DRAFT WORKING PAPER

Cutting the Losses: Reassessing the Costs of Import Competition to Workers and Communities

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Abstract

In any dynamic economy, there is a risk of job loss. Job loss resulting from foreign rather than domestic competition has come under intense scrutiny recently with Britain's exit from the European Union and the election of Donald Trump as president of the United States. While economists generally conclude that trade is broadly enriching, recent works have brought attention to the costs of trade to workers and communities. At the individual level, I find that the risk of layoff and unemployment to workers in trade-exposed sectors is comparable — or even lower — than the risk to workers in non-traded sectors and that these risks have not increased during the period of more intense competition with Chinese imports. At the community level, Autor, Dorn and Hanson (2013) find that local areas have experienced slower job and wage growth and higher unemployment because of import competition with China. Upon analyzing their data, I conclude that their results are biased by the weaker macroeconomic performance of 2000-2007 relative to the 1990s. When I analyze inter-local area economic changes—rather analyzing changes within and across areas—I fail to reject the null hypotheses that import competition has no effect on wage or employment growth, except within the manufacturing sector during the most recent period, or that it has no effect on many other outcomes, including labor force participation, intergenerational mobility, and mortality. During each period, import competition actually predicts an increase in average wages for manufacturing workers, as well as non-manufacturing during the 1990s period, and import competition predicts a shift toward college educated non-manufacturing jobs in the second period. I conclude that foreign competition does not appear to elevate the risk of job loss to a greater extent than domestic competition, and people living in the communities most exposed to foreign competition are no worse off on average.

[1] I would like to thank David Autor, David Dorn and Gordon Hanson for responding to my request for comments on earlier drafts. Their comments and their rich online data resources hosted on David Dorn's website (www.ddorn.net) greatly facilitated the replication and extension of their work and helped me improve upon earlier versions. This draft also benefited from discussion with Mark Muro and Andrew Reamer and access to the George Washington Institute of Public Policy, where I am a visiting scholar. Finally, my Gallup colleagues Diana Liu, Andrew Dugan, Matthew Hoover and Anuradha Uduwage provided helpful comments and suggestions.

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1. Introduction

The literature on trade

Since the earliest known writings on economics, scholars have argued that trade facilitates human welfare. In both ancient Greece and 18th-century Scotland, respectively, Plato (Jowett, trans. 2015) and Smith (1776) argued that trade fosters the specialization of occupational tasks, allowing individuals to become more productive, and that these productivity gains lower the costs of producing goods and services. Their rationale applies whether the exchanges are between people located in the same city or distinct polities.

Modern empirical scholarship based on cross-country and inter-industry evidence continues to find that international trade contributes to economic growth (Estevadeordal & Taylor, 2013; Chen, Imbs & Scott, 2009). At the same time, a long-standing theory is that trade reallocates tasks based on issues such as the relative prices of the factors of production, as in the Heckscher-Ohlin framework. This should tend to shift low-skilled production to developing countries, while tradable industries in developed countries become more capital-intensive (Bernard, Jensen & Schott, 2006).

The field of urban economics provides another perspective on trade within and between countries. There is strong evidence showing that urban workers are more productive than those in rural areas largely because population density facilitates trade and specialization (Combes, Duranton, Gobillon, Puga & Roux, 2012). Urbanization itself is tantamount to economic development and has been linked directly to international trade in either raw materials or industrial products, which increases incomes and demand for local services (Gollin, Jedwab & Vollrath, 2016).

Whether exchanges take place within or between countries, trade relationships are increasingly understood as complex and multifaceted in that a large portion of trade occurs within the same firm or between firms affiliated by common ownership (Bernard, Jensen & Schott, 2005). Likewise, workers are more likely to be employed by a firm that exports and imports rather than one that only exports. Trading firms, meanwhile, were more productive and saw higher employment growth during the 1990s than firms that did not trade (Bernard, Jensen & Schott, 2005). At the establishment level, manufacturing establishments were more likely to survive at least 10 years between 1992 and 2007 if they were highly productive, exported and traded with a foreign affiliate in a low-wage country (Rigby, Kemeny & Cooke, 2016).

Yet, despite the advantages of higher output per worker and lower-cost goods and services, trade is not without conflicts and costs, at least in the short run, as is consistent with Heckscher-Ohlin models. U.S. manufacturing employment peaked in 1979; by 2016, there were 7.3 million fewer jobs in that industry, with roughly two-thirds of those losses concentrated in the 21st century. While trade critics were more prominent in earlier eras of U.S. politics, two of the leading presidential candidates in 2016 — Donald Trump and Sen. Bernie Sanders — were highly critical of trade during their campaigns, particularly trade with China.[2] After his

[2] See, for example, Peter Coy's "Trump and Sanders have a point about trade with China: When U.S. imports rise, so do unemployment and disability payments," *Bloomberg Businessweek*, April 19, 2016.

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inauguration, one of Trump's first actions was to write a presidential memorandum to the U.S. Trade Representative ordering withdrawal from the Trans-Pacific Partnership.[3]

Recent economics literature provides evidence that trade with China has at least partly contributed to the loss of manufacturing jobs starting in the 2000s. Acemoglu, Autor, Dorn, Hanson and Price (2016) and Pierce and Schott (2016) find that the rapid surge in Chinese imports during the 2000s caused a large loss of manufacturing jobs.[4] When exposed to competition from low-wage countries, plants are more likely to shut down (Rigby, Kemeny & Cooke, 2016). Meanwhile, a handful of articles finds that workers are more likely to suffer a loss in income when import competition is high (Kletzer, 2000; Ebenstein, Harrison, McMillan & Phillips, 2014; Autor, Dorn, Hanson & Song, 2014). Hummels, Jorgensen, Munch and Xiang (2014) find that offshoring causes Danish firms to reduce pay for their low-skilled workers and increase pay for their high-skilled workers. Beyond manufacturing, ADH also find that Chinese imports have damaged local area economies more broadly.

Two research papers explicitly test whether import competition from low-wage countries increases the risk of unemployment for workers in respective industries. Kemeny, Rigby and Cooke (2014) conclude that import competition does increase the risk of unemployment for workers, but only for those with no postsecondary education. Their identification strategy, however, does not account for pre-exposure trends in unemployment and may miss the long-standing relationship between unemployment and industry structure for less-educated workers. Autor et al. (2014) do account for prior trends and find that import competition has no significant effect on the probability of employment but does increase employment in other manufacturing industries as workers transition to new jobs.[5]

A point not often raised in trade literature is that most job loss results entirely from domestic competition (Stephens, 2001). Economists generally agree that competition is an essential ingredient of economic prosperity, but it is unclear what special considerations should be given to workers and businesses exposed to foreign competition. Workers laid off in other sectors — such as construction and retail — are also harmed by displacement but rarely receive attention in trade literature (Brand, 2015).

Given that the difficulties of transitioning to new employment may be related to an individual's degree of industry-specific training and knowledge (Ormiston, 2014), one might argue that manufacturing workers deserve special protection from competition. However, research shows that workers laid off in other industries — including professional services — experience sharper wage losses than those laid off in manufacturing (Couch & Placzek, 2010). Moreover, Autor et al. (2014) find that manufacturing workers who stay at the same firm suffer larger earning losses than those entering a new job either inside or outside the manufacturing industry, which suggests that firm-specific and even industry-specific knowledge are not as important as other

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[3] See Donald Trump's "Presidential Memorandum Regarding Withdrawal of the United States from the Trans-Pacific Partnership Negotiations and Agreement," Jan. 23, 2017, retrieved from https://www.whitehouse.gov/the-press-office/2017/01/23/presidential-memorandum-regarding-withdrawal-united-states-trans-pacific

[4] Acemoglu et al. (2016) estimate the China effect caused a loss of 2.0 to 2.4 million manufacturing jobs from 1999 to 2011, which amounts to approximately 31% to 38% of the total number lost.

[5] Specifically, Autor et al. (2014) regress the number of years with positive earnings on import exposure and fail to reject the null hypothesis of no relationship (see Table 3 in their study). In Table 4, they find that import competition predicts an increase in employment outside the original industry but still within the broader manufacturing sector.

factors in determining wages for manufacturing workers. One such factor is the health of the overall macro economy. Workers displaced during times of low unemployment face relatively mild earnings losses, whereas those displaced during recessions or high-unemployment periods experience larger losses (Davis & von Wachter, 2011).

Aim of this research

Trade theory and trade policy would benefit from a clearer understanding of two issues that motivate this empirical study: To what extent does trade liberalization with low-wage countries increase the risk of job displacement, beyond its level during periods of lower competition or in other domestic industries whose products are locally sold? And how does import competition affect local communities, including workers in other sectors?

To answer the first question, I examine various measures of layoff risk across administrative and survey-based data sources and time periods and conclude that the risk of layoff is no higher in trade-exposed industries and did not rise during the most recent period of intense competition. A more formal analysis merges trade exposure data with individual records from the U.S. Census Bureau's Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). Using difference-in-difference estimation for millions of workers from 1968 to 2016, I compare unemployment rates, sector-to-sector transitions and other outcomes across industries more or less exposed to trade and during periods of greater or less competition (particularly 2001 to 2016), associated with Chinese and low-wage country imports. I again find no evidence that import competition increases the risk of unemployment. Despite a large net job loss in manufacturing over the period of import competition, it seems that manufacturing workers benefit from a low risk of being laid off and an ability to transition to other sectors.

To address the second question, I revisit the findings of ADH. They conclude that Chinese imports cause local areas to experience lower aggregate employment growth; a rise in the unemployment rate; a drop in wages, income and labor force participation; and an increased reliance on Social Security and other government transfer payments. This article has been extremely influential among social scientists, judging from citation counts, and it has been widely cited in popular media. A summary of their work and review of the trade literature (Autor, Dorn & Hanson, 2016) earned an award for best political economy research of 2016 by *The Washington Post*.[6] Their 2013 paper brought about significant advances in developing methods to measure the causal effect of import competition.

After replicating the ADH results (using their publicly available data and code) and assessing the robustness of their model, I conclude that their econometric specifications are biased by a coincidence in timing. Essentially, their results — or rather, those applying beyond the manufacturing sector — depend entirely on comparing local economic performance from the 1990s to the early 2000s and noting that import-exposed areas performed relatively worse during the 2000s than they did in the 1990s.

