5.[57]

Our more rigorous derivation in the previous subsection makes it clear that the first-order effect cannot be isolated from higher-order effects, since an increase in m_j will have an impact on y_k and from there on the sectors supplying inputs to k and so on. Letting $\mathbf{A}_i$ denote the ith column of $\mathbf{A}$, $\mathbf{A}_i^2$ denote the ith column of $\mathbf{A}^2$, and so on, we can obtain

$$\begin{aligned}
(d\ln\tilde{y}_i)_{\text{full}} = \left(\sum_{j=1}^{n}\frac{d\tilde{y}_i}{d\tilde{m}_j}\times d\tilde{m}_j\times\frac{1}{\tilde{y}_i}\right)_{\text{full}} &= -(\mathbf{e}_i'\cdot\mathbf{d}\tilde{\mathbf{m}}\times\frac{1}{\tilde{y}_i}+(\mathbf{A}_i)'\cdot\mathbf{d}\tilde{\mathbf{m}}\times\frac{1}{\tilde{y}_i}+(\mathbf{A}_i^2)'\cdot\mathbf{d}\tilde{\mathbf{m}}\times\frac{1}{\tilde{y}_i}+\ldots)\\
&= -(\mathbf{e}_i'+(\mathbf{A}_i)'+(\mathbf{A}_i^2)'+\ldots)\cdot\mathbf{d}\tilde{\mathbf{m}}\times\frac{1}{\tilde{y}_i}\\
&= -((\mathbf{I}-\mathbf{A}')_i^{-1})\cdot\mathbf{d}\tilde{\mathbf{m}}\times\frac{1}{\tilde{y}_i}
\end{aligned}$$

Using the same notation as above, this can be rewritten as

$$\begin{aligned}
\mathbf{d}\ln\mathbf{y} &= -\left(\mathbf{I}-\hat{\mathbf{A}}'\right)^{-1}\mathbf{\Lambda}\mathbf{d}\hat{\mathbf{m}}\\
&= -\hat{\mathbf{H}}'\mathbf{\Lambda}\mathbf{d}\hat{\mathbf{m}},
\end{aligned}$$

confirming (7).

Downstream Effects

Downstream effects simply correspond to effects that spread downstream following the input-output matrix $\mathbf{A}$, and in our empirical work we construct first-order and full downstream effects as $-(\mathbf{I}+\mathbf{A})\mathbf{\Lambda}\mathbf{d}\hat{\mathbf{m}}$ and $-(\mathbf{I}-\mathbf{A})^{-1}\Lambda\mathbf{d}\hat{\mathbf{m}}$, respectively.

The above derivation confirms that, in our baseline model, there are no downstream effects from changes in imports. This result, however, depends on certain assumptions. First, the focus on competitive equilibrium in which there are no relationship-specific investments between input suppliers and customers is important. Second, the feature that there are no price effects, which will no longer be true with departures from perfectly competitive markets, also plays a major role.

[57] Using (4), we can rewrite $\sum_{j=1}^{n}\hat{a}_{ji}\times d\tilde{m}_j\times\frac{1}{\tilde{y}_j}$ as $\sum_{j=1}^{n}\frac{\tilde{x}_{ji}}{\tilde{y}_i}\frac{d\tilde{m}_j}{\tilde{y}_j}$, which clarifies that the upstream effect on industry i is a sales-weighted average of the proportional import shocks experienced by its customers j. In our empirical work, import changes correspond to changes in Chinese import penetration, and the weights are constructed using the 1992 BEA benchmark input-output table. Our empirical measure also denominates import changes by U.S. market volume in each industry (shipments plus imports minus exports), rather than by industry shipments.

In particular, without the competitive equilibrium assumption, the increase in imports may drive some producers out of the market, and this may have a negative impact on firms that are their customers, creating negative downstream effects. Conversely, if there are declines in the prices of goods being imported more intensively from China, this may create positive downstream effects as customers using these goods as inputs can expand their operations.

Ultimately, whether there are downstream effects or not is an empirical question, and our results do not provide much evidence for sizable downstream effects.

References

Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price. 2014a. Import competition and the great U.S. employment sag of the 2000s. NBER Working Paper no. 20395.

——. 2014b. Return of the Solow paradox? IT, productivity, and employment in U.S. manufacturing. *American Economic Review Papers & Proceedings* 104, no. 5: 394-399.

Acemoglu, Daron, Vasco Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. The network origins of aggregate fluctuations. *Econometrica* 80, no. 5: 1977-2016.

Amiti, Mary, and David E. Weinstein. 2011. Exports and financial shocks. *Quarterly Journal of Economics* 126, no. 4: 1841-1877.

Artuç, Erhan, Shubham Chaudhuri, and John McLaren. 2010. Trade shocks and labor adjustment: a structural empirical approach. *American Economic Review* 100, no. 3: 1008-1045.

Autor, David H., and David Dorn. 2013. The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review* 103, no. 5: 1553-1597.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. The China syndrome: local labor market effects of import competition in the United States. *American Economic Review* 103, no. 6: 2121-2168.

——. 2014. Untangling trade and technology: evidence from local labour markets. *The Economic Journal* (forthcoming).

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song. 2014. Trade adjustment: worker level evidence. *Quarterly Journal of Economics* 129, no. 4: 1799-1860.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. Computing inequality: have computers changed the labor market? *Quarterly Journal of Economics* 113, no. 4: 1169-1213.

Balsvik, Ragnhild, Sissel Jensen, and Kjell G. Salvanes. 2014. Made in China, sold in Norway: local labor market effects of an import shock. IZA Discussion Paper no. 8324, July.