Unstacking their model results in the collapse of most of their 45 significant findings. Taken together, commuting zones performed no better or worse in a given period (such as 1990-2000, 2000-2007 or 1990-2014) when heavily exposed to Chinese imports. During the 1990s, exposure to import competition actually predicts higher wages overall and for manufacturing

[6] See Daniel Drezner's "The best work on political economy in 2016," *The Washington Post*, Dec. 30, 2016.

workers, higher non-manufacturing employment growth for college workers, and population growth among people aged 35 to 64. During the 2000s, these highly exposed areas, experienced a shift in employment toward non-manufacturing college educated workers and higher wage growth in manufacturing. Other outcomes—such as overall wage growth, employment growth, changes in unemployment—were indistinguishable from the average local area, except these placed suffered disproportionate manufacturing job losses. ADH find that 27 significant outcomes beyond manufacturing and transfer payments were worse because of import competition in their stacked model. None of these were significant from 1990 to 2000, and only one was significant from 2000 to 2007. This outcome — a drop in labor force participation rates among non-college workers — becomes insignificant after adding local area-level controls for racial demographics and population age.

I extend the ADH model beyond 2007 to 2011 and 2014 and examine changes from 1990 to 2014. Again, I find no effect from import competition on broad negative economic outcomes, including wage changes, changes in mortality rates and intergenerational mobility. The only negative effect of import competition that remains significant and robust is manufacturing job loss.

I conclude that the economic losses from trade are not as severe as the economics literature currently implies. Workers in the most import-exposed sectors face a risk of layoff and unemployment that is comparable to workers in other sectors, where competition comes almost exclusively from domestic businesses. While it is likely that less import competition would further lower the risk of displacement and boost wages for manufacturing workers, less competition would likely lead to a reduction in the ratio of product quality to price and a drop in consumer welfare. I accept the Autor et al. (2014) finding that import competition lowers wages for U.S. workers in the affected industries — but even still, I find that workers in the manufacturing sector continue to earn a sizable wage premium compared to those with similar experience and education levels in other sectors.

At the community level, these results should not be taken to mean that de-industrialization has been harmless to individuals or even communities. Rather, the results imply that de-industrialization as a result of Chinese import competition plays out no differently than de-industrialization as a result of other forces — such as domestic competition or technological change. Communities relying more heavily on industries facing import competition perform no worse in this study on summary measures of economic development and consistently show higher growth rates in establishments. They seem to find ways to adapt, maintain wage growth and launch new enterprises.

In summary, competition from foreign establishments seems to have very similar effects as competition from domestic establishments at the individual and community levels.

This paper proceeds with a brief background discussion on the most relevant changes in U.S. manufacturing employment, wages and imports. Section 3 analyzes individual-level displacement risk in the industries subject to the most intensive import competition. Section 4 analyzes the effects of import competition on local areas, using ADH and Acemoglu et al. (2016) databases, and Section 5 concludes.

2. Trends in U.S. manufacturing employment, wages and imports

U.S. manufacturing employment peaked in 1979 at 19.5 million workers. By the end of 2016, this figure had fallen by about 37%, to 12.3 million. Most of these losses — approximately 5

million — occurred between 2000 and 2016, particularly from 2007 to 2010.[7] The 2000-to-2010 period thus stands out historically as the largest job-loss period for U.S. manufacturing and as a time with significant increases in the trade deficit, as Chinese imports ramped up. These changes are represented below (Figure 1), as imports — adjusted for inflation — divided by the number of workers in the U.S. manufacturing sector. Almost all Chinese imports (99%) can be classified into the manufacturing sector.[8] Imports per manufacturing worker went from $8,000 in 2000 to $40,000 in 2015. Import growth was strong in the 1990s and continued to grow at a much faster pace in the 2000s. The value of Chinese imports exceeded the value of Mexican imports for the first time in 2003, and the negative trade balance with China is currently 5.4 times larger than it is with Mexico.

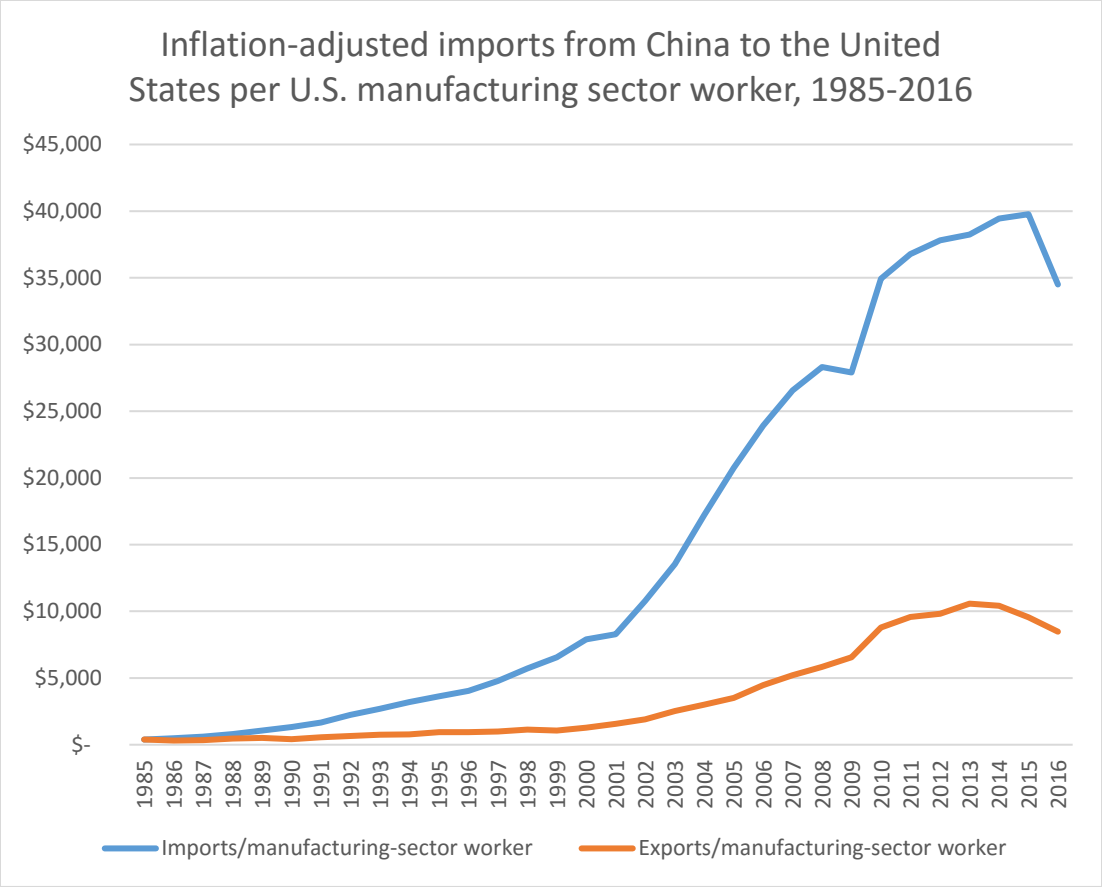
There is good reason to believe that import competition will have regional effects, as a substantial share of the imports are produced in a select few sectors. U.S. International Trade Commission (USITC) data show that 40% of the total value of Chinese imports to the U.S. from 2000 to 2015 occurred in the computer and electronics industry ($149 billion in nominal dollars). Two-thirds of the total value of Chinese imports were classified in that industry and four others: electrical equipment, appliance and component manufacturing; machinery manufacturing; apparel manufacturing; and miscellaneous manufacturing, which consists largely of toys and sporting goods.[9]

Employment in manufacturing, advanced services and other industries that rely heavily on international trade is highly concentrated in specific counties, metropolitan areas and states (Helper, Krueger & Wial, 2012; Muro, Rothwell, Andes, Fikri & Kulkarni, 2015). Thus, the early 21st century serves as an excellent test case for upper-bound estimates of damage from global import competition at the individual and community levels.

[7] U.S. Bureau of Labor Statistics (BLS), All Employees: Manufacturing [MANEMP], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/MANEMP, Jan. 13, 2017. Recessions triggered large manufacturing layoffs in earlier periods as well. The 10-year period ending in March 1983 saw a loss of 1.8 million jobs in the sector. Losses at that scale did not occur again until the early 1990s recession, with another 1.8 million loss over 10 years. Losses were then quite small until the recession of the early 2000s; another 1.8 million manufacturing jobs were lost over a 10-year period ending in 2002. Losses accelerated thereafter.

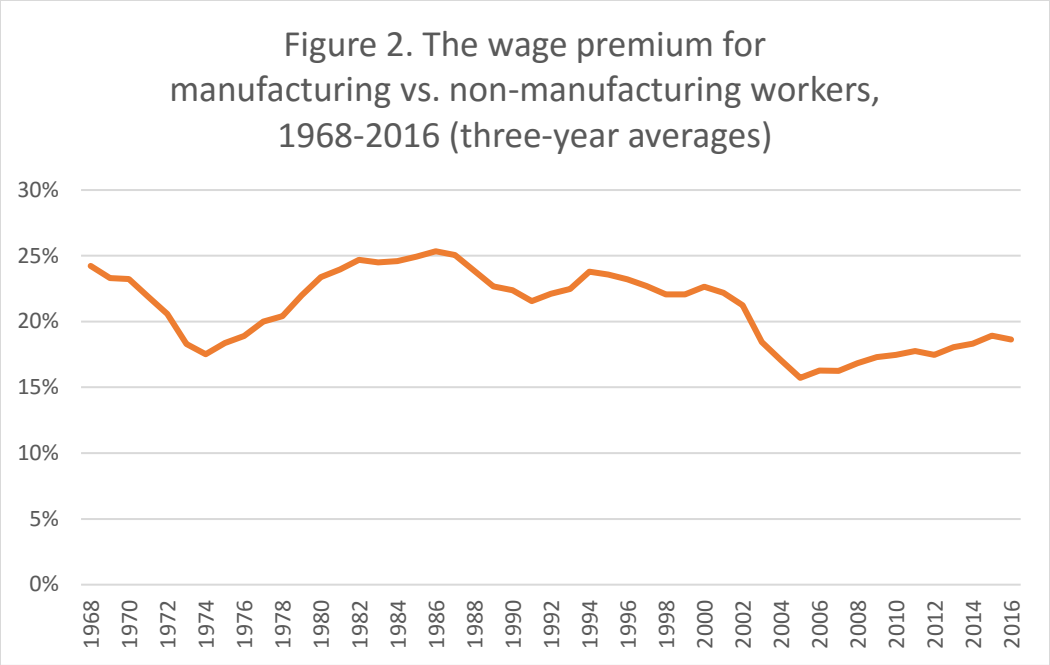
[8] Source: U.S. Census Bureau Foreign Trade database. USITC data indicate that 99% of imports from China by value are manufacturing-sector products. Employment data are from the U.S. Bureau of Economic Analysis (BEA) for all years except 2016, in which case they are from the BLS. Values are adjusted for inflation using the BEA GDP price index.

[9] These industries also account for about two-thirds of total imports using Acemoglu et al. (2016) data from 1991 to 2011. At the two-digit Standard Industrial Classification (SIC) level, they are 36, 35, 23 and 39.



Sources: USITC, BEA

While it is well-known that manufacturing workers enjoy a wage premium, there has been little discussion about how wages have changed throughout this period of falling employment and rising import competition. In light of the literature linking import competition to reduced wages, a reasonable hypothesis is that this wage premium has been greatly eroded, if not entirely eliminated. Somewhat surprisingly, manufacturing workers still earned a wage premium of 19% in 2016, meaning the average manufacturing worker earns 19% more than the average non-manufacturing worker of the same gender with the same work experience and level of education. This is calculated using a standard Mincerian wage regression framework for the employed working-age population. The coefficient on manufacturing employment is reported, averaged over three-year periods. This premium remained high throughout the 1990s but took a notable dip from 2000 to 2007, falling from 23% to 16%. It recovered somewhat to 19% by 2016.



Source: IPUMS-CPS. Regression of log of wage income on manufacturing binary variable for employed population aged 18 to 64. The coefficient on manufacturing is reported, conditional on binary educational categories for some college, associates degree, bachelor's degree and postgraduate degree; a cubic in age; and gender. Sample weights are included.

3. Individual risk of displacement from trade and its consequences

Summary evidence

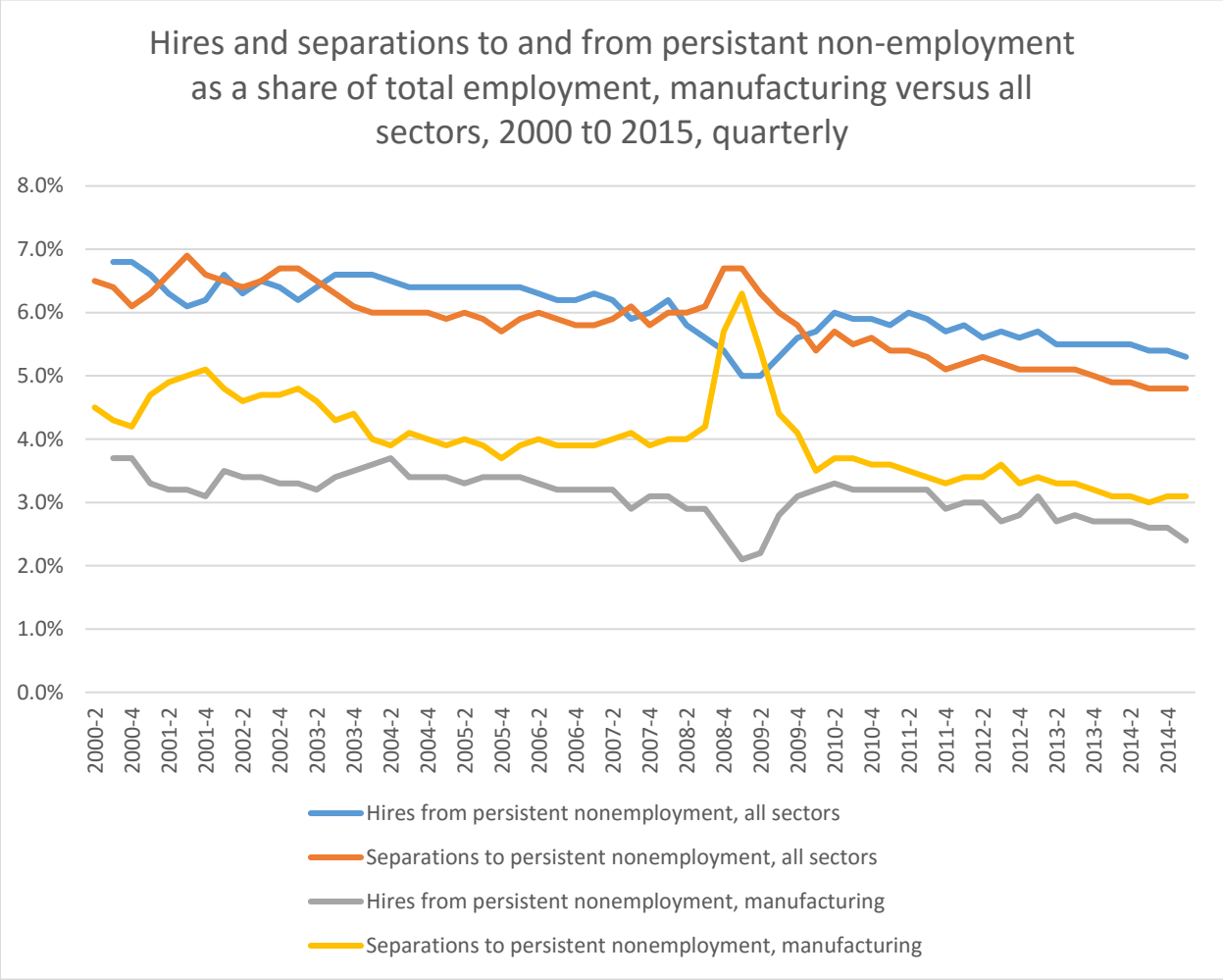
Second only to wages, one of the most important qualities of a job is security (Farber, 2008). Therefore, the first step in evaluating potential harm from trade is to determine how job security in the traded sectors differs from job security in all sectors and how this has changed during the period of rapidly rising imports. There is no prima facie reason to believe traded sectors will exhibit lower levels of job security compared with non-traded sectors. In a market economy, businesses across sectors face competition and disruption from potential entrants, innovation or even bad luck. Just because a sector exports goods does not make it inherently more exposed to competition. Indeed, intellectual property protections, barriers to international trade from tariffs, language differences, geographic distance and high capital costs may shelter goods exporters from competition relative to barbers, restaurants and other domestic businesses.

To examine various measures of displacement risk, I compile data from a combination of administrative and survey-based data sources and show the results in Table 1, contrasting manufacturing-sector outcomes from total or non-manufacturing for the period preceding the China shock (pre-2001), if available, and the period since. A number of stylized facts emerge from this exercise, which previous works have not noted.

[Table 1]

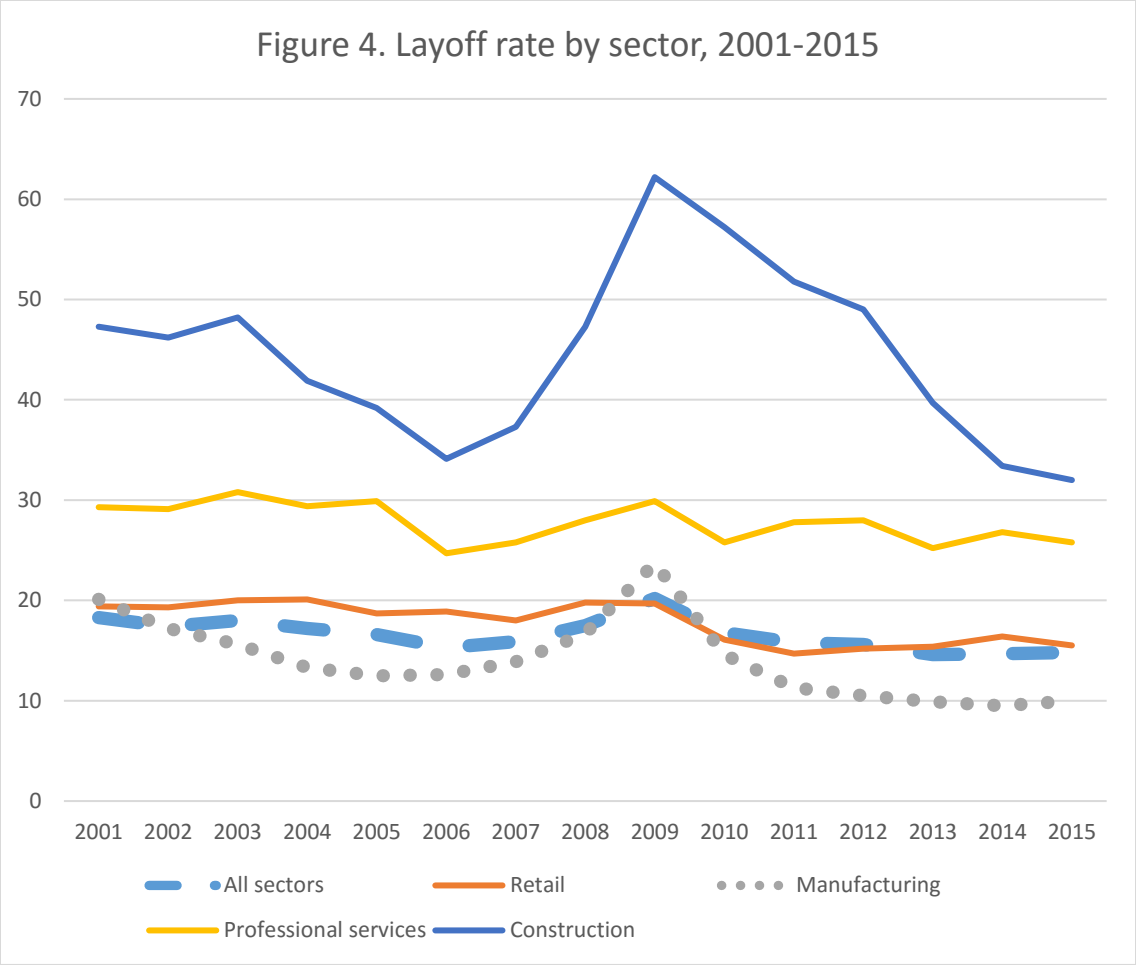
First, employer versus employee-based data sources differ as to the risk of being laid off or even separated from an employer in the manufacturing sector, but neither source shows the relative risk for manufacturing workers rising during the period of increasing import competition.

Let's begin with employer-based data. Administrative records from Longitudinal Employer-Household Dynamics (LEHD) — which are matched through tax records — show a lower risk of manufacturing workers being separated into persistent unemployment. Persistent unemployment is defined as at least one quarter of unemployment. It is uniformly lower for manufacturing workers than workers in all sectors throughout the period of intense import competition. Though it clearly spiked in 2009, this separation rate has been declining since 2001, even as the trade deficit with China has grown, along with imports per worker. Notably, the manufacturing-sector hiring rate is also much lower.