Becker, Randy, Wayne Gray, and Jordan Marvakov. 2013. NBER-CES manufacturing industry database. NBER Technical Notes.

Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott. 2006. Survival of the best fit: exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants. *Journal of International Economics* 68, no. 1: 219-237.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2015. Trade induced technical change? The impact of Chinese imports on innovation, IT, and productivity. *Review of Economic Studies* (forthcoming).

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. 2012. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics* 97, no. 2: 339-351.

Charles, Kerwin Kofi, Eric Hurst, and Matthew J. Notowidigdo. 2013. Manufacturing decline, housing booms, and non-employment. NBER Working Paper no. 18949.

Chor, Davin, and Kalina Manova. 2012. Off the cliff and back? Credit conditions and international trade during the global financial crisis. *Journal of International Economics* 87, no. 1: 117-133.

De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. 2014. Prices, markups, and trade reform. NBER Working Paper no. 17925.

Dix-Carneiro, Rafael, and Brian K Kovak. 2015. Trade reform and regional dynamics: evidence from 25 years of Brazilian matched employer-employee data. Mimeo, January.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske. 1997. Workers, wages, and technology. *Quarterly Journal of Economics* 112, no. 1: 253-290.

Eaton, Jonathan, Samuel Kortum, Brent Neiman, and John Romalis. 2013. Trade and the global recession. Mimeo, May.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips. 2014. Estimating the impact of trade and offshoring on American workers using the Current Population Surveys. *Review of Economics and Statistics* 96, no. 4: 581-595.

Ellison, Glenn, Edward Glaeser, and William Kerr. 2010. What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review* 100, no. 3: 1195-1213.

Feenstra, Robert C. 2003. *Advanced international trade: theory and evidence.* Princeton, NJ: Princeton University Press.

Feenstra, Robert C., and Gordon H. Hanson. 2005. Ownership and control in outsourcing to China: estimating the property rights theory of the firm. *Quarterly Journal of Economics*, 120, no. 2: 729-762.

Goldberg, Pinelopi, Amit Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. Imported intermediate inputs and domestic product growth: evidence from India. *Quarterly Journal of Economics* 125, no. 4: 1727-1767.

Hanson, Gordon. 2012. The rise of middle kingdoms: emerging economies in global trade. *Journal of Economic Perspectives* 26, no. 2: 41-64.

Harrison, Ann, John McLaren, and Margaret McMillan. 2011. Recent perspectives on trade and inequality. *Annual Review of Economics* 3: 261-289.

Harrison, Ann, and Margaret McMillan. 2011. Offshoring jobs? Multinationals and U.S. manufacturing employment. *Review of Economics and Statistics* 93, no. 3: 857-875.

Hart, Oliver, and John Moore. 1990. Property rights and the nature of the firm. *Journal of Political Economy* 98, no. 6: 1119-1158.

Houseman, Susan N., Timothy J. Bartik, and Timothy J. Sturgeon. 2015. Measuring manufacturing: how the computer and semiconductor industries affect the numbers and perceptions. In *Measuring Globalization: Better Trade Statistics for Better Policy: Volume 1*, Susan N. Houseman and Michael Mandel, eds. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, 151-194.

Hsieh, Chang-Tai, and Ralph Ossa. 2011. A global view of productivity growth in China. NBER Working Paper no. 16778.

Krueger, Alan B. and Robert M. Solow. 2002. *The roaring nineties: can full employment be sustained?* New York: Russell Sage Foundation.

Levchenko, Andrei A., Logan T. Lewis, and Linda L. Tesar. 2010. The collapse of international trade during the 2008-09 crisis: in search of the smoking gun. *IMF Economic Review*, 58, no. 2: 214-253.

Li, Hongbin, Lei Li, Binzhen Wu, and Yanyan Xiong. 2012. The end of cheap Chinese labor. *Journal of Economic Perspectives* 26, no. 4: 57-74.

Long, John B. Jr., and Charles I. Plosser. 1983. Real business cycles. *Journal of Political Economy* 91, no. 1: 39-69.

McLaren, John, and Shushanik Hakobyan. 2012. Looking for local labor market effects of NAFTA. Mimeo, July.

Mian, Atif, and Amir Sufi. 2014. What explains the 2007-2009 drop in employment? *Econometrica* 82, no. 6: 2197-2223.

Moffitt, Robert A. 2012. The reversal of the employment-population ratio in the 2000s: facts and explanations. *Brookings Papers on Economic Activity* 1: 201-264.

Muendler, Marc, and Sascha O. Becker. 2010. Margins of multinational labor substitution. *American Economic Review* 100, no. 5: 1999-2030.

Naughton, Barry. 2007. *The Chinese economy: transitions and growth.* Cambridge, MA: MIT Press.

Notowidigdo, Matthew J. 2013. The incidence of local labor demand shocks. University of Chicago Booth School working paper, March.

Pierce, Justin R. and Peter Schott. 2012. A concordance between ten-digit U.S. harmonized system codes and SIC/NAICS product classes and industries. *Journal of Economic and Social Measurement* 37, no. 1-2: 61-96.

Pierce, Justin R, and Peter K Schott. 2015. The surprisingly swift decline of U.S. manufacturing employment. Yale Department of Economics Working Paper, November.

Tolbert, Charles M. and Molly Sizer. 1996. U.S. commuting zones and labor market areas. A 1990 update. Economic Research Service Staff Paper no. 9614.

Williamson, Oliver. 1975. *Markets and hierarchies: analysis and antitrust implications.* Free Press: New York.

Zhu, Xiaodong. 2012. Understanding China's growth: past, present, and future. *Journal of Economic Perspectives* 26, no. 4: 103-24.