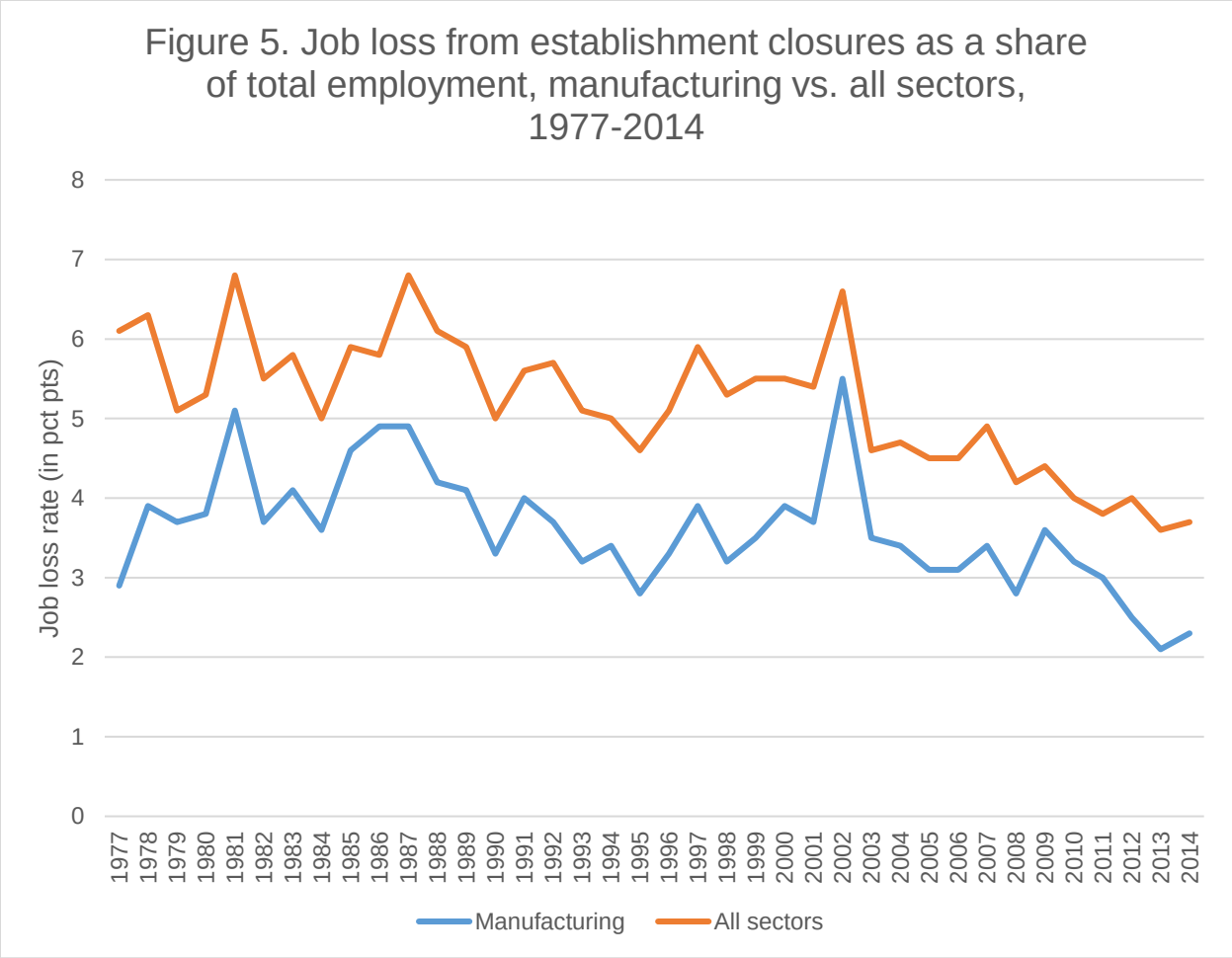
Sources: U.S. Census Bureau, LEHD

Likewise, data from the Job Openings and Labor Turnover Survey (JOLTS) of employers tell a similar story. The layoff rate is consistently lower for manufacturing workers than for workers in all sectors. The rate is roughly two to three times higher for construction workers compared to manufacturing and is even higher for professional service workers, a sector that has experienced long-term employment growth. This sector includes architecture, engineering, computer design, legal services, accounting, advertising, scientific research and other professions.



Sources: BLS, JOLTS

Relatedly, administrative data from the U.S. Census Bureau's employer-based Business Dynamic Statistics (BDS) suggest workers in other domestic sectors are more likely than manufacturing employees to lose their job due to establishments closings, which occurs, for instance, when a factory is moved overseas. Moreover, the risk of job loss from these closings has declined over time as imports have increased, after a brief spike in 2002.



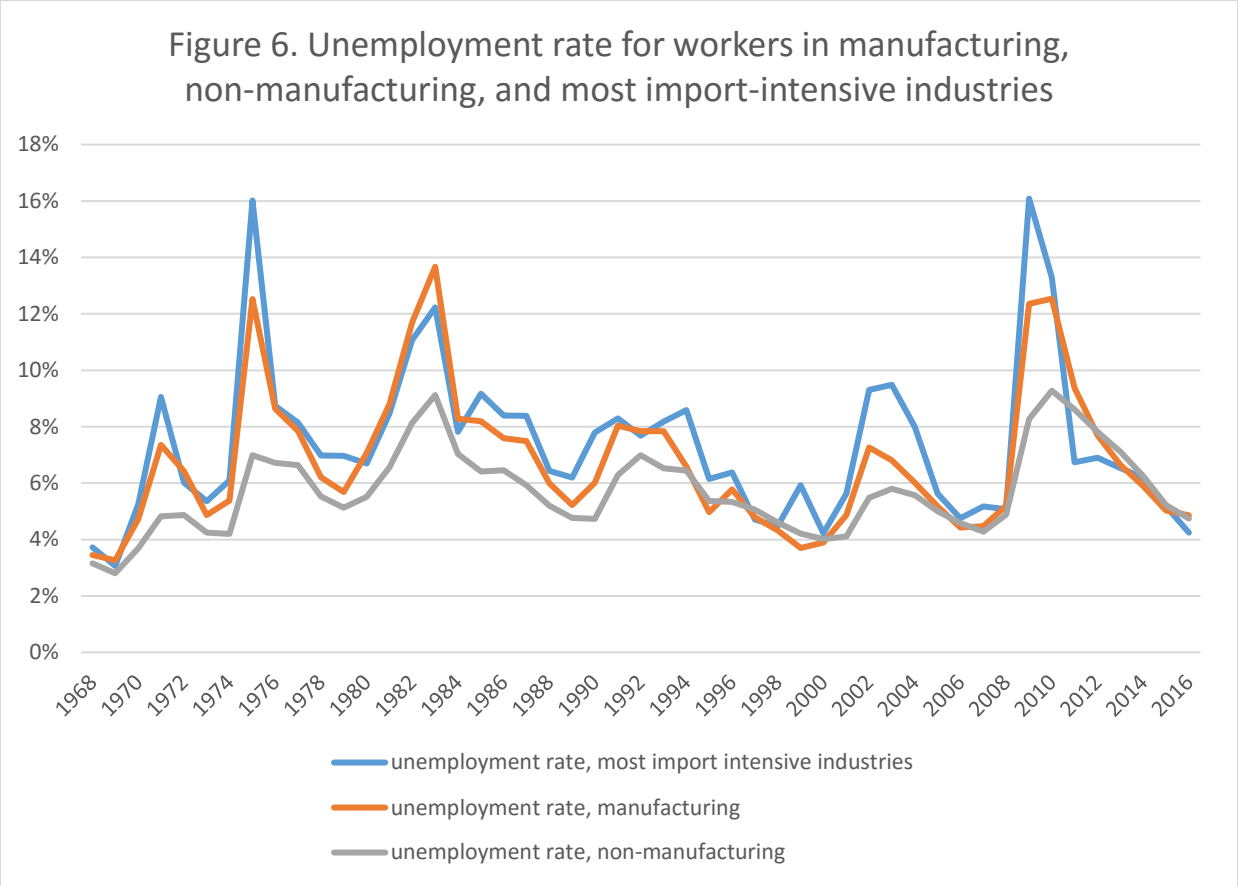
Sources: U.S. Census Bureau, BDS

Employee-based survey data from the CPS tell a somewhat different story. The CPS ASEC database asks jobless respondents why they are unemployed. At first glance, manufacturing workers appear to be slightly more likely to say they are unemployed for reasons that can be characterized as involuntary (laid off, lost job for other reasons or temporary job ended). However, this likelihood disappears entirely after controlling for education status; indeed, manufacturing workers are slightly less likely to say they are unemployed for involuntary reasons. Less ambiguously, the Displaced Worker Supplement to the CPS shows a much higher risk of displacement for manufacturing workers.[10]

Below, Figure 6 plots the unemployment rate for manufacturing workers, non-manufacturing workers and workers in the eight most import-intensive industries, after matching Acemoglu et

[10] The data reported here are cut by the current or most recent industry. An ideal measure, however, would report displacement rates by one's industry of employment at some time in the past. To reconstruct such a metric from the Displaced Worker Supplement, I calculate the share of all displaced workers by the industry of their lost job and compared it with the current distribution of workers across industries. I find that manufacturing workers are more likely to be displaced using the ratio of these two distributions.

al. (2016) data to the CPS ASEC.[11] It is clear that unemployment rates have long been higher for manufacturing workers and the industries that later came to compete with Chinese-based establishments. In 1975, for example, the most import-intensive industries saw a massive spike in unemployment to 16%, which was not matched again until the Great Recession. Yet, in 2016, the unemployment rate among the most import-intensive industries was slightly lower than both the manufacturing and non-manufacturing unemployment rates.



Source: CPS ASEC

As to why employee data show greater risk than employer data, there are at least three possible ways to reconcile the differences between employer and employee data sources, aside from survey error. First, the unemployment rate and involuntary unemployment rate could be higher even if displacement risk were lower. The reason for this is that displacement in other sectors — such as restaurants — could lead very quickly to another job offer, given the density of establishments and the high hiring rate. Below, I present evidence for this in that long-term unemployment rates are higher for former manufacturing workers. Thus, low dynamism in manufacturing could explain the unemployment rate, even if workers are rarely laid off.

Second, there are important classification issues. Employee-based records rely on subjective industry reporting. Workers employed by a staffing, administrative services or consulting firm in

[11] These are industries with import per workers scores above 100, using the AADHP measure. These include apparel, electrical machinery, household appliances, leather products, machinery, fabricated textiles, other rubber products, and radio, television, and communications.

the service sector may consider themselves to be in the manufacturing sector if they are assigned to a manufacturing plant or are consulting with clients who work for a manufacturing company. Employer-based tax and survey data, however, would likely classify these workers as part of the service sector. This bias could go the other way as well. Workers who provide administrative or managerial services within a large manufacturing establishment may interpret their industry to be in the service sector.

Third, workers in different industries may provide different interpretations as to why they have become unemployed, which is particularly relevant for the Displaced Worker Supplement to the CPS. In this survey, a worker is defined as displaced if the following conditions are met: He or she has lost *or left* a job within the previous three years, and the reason for exit is that the plant or company closed or moved, the position or shift was abolished, or there was insufficient work.[12] Manufacturing workers who lost or left a job within three years are roughly twice as likely to meet the criteria for displacement as non-manufacturing workers (96% compared with 56% of non-manufacturing workers who lost or left their job). The gap is largely explained by the fact that job-leavers in the manufacturing sector are far more likely than job-leavers outside of manufacturing to report that their plant or company closed or moved (41% vs. 20%, respectively) and that there is insufficient work for them (38% vs. 28%). It is possible that manufacturing workers who voluntarily quit are more likely to report leaving because of insufficient work, possibly in anticipation of a possible establishment closing.

Data from the Displaced Worker Supplement show that displacement from manufacturing is slightly more costly in terms of lost wages and more likely to result in a move across industries. However, wage data are collected for only a small subset of workers, and previous wage data and previous industry classifications are only available for workers who lost or left their job. Combined with the subjective issues involving the definition of displacement and the relatively small sample size compared with the CPS ASEC or administrative sources analyzed in the literature (Autor et al., 2014), I focus on other sources for the subsequent analysis.

I next turn to more systematic evidence on the role of trade in predicting a higher risk of displacement and related outcomes.

CPS regression-based evidence for risk of displacement

To test whether import competition correlates with an elevated risk of negative employment outcomes, I use a difference-in-difference estimation strategy based on individual CPS ASEC data from 1968 to 2016. The model uses probit regression in the following form:

$$1. Y_{i,t,s} = \alpha + \beta TE_{t,s} + T_t + E_s + X_{i,t,s} + G + \varepsilon_s$$

T refers to the time period of more intense import competition, namely 2001 to 2016. *E* refers to a more trade-exposed sector, either manufacturing or the industries with the highest value of imports per worker, using ADH methods and an industry-based measure of import competition from the related Acemoglu et al. (2016) paper and online replication files.[13] I also construct a

[12] U.S. Census Bureau, January 2010. Displaced Worker, Employee Tenure, and Occupational Mobility Supplement, retrieved from https://www.census.gov/prod/techdoc/cps/cpsjan10.pdf.
[13] I create a crosswalk between the Acemoglu et al. (2016) SIC-based industry codes to the IND1990 codes in IPUMS-CPS, using materials from David Dorn's website as assistance

similar measure using the change in industry-level imports from China from 2000 to 2016 per worker in 1999, using IPUMS-CPS data and USITC imports for consumption data by industry.[14] Workers are matched to their current industry if they are working or are matched to the industry in which they last worked if they are not working.

The *X* variable is an index of individual-level covariates, including educational attainment, age and gender. *G* captures geographic fixed effects, in this case from states.

Y is a binary variable, including unemployment, unemployment as a result of involuntary separation, long-term unemployment, and whether or not the worker is in the labor force.

The difference-in-difference identification comes from the difference between unemployment (or another outcome) in the pre-import-intensive period and unemployment in the post-import-intensive period for manufacturing-sector workers (or workers in the most trade-exposed industries), which is the first difference, compared with non-manufacturing-sector workers (the second difference). This approach controls for the long-term characteristics of manufacturing workers that might affect their risk of displacement. It also controls for the broad macroeconomic conditions of the early 21st century that affected all industries.

As a robustness check, I use Acemoglu et al. (2016) instrumental variable data and strategy, which uses variation in import competition per worker in other developed countries to identify U.S.-based import competition per worker in the same industry. The idea is that this removes demand effects from the industries and isolates the supply shock from China's rising productive capacity.

[TABLE 2]

The results clearly show that import competition does not raise the risk of unemployment in general or the risk of voluntary unemployment specifically. Nor does import competition predict an increase in the probability of workers exiting the labor market. This result holds whether one measures import competition within the manufacturing sector in the most import-intensive period, or performs more fine-grained industry-based measures based on actual Chinese imports. Moreover, there is no evidence that imports cause higher unemployment in these data, relative to other industries and other time periods.

Involuntary unemployment is somewhat higher in the industries most exposed to Chinese imports, but this apparently has little to do with the intensity of import competition because the 2001-to-2016 period did not increase this risk. Unemployment, involuntary unemployment and long-term unemployment are no higher in the manufacturing sector during the import-intensive period, conditional on these parsimonious controls for age, education, gender and state effects.

There is stronger evidence that import competition affects long-term unemployment. The import exposure measure is significant but very weak. A one-standard-deviation increase in import exposure predicts less than a 0.02-percentage-point increase in the long-term unemployment rate. It may be that unemployed workers in these sectors have a harder time finding work in the same industry because of the low hiring rate, and that prolongs their job search.

(http://www.ddorn.net/data.htm). I then sum import competition by industry for each SIC87 across IND1990 codes and merge this result into the CPS database.

[14] I developed a crosswalk between three-digit North American Industry Classification System (NAICS) and IND1990 using IPUMS reference materials.

An alternative explanation for why import competition predicts long-term unemployment is that workers in import-competitive industries are more likely than other unemployed workers to get unemployment insurance benefits, and this tendency may have increased during the Great Recession. When I add a control for the manufacturing sector, the import effect (i.e., imports per worker interacted with the exposure period) becomes insignificant.[15] Unemployment insurance has been found to extend the duration of unemployment (Farber & Valletta, 2015), and data from the Displaced Worker Supplement show that former manufacturing workers who meet the criteria for being displaced were much more likely than other displaced workers to receive unemployment insurance (59% vs. 42%, respectively) during the 1996-to-2014 period. Moreover, eligibility for long-term unemployment benefits was expanded during the Great Recession, and so was the recipiency rate for unemployed workers.[16] For displaced manufacturing workers, the share receiving unemployment insurance peaked at 68% in 2010, whereas the figure for non-manufacturing workers reached 47%.

4. Assessing regional harm from import competition

Methods used to assess local effects

This section presents an analysis of the regional effects of import competition, as analyzed by ADH. I start by replicating their exact specifications and results using their data and then make adjustments and extensions of their model to test the robustness of the results.
They run the following model across many different outcomes:

$$2.\, \Delta Y_r = \Delta IMP_r + X_{r,t} + T_t + u$$

Here, *Y* is an economic outcome in a region (*r*), which is measured as changing over time from 1990 to 2000 (period 1) or 2000 to 2007 (period 2). *T* is a period fixed effect. The main variable of interest is imports per worker. This calculates the summation across all industries in the change in Chinese imports over period 1 or period 2, divided by total regional employment. It then multiplies this by the region's share of U.S. employment. The hypothesis is that a region's share of national import competition is closely related to its share of employment in each of the relevant industries. Thus, this is a proxy for the value of imports on a per-worker basis that are competing with workers in the region.

Regional units are commuting zones (CZs), which are like metropolitan areas but more comprehensive in that they include nonmetropolitan counties, and hence all U.S. counties. As explained by ADH, CZs define a local labor market based on either a single county or cluster of counties and are determined based on actual commuting patterns from U.S. Census Bureau data.

The control variables in *X* are determined at the start of each period and include measures meant to capture the share of workers in routine occupations (who are theoretically more subject to technological displacement), the share of workers susceptible to outsourcing, the female share of the workforce, the bachelor's degree attainment rate, the foreign-born share of the population, U.S. Census division dummy variables, and the share employed in

[15] These results are available upon request.
[16] See Casey Mulligan's "Unemployment Compensation Over Time," *The New York Times*, Dec. 21, 2011.

manufacturing. ADH also use an instrument for import per worker, based on imports into other developed countries. This is their basic model, which they use across 75 regressions.

ADH combine the changes across both periods into one regression. The advantage of doing this is that it doubles the sample size (from 722 to 1,444) and allows for variation both within CZs (over time) and across CZs (comparing one place with another), making type II errors (falsely accepting a null hypothesis) less likely. The problem with this setup is that it makes type I errors (falsely rejecting a null hypothesis) more likely. The within-CZ comparison is subject to bias from timing effects. Macroeconomic conditions were much stronger from 1990 to 2000 than from 2000 to 2007, or subsequently. If manufacturing-based areas are more sensitive to slower economic growth — as seems to be the case during explicit recessions — the weak performance of the 2000s may exacerbate manufacturing decline and put a disproportionate drag on the wheels of commerce in local areas heavily dependent on manufacturing.

Along these lines, the economics literature recognizes that there has been a sharp slowdown in U.S. productivity growth since the 1970s. There is a great deal of debate about why this is the case, which is beyond the scope of this analysis, but scholars have not attributed it to import competition (Gordon, 2016; Bloom, Jones, Van Reenen & Webb, 2017; Baily & Montalbano, 2016; Rothwell, 2016).

The ADH paper ends at 2007.[17] One possibility is that the negative effects of import competition played out during and after the Great Recession — so I extend the analysis through 2014, using employment status data from the five-year American Community Survey (ACS) for 2010-2014, as well as employment, establishment and pay data from the Quarterly Census of Employment and Wages (QCEW) up to 2014.

To better measure import competition through this later period, I use the Acemoglu et al. (2016) import competition measure that covers the period from 1999 to 2011, and I supplement this with my own measure using three-digit QCEW data, combined with U.N. Comtrade data to construct the instrument.[18] By contrast, ADH and Acemoglu et al. (2016) rely on County Business Patterns (CBP). Using CBP allows them to employ a novel and sophisticated technique to allocate missing industry-level employment records withheld by the U.S. Census Bureau for privacy reasons. The downside is that CBP data are less accurate because they represent a snapshot in time. They rely on March 12 employment records for a given year, whereas QCEW averages employment with and across quarters of reported data throughout the entire year. QCEW also reports “high-level” data, which avoids almost all disclosure suppressions at the sector level for manufacturing, though there are significant disclosure problems with certain three-digit industries such as electrical equipment, appliance and

[17] They, however, use 2006-2008 three-year ACS data to measure many of their outcomes.

[18] I follow Autor et al. (2013) in using imports to other countries as an instrument for imports into the U.S., which eliminates U.S.-specific demand effects from the import measure. The chosen countries reflect diversity in GDP per capita and geography, without including the very poorest nations, which likely have different trade patterns with China. The list of 10 is as follows: Australia, Brazil, Canada, Germany, Japan, Republic of Korea, Spain, Sweden, Switzerland and the United Kingdom. Import data for each of those countries were taken from the U.N. Comtrade database. HTS product codes were matched to three-digit NAICS using a crosswalk provided by the U.S. Census Bureau. Six-digit HTS codes to NAICS matches were replaced with five digits (and four digits, when available) so that more accurate matches prevailed over less accurate ones.

component manufacturing.[19] Finally, I also use a more straightforward measure of import competition — the initial period (measured in 1999) share of employment in the industries responsible for most (two-thirds) of Chinese imports, using Acemoglu et al. (2016) jobs data by industry.[20]

The regression framework is the same as that used by ADH — except, again, I unstack the models and test whether increased exposure to import competition in 1999 or 2000 predicts worse performance by 2011 or 2014, using the instrumental variable identification strategy and the same set of covariates as ADH.

For this exercise, I test 21 different outcomes, including those that go well beyond the ADH paper. I test aggregate employment growth, which ADH do not test. I also examine whether import competition predicts the level of unemployment, average wages and median household income. If the import shock has had cumulative negative effects since the early 1990s, one would expect this to not only slow the growth rate but also to manifest itself in lower equilibrium economic development.

Beyond the usual economic outcomes, I test whether import competition predicts changes in age-adjusted mortality using data from the Centers for Disease Control and Prevention. Following Case and Deaton (2015), there has been an effort to better understand the causes of rising mortality among middle-aged whites.

I also test whether import competition has led to lower upward mobility. Specifically, I test whether import competition has tightened the relationship between parental income and offspring income at age 26 and parental income and offspring enrollment in college by age 19, using data from Chetty, Hendren, Kline, Saez and Turner (2014). This covers adults born between 1980 and 1993, who would have been growing up or reaching early adulthood during a period of rising import competition and declining U.S. manufacturing employment. While job loss, generally, does not appear to harm the children of those who lose their job, as found by Hilger (2016), it may be that displacement from manufacturing — and mass layoffs — have more severe effects on families and communities.

Results from analysis of import competition on local economic changes

As summarized in Table 3, ADH run 75 regressions of the form described above (in Tables 3 through 9 of their publication). They find negative and significant effects from import competition on regional economic outcomes in 46 of those models. Seven of the 46 could be characterized as applying to only the manufacturing sector, but 39 apply beyond the manufacturing sector and 24 apply across all sectors and demographic groups. The implication is that the damage from

[19] For the year 2000, the county employment coverage of manufacturing for the average state, weighted by population, is 98.7% using these files. This result is obtained by summing county manufacturing employment with the state level and comparing the total with what is reported in the state aggregate file. Coverage is lower at lower levels of industry aggregation. At the three-digit NAICS industry level, employment coverage is 79.5% for manufacturing, weighted by state industry employment. For the computer and electronics industry, coverage is 89.4%, but for electrical equipment, appliance and component manufacturing, it is 57.4%. For machinery manufacturing, coverage is 86.4%; it is 70.8% for apparel manufacturing and 86.1% for miscellaneous manufacturing. These five industries account for two-thirds of Chinese imports from 2000 to 2015, according to data from the USITC DataWeb.
[20] As noted above, these are SIC codes 36, 35, 23 and 39, corresponding to electronics, computer equipment, apparel and miscellaneous manufacturing (toys).

trade reaches far beyond the manufacturing sector and is, in some ways, devastating to local economies.

If the negative effects of import competition on local economic conditions are robust, the areas more exposed to import competition should exhibit worse outcomes over the period of extraordinary intensification of import competition — from 2000 to 2007. It should also be the case that areas subject to lower-level import competition in the industries experiencing the most rapid growth throughout the 1990s perform worse than areas with higher job concentrations in either domestic industries or export industries with greater shelter from developing-country competition. Indeed, if neither of these conditions were met, it would be difficult to accept the results from the stacked model as robust and valid.

Table 3 summarizes the results of running period specific models, and Appendix Table 1 reports the full results in detail. The results radically change the interpretation of the causal effect of import competition on local economic development.

Start with the 2000-to-2007 period. Of the 39 significant models published by ADH that apply to workers outside the manufacturing sector, only two remain significant in the expected direction during 2000 to 2007. One shows that a one-standard-deviation increase in imports per worker lowered the labor force participation rate for non-college workers by one percentage point. The other shows that imports per worker predict an increase in transfer payments related to education, which is not necessarily a negative outcome since these transfers consist mostly of student loan aid and Pell Grants for higher education. Neither of these effects is robust when controlling for race and age (namely, median age and the shares of the population that are black, Hispanic and white, each measured separately). Another significant effect, which I do not code as negative, is that the share of college-educated workers outside of manufacturing increased as a share of total population in more import-exposed areas. In summary, there is no evidence from the ADH data that the areas most vulnerable to import competition in 2000 were worse off on any economic measure in 2007, except those pertaining directly to manufacturing job loss.

Three outcomes are positive and significant during the 2000-to-2007 period. The results show that wages increase for manufacturing workers and for the average college-educated workers as import competition increases. Moreover, employment to population ratios shift in favor of college-educated workers outside of manufacturing.

Remarkably, for the 1990-to-2000 period, there is no evidence that import competition resulted even in manufacturing job loss. Indeed, many of the manufacturing-specific models show that import competition resulted in a large increase in the average wages of manufacturing workers. The positive wage effect is evident outside of the manufacturing sector, particularly for non-college educated workers and males. Taken literally, these models show that import competition during the 1990s caused a substantial increase in wages for the average worker. These models also show that import competition increased employment growth for college-educated, non-manufacturing-sector workers and population growth for people aged 35 to 64.

Of the 45 models with significant effects in the stacked regression, only five retain significance in the expected direction during 1990 to 2000, and each of these pertain to transfer payments. These results could be explained by the population growth of pre-retirement-age workers, as health problems and risk of retirement are increasingly sharply with age. Overall, it appears that import competition in the 1990s was, if anything, largely beneficial to the average worker in the local areas most exposed to competition.

While Chinese import competition is a weak predictor of economic harm in these models, the preliminary share of employment in manufacturing—measured at the start of 2000—is a strong predictor or economic harm from 2000 to 2007 on a number of measures, including changes in wages and labor force participation, though not unemployment.[21] During the 1990s, by contrast, there is very little evidence of harm from manufacturing orientation or trade exposure in terms of unemployment, labor force participation, or wages. The 2000 to 2007 findings imply that job losses as a result of other factors— possibly domestic competition, uncompetitive business models, an inability to recruit or attract skilled workers, poor management, burdensome regulations, or technological change—were damaging and much more so than job losses as a result of trade competition. Ultimately, detailed firm level data would be needed to better understand why these jobs were lost.

[TABLE 3]

Extending the analysis through 2014, I again find no evidence that import competition results in broad harm to local economies. Columns 1 and 2 use 2SLS, using the instrumental variable described above. Of the 21 models, only one shows significant negative effects from the Acemoglu et al. (2016) import-per-worker measure, and this is on manufacturing employment growth (see Column 1 of Table 4). These results do show a significant and positive effect on growth in non-manufacturing establishments, suggesting a potential channel for diversification away from manufacturing. The results are qualitatively the same using a QCEW-based measure of import competition with no corrections for privacy disclosures.

[TABLE 4]

As a robustness check, I also test an Ordinary Least Squares (OLS) model using the 1999 share of jobs in the most import-intensive industries. This relaxes the endogeneity assumption but addresses the simpler issue of whether local areas with high employment concentrations in the most import-intensive industries experience economic decline. The results are very similar to the other models, except this specification shows a significant drop in labor force participation and an increase in age-adjusted mortality. Neither result, however, includes a control for the share of blacks in the area in 2000.[22] This measure of exposure also predicts significant growth in the total number of establishments as well as non-manufacturing establishment growth. I conclude that there is no robust evidence that more import-exposed areas performed worse from 2000 to 2014.

For the principal measures of local economic development, I also re-estimate changes over the entire period of 1990 to 2011, using the Acemoglu et al. (2016) measure of imports per worker and their instrumental variable. I do not find significant effects of import competition on average pay per worker or on employment growth. The coefficient is actually positive but insignificant for employment growth. I do find evidence that establishment growth is significantly higher, suggesting an increase in entrepreneurial activity in response to import competition. These results are shown in Appendix Table 2.

5. Conclusion

[21] This discussion summarizes the coefficient on initial manufacturing employment shares from Appendix Table 1, which is omitted from the table to save space.

[22] Black mortality rates started much higher but fell more sharply than other groups over the period. The other results — including for Columns 1 and 2 — are robust to including this additional control.

Britain's decision to leave the European Union and the election of Donald Trump are often cited as two main examples of public discontent with globalization and international trade. Research on the topic finds that U.S. adults were no more likely to favor Trump if they were living in an area experiencing higher import competition or manufacturing job loss, but Trump supporters were more likely to oppose trade agreements (Rothwell & Diego-Rosell, 2016). In any case, politicians in the U.S. and elsewhere have long emphasized the harm from trade, while economists have emphasized the gains.

Clearly, there is a need to better understand and convey to the public all of the consequences, positive and negative, that come with trade. In that vein, one important achievement of the ADH paper is its innovative methodology and framework, which has allowed scholars to better understand how import competition affects local areas. Nonetheless, my analysis and extension — which greatly benefited from Autor et al.'s coding and data — conclude that their findings about the harm from import competition at the community level are not robust, beyond the manufacturing sector, and, even then, only in the later period. At the individual level, and consistent with results from Autor et al. (2014), I find that workers in import-intensive industries have a strong attachment to the labor force and are as likely to be employed as workers in other industries.

Autor et al.'s influential 2013 paper and related work have shaped an emerging view in the economics literature that trade with China has been highly disruptive and damaging to a large swath of the U.S. population — and, by extension, workers in other developed countries. Its frequent citation in popular media has reinforced this view among politicians, policy leaders and commentators, even if the net effects of trade bring about broader efficiency and income growth, as the authors have stated elsewhere.[23] Though the paper makes an enormous methodological contribution and provides further and robust evidence that Chinese imports—rather than only technological change—reduced U.S. manufacturing employment, the evidence presented here suggests the paper's most important findings do not withstand further scrutiny.

Taken together, these results suggest that competition between businesses has similar effects on the labor market and on local economic development regardless of whether it occurs within national borders or across them. If China had remained a communist country and closed to trade, it is quite likely that manufacturing workers around the world would have enjoyed higher wage growth. While manufacturing job loss probably would not have been as significant, the increased competition from China did not create labor market conditions that appear dramatically different than what workers face in other industries such as retail, restaurants and engineering firms. In fact, the evidence is clear that manufacturing work remains a source of relatively high pay, long tenure, and low layoff risk, despite the intensity of import competition. Meanwhile, public efforts to minimize the real harm from displacement through active labor market policies and workforce development should constantly be examined and improved. It is unclear, however, why re-training policies should only help displaced manufacturing workers while ignoring restaurant servers, construction workers, nannies, cashiers, nurses, actors, hairstylists and other workers who often face even higher risk of displacement.

[23] See David Autor's interview with Chris Arnold, "China Killed 1 Million U.S. Jobs, But Don't Blame Trade Deals" All Things Considered, National Public Radio, April 18, 2016; or his interview with Russ Roberts "David Autor on Trade, China, and U.S. Labor," EconTalk, March 14, 2016, available at http://www.econtalk.org/archives/2016/03/david_autor_on_1.html

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Table 1. Various measures of job displacement risk in manufacturing and other sectors before and after 2001 by source

	Pre China-shock		Post China-shock, 2001-present	
	Manufacturing	All sectors	Manufacturing	All sectors
Layoffs per worker X 100	.	.	16.6	14.1
Separations to persistent unemployment per worker X 100	.	.	4	5.8
Hires from persistent unemployment per worker X 100	.	.	3.1	6
Jobs lost from establishment closings per worker X 100	3.8	5.6	3.2	4.5
Jobs lost from establishment openings per worker X 100	3.4	6.8	2.5	5.3
	Manufacturing	Non-manufacturing	Manufacturing	Non-manufacturing
Unemployment rate if unemployed because of job loss X 100, conditional on previous year's sector	3.2	2.7	3.8	3.1
Unemployment rate if unemployed because of job loss X 100, conditional on previous year's sector, High school or lower education	4.1	3.9	4.8	4.6
Share of unemployed workers out of work because of involuntary separation	73.8	60.7	78.7	67.1
Unemployment rate X 100, conditional on previous year's sector	5.5	5.1	5	4.8
Unemployment rate X 100, sector determined by most recent primary job	6.7	5.9	6.7	6.5
Long-term unemployment rate X 100, conditional on previous year's sector	0.1	0	0.1	0.1
Persistence in same sector from last year, conditional on working last year	82.1	77.5	82.3	80.5
Average job tenure in years	.	.	9.3	7.4
Displacement rate over three years X 100, conditional on labor force participation			10.9	6
Rate of job loss over three years X 100, conditional on labor force participation	.	.	11.3	10.2
Share working in same industry as lost job if displaced within last three years X 100, conditional on labor force participation	.	.	25.6	38.1
Share working in same sector as lost job if displaced within last three years X 100, conditional on labor force participation	.	.	48.5	55
Share experiencing a real wage increase over lost job if displaced within last three years X 100, conditional on currently employed	.	.	34.1	42.1

Note: Row 1 is from BLS JOLTS, 2001-2015; Rows 2-3 are from U.S. Census Bureau, LEHD, 2000-Q2 to 2015-Q2; Rows 4-5 are from U.S. Census Bureau, Business Dynamic Statistics, 1977-2014; Rows 6-8 are from CPS Annual Social and Economic Supplement, 1988-2016 and 9-12 from 1962-2016; Row 13 is from CPS Job Tenure and Occupational Mobility Supplement, 2002-2014; Rows 14-18 are from CPS Displaced Worker Supplement, 2002-2014. All CPS data are from IPUMS-CPS.

Table 2. Difference in differences probit regression of trade exposure on unemployment and labor market status

	Unemployed	Involuntary unemployed	Unemployed long-term	Out of labor force
	1	2	3	4
Manufacturing X period 2001-2016	-0.00240	0.000642	-0.00110	-0.0751*
	(0.00328)	(0.00178)	(0.000713)	(0.0438)
Manufacturing sector	0.00432	0.0110	0.00554***	-0.232
	(0.00831)	(0.00726)	(0.00140)	(0.174)
Period 2001-2016 (omitting 1968-2000)	0.0162***	0.00768***	0.00812***	-0.00296
	(0.00181)	(0.00244)	(0.00177)	(0.0111)
Observations	3,719,688	3,127,651	4,908,320	4,875,583
Pseudo R-squared	0.0500	0.0352	0.0397	0.149
	5	6	7	8
ADH Chinese import shock 1999-2011 X period 2001-2016	0.000639	0.000334	0.000420***	-0.227
	(0.000612)	(0.000371)	(0.000104)	(0.190)
ADH Chinese import shock 1999-2011	0.00178**	0.00257***	0.000617***	-0.0908
	(0.000884)	(0.000448)	(0.000180)	(0.0981)
Period 2001-2016 (omitting 1968-2000)	0.0159***	0.00762***	0.00771***	-0.0312
	(0.00160)	(0.00248)	(0.00169)	(0.0227)
Observations	3,719,688	3,127,651	4,908,320	4,875,583
Pseudo R-squared	0.0501	0.0344	0.0380	0.120
	9	10	11	12
Instrumented ADH Chinese import shock 1999-2011 X period 2001-2016	0.000697	0.000991	0.00152***	-0.00479
	(0.000569)	(0.000741)	(0.000394)	(0.00650)
Instrumented ADH Chinese import shock to other countries 1999-2011	4.13e-05	7.64e-05***	1.29e-05***	-0.000805
	(2.77e-05)	(2.42e-05)	(4.84e-06)	(0.000578)
Period 2001-2016 (omitting 1968-2000)	0.0168***	0.00875***	0.00845***	-1.52e-05
	(0.00170)	(0.00283)	(0.00177)	(0.0141)
Observations	3,719,688	3,127,651	4,908,320	4,875,583
Adj R-squared	0.026	0.009	0.005	0.118
	13	14	15	16
Chinese import shock 2001-2016 X period 2001-2016	0.000703	0.000463	0.000280***	-0.904*
	(0.000564)	(0.000572)	(8.33e-05)	(0.545)
Chinese import shock 2001-2016	-0.000320	0.000568	9.64e-05	-0.333*
	(0.000800)	(0.000479)	(0.000114)	(0.186)
Period 2001-2016 (omitting 1968-2000)	0.0155***	0.00738***	0.00761***	-0.0470**
	(0.00165)	(0.00251)	(0.00171)	(0.0203)
Observations	3,719,687	3,127,650	4,908,319	4,875,582
Pseudo R-squared	0.0499	0.0331	0.0373	0.122

Source: IPUMS-CPS, Annual Social and Economic Supplement, 1968-2016. Industry refers to current job as of last week or most recent job. Sample restricted to people aged 18 to 64. Robust standard errors in parentheses, clustered at industry level (ind1990). *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted using wtsupp. All models include controls for cubic in age, male, asian race, hispanic ethnicity, and black race (white non-hispanic is reference category), and educational attainment categories. The second panel (5-8), uses AADHP measure of imports per worker. The third panel (9-12) uses imports to other countries times the time period variable as an instrument for the time-import-competition measure. The bottom panel uses CPS data aggregated to industry level to construct import shock measure, combining it with USITC change in imports from China from 2000 to 2016. The final measure divides the value of the change in imports from 2000 to 2016 by the number of workers in the sector in 1999. All models use probit regression except the 2SLS, which uses OLS in order to cluster errors on industries.

Table 3. Summary of Robustness of ADH Results to Regression Analysis by Period

	Original Stacked Model	1990-2000 changes	2000-2007 changes
	1	2	3
Number of models with significant causal effect of imports per worker on economic outcomes at 95% confidence intervals			
All 73 models	45	14	11
Number with significant causal effect showing imports cause economic harm			
All 73 models	45	5	8
Models testing manufacturing outcomes	6	0	6
Models testing non-manufacturing outcomes	39	5	2
Models testing aggregate outcomes across sectors and demographic groups	24	5	1
Models testing transfer payments	12	5	1
Models not testing transfer payments or manufacturing	27	0	1

Note: Sample size is 722 CZs (1,444 for first column). The original stacked models are published in Tables 3-9 in ADH. Aggregate outcomes defined as those pertaining to total population universe, rather than demographic or sector-only subsample. Full details available in Appendix Table 1.

Table 4. 2SLS and OLS regression of imports per workers on various commuting zone level economic outcomes--extended time period

	AADHP imports per worker, 1999-2011, instrumented	QCEW-based imports per worker, 2000-2014, instrumented	Share of total CZ jobs in most exposed industries, 1999
	1	2	3
median income growth, 2000-2014	-0.007	-10.349	0.180
	(0.019)	(7.172)	(0.199)
change in labor force participation, 2000-2014	-0.004*	-0.723	-0.054**
	(0.002)	(0.660)	(0.026)
change in unemployment rate, 2000-2014	0.004	1.919	-0.023
	(0.003)	(1.269)	(0.032)
Growth in employment, 2000-2014	-0.019	0.104	0.079
	(0.013)	(5.382)	(0.308)
Growth in pay per worker, 2000-2014	0.015	-1.019	-0.056
	(0.012)	(4.984)	(0.265)
Growth in number of establishments, 2000-2014	0.040*	12.655*	0.872**
	(0.021)	(7.480)	(0.390)
Growth in population, 2000-2014	0.001	1.144	0.411
	(0.024)	(9.840)	(0.434)
Change in age-adjusted mortality rate, 2000-2014	1.367	2771.495	218.414***
	(6.966)	(2149.031)	(72.532)
Growth in employment, 1999-2011, using AADHP estimates	-0.032	-13.161	-0.117
	(0.024)	(10.026)	(0.410)
Growth in manufacturing employment, 1999-2011, using AADHP estimates	-0.098***	-25.423***	-1.592***
	(0.024)	(8.389)	(0.476)
Growth in non-manufacturing employment, 1999-2011, using AADHP estimates	-0.001	-6.964	0.359
	(0.027)	(10.604)	(0.453)
Growth in non-manufacturing employment, 2000-2014, using QCEW	0.001	6.269	0.414
	(0.016)	(5.929)	(0.339)
Growth in non-manufacturing establishments, 2000-2014, using QCEW	0.052**	11.364	0.968**
	(0.022)	(7.788)	(0.404)
Change in share working out of county of residence, 2000-2015	0.003	1.921*	0.020
	(0.002)	(1.123)	(0.030)
Change in share who are self-employed, 2000-2015	0.002*	0.730*	0.027

	(0.001)	(0.380)	(0.017)
Growth in workers who reside in CZ, 2000-2015	-0.111	9.417	-0.494
	(0.147)	(76.367)	(2.158)
Unemployment rate, 2009-2014	0.000	-0.012	-0.055
	(0.003)	(1.214)	(0.043)
Ln median household income, 2009-2014	-0.018	-3.112	-0.646*
	(0.024)	(7.269)	(0.323)
In pay per worker, 2014	-0.038	-2.767	-0.610
	(0.037)	(9.594)	(0.551)
Change in intergenerational elasticity of income, 1980-1986 birth cohorts	0.000	-0.674	0.096
	(0.004)	(1.147)	(0.067)
Change in intergenerational elasticity of education, 1984-1993 birth cohorts	0.011	4.885	0.268
	(0.017)	(5.772)	(0.262)

Note: N =722 commuting zones, except 622 and 616 respective in final two rows, respectively. Models replicate those used in Tables 3-9 of ADH. Coefficients and standard errors are shown for imports per worker, instrumented using data from AADHP. All models include the control variables used in ADH Tables 3-9. They include start-of-period measures for manufacturing share of employment, the foreign-born population share, the female share of workers, an index for the share of jobs in routine occupations, index for share of jobs susceptible to outsourcing, and census division binary variables. Errors are clustered at the state level. Controls are measured in 2000. The instrumental variable is from AADHP. Column 3 uses data from AADHP to measure the CZ job share in import-intensive industries and SIC codes 36, 35, 23, and 39, corresponding to electronics, computer equipment, apparel, and miscellaneous manufacturing (toys).

Appendix

Appendix Table 1. Causal effect of imports per worker on various economic outcomes at CZ level using stacked and unstacked models

ADH label	Dependent variable	Original Stacked Model	1990-2000 changes	2000-2007 changes
d_sh_empl_mfg	change in mfg employment/working age pop	-0.596***	-0.222	-0.469***
		(0.099)	(0.169)	(0.123)
lnchg_popworkage	change in log population, 16-64	-0.050	1.080	0.178
		(0.746)	(0.743)	(0.960)
lnchg_popworkage_edu_c	change in log population, college educated 16-64	-0.026	1.319*	0.210
		(0.685)	(0.790)	(0.941)
lnchg_popworkage_edu_nc	change in log population, non-college educated 16-64	-0.047	1.099	0.188
		(0.823)	(0.885)	(0.990)
lnchg_popworkage_age1634	change in log population, 16-34	-0.138	0.548	0.444
		(1.190)	(1.121)	(1.270)
lnchg_popworkage_age3549	change in log population, 35-49	0.367	1.506***	0.268
		(0.560)	(0.582)	(0.912)
lnchg_popworkage_age5064	change in log population, 50-64	-0.138	2.311***	-0.010
		(0.651)	(0.764)	(0.899)
lnchg_no_empl_mfg	change in log population, mfg	-4.231***	-0.778	-3.671***
		(1.047)	(1.203)	(1.390)
lnchg_no_empl_nmfg	change in log population, non-mfg	-0.274	1.372*	0.615
		(0.651)	(0.770)	(0.912)
lnchg_no_unempl	change in log population, unemployed	4.921***	-0.741	3.087*
		(1.128)	(1.944)	(1.725)
lnchg_no_nilf	change in log population, not in labor force	2.058*	1.398	0.709
		(1.080)	(1.109)	(1.019)
lnchg_no_ssadiswkrs	change in log population, SSDI recipients	1.466***	2.049**	0.606
		(0.557)	(0.849)	(0.630)
d_sh_empl_nmfg	change in non-mfg employment/working age pop	-0.178	0.195	0.230*
		(0.137)	(0.202)	(0.118)
d_sh_unempl	change in unemployed/working age pop	0.221***	-0.052	0.109
		(0.058)	(0.088)	(0.099)
d_sh_nilf	change in not in labor force/working age pop	0.553***	0.080	0.130

		(0.150)	(0.157)	(0.085)
d_sh_ssadiswkrs	change in SSDI recipients/working age pop	0.076***	0.086***	0.023
		(0.028)	(0.023)	(0.044)
d_sh_empl_mfg_edu_c	change in college mfg workers/working age pop	-0.592***	-0.006	-0.496***
		(0.125)	(0.220)	(0.138)
d_sh_empl_nmfg_edu_c	change in college non-mfg workers/working age pop	0.168	0.199	0.525***
		(0.122)	(0.185)	(0.167)
d_sh_unempl_edu_c	change in college unemployed/working age pop	0.119***	-0.006	0.059
		(0.039)	(0.064)	(0.063)
d_sh_nilf_edu_c	change in college out of labor force/working age pop	0.304***	-0.187	-0.087
		(0.113)	(0.148)	(0.091)
d_sh_empl_mfg_edu_nc	change in non-college mfg workers/working age pop	-0.581***	-0.263	-0.432***
		(0.095)	(0.167)	(0.122)
d_sh_empl_nmfg_edu_nc	change in non-college non-mfg workers/working age pop	-0.531***	0.144	-0.007
		(0.203)	(0.232)	(0.177)
d_sh_unempl_edu_nc	change in non-college unemployed/working age pop	0.282***	-0.087	0.115
		(0.085)	(0.112)	(0.137)
d_sh_nilf_edu_nc	change in non-college out of labor force/working age pop	0.831***	0.206	0.325**
		(0.211)	(0.196)	(0.140)
d_avg_lnwkwage	change in average log wages	-0.759***	0.966**	-0.135
		(0.253)	(0.478)	(0.359)
d_avg_lnwkwage_m	change in average log wages, males	-0.892***	1.058**	-0.236
		(0.294)	(0.528)	(0.424)
d_avg_lnwkwage_f	change in average log wages, females	-0.614***	0.426	0.030
		(0.237)	(0.376)	(0.307)
d_avg_lnwkwage_c	change in average log wages, college workers	-0.757**	0.614	-0.205
		(0.308)	(0.426)	(0.399)
d_avg_lnwkwage_c_m	change in average log wages, male college workers	-0.991***	0.471	-0.372
		(0.374)	(0.455)	(0.478)
d_avg_lnwkwage_c_f	change in average log wages, female college workers	-0.525*	0.505	0.029
		(0.279)	(0.391)	(0.344)
d_avg_lnwkwage_nc	change in average log wages, non-college workers	-0.814***	1.033**	0.142
		(0.236)	(0.419)	(0.383)
d_avg_lnwkwage_nc_m	change in average log wages, male non-college workers	-0.703***	1.466***	0.290
		(0.250)	(0.478)	(0.457)

d_avg_lnwkwage_nc_f	change in average log wages, female non-college workers	-1.116***	-0.082	-0.165
		(0.278)	(0.334)	(0.327)
lnchg_no_empl_mfg_edu_c	change in log employment in mfg, college workers	-3.992***	0.829	-3.413***
		(1.181)	(1.781)	(1.077)
lnchg_no_empl_mfg_edu_nc	change in log employment in mfg, non-college workers	-4.493***	-0.305	-4.242**
		(1.243)	(0.996)	(1.903)
lnchg_no_empl_nmfg_edu_c	change in log employment in non-mfg, college workers	0.291	1.611**	1.047
		(0.590)	(0.797)	(0.860)
lnchg_no_empl_nmfg_edu_nc	change in log employment in non-mfg, non-college workers	-1.037	1.244	0.221
		(0.764)	(0.880)	(1.031)
d_avg_lnwkwage_mfg	change in log wage in mfg	0.151	1.600**	1.214**
		(0.482)	(0.694)	(0.572)
d_avg_lnwkwage_mfg_c	change in log wage in mfg, college workers	0.458	1.043*	1.177**
		(0.340)	(0.598)	(0.495)
d_avg_lnwkwage_mfg_nc	change in log wage in mfg, non-college workers	-0.101	1.611***	1.030*
		(0.369)	(0.616)	(0.564)
d_avg_lnwkwage_nmfg	change in log wage in non-mfg	-0.761***	0.493	-0.085
		(0.261)	(0.358)	(0.366)
d_avg_lnwkwage_nmfg_c	change in log wage in non-mfg, college workers	-0.743**	0.482	-0.156
		(0.297)	(0.324)	(0.376)
d_avg_lnwkwage_nmfg_nc	change in log wage in non-mfg, non-college workers	-0.822***	0.291	0.196
		(0.246)	(0.384)	(0.405)
lnchg_trans_totindiv_pc	change in log transfers per worker	1.013***	0.510	0.728*
		(0.327)	(0.619)	(0.429)
lnchg_trans_taaimp_pc	change in log TAA transfers per worker	14.406*	21.894*	-6.514
		(7.588)	(12.659)	(10.307)
lnchg_trans_unemp_pc	change in log unemployment insurance transfers per worker	3.460*	-3.708	4.475
		(1.869)	(3.963)	(2.821)
lnchg_trans_ssaret_pc	change in log SSA retirement transfers per worker	0.717*	0.325	0.062
		(0.383)	(0.699)	(0.543)
lnchg_trans_ssadis_pc	change in log SSA disability transfers per worker	1.960***	1.540*	0.721
		(0.690)	(0.787)	(0.835)
lnchg_trans_totmed_pc	change in log medical transfers per worker	0.542	0.039	0.810
		(0.489)	(1.131)	(0.665)
lnchg_trans_fedinc_pc	change in log federal income transfers per worker	3.039***	1.485	0.957

		(0.957)	(1.941)	(0.768)
lnchg_trans_othinc_pc	change in log other income transfers per worker	1.077	-0.630	1.248
		(2.198)	(1.908)	(1.921)
lnchg_trans_totedu_pc	change in log education assistance transfers per worker	2.779**	2.106	4.125*
		(1.315)	(2.826)	(2.345)
d_trans_totindiv_pc	change in dollar amount transfers per worker	57.730***	22.656	41.073
		(18.406)	(17.803)	(34.251)
d_trans_taaimp_pc	change in dollar amount TAA transfers per worker	0.234	0.177	-0.064
		(0.174)	(0.112)	(0.259)
d_trans_unemp_pc	change in dollar amount unemployment insurance transfers per worker	3.421	-2.174	2.259
		(2.262)	(4.290)	(3.135)
d_trans_ssaret_pc	change in dollar amount SSA retirement transfers per worker	9.998*	-1.167	0.920
		(5.446)	(7.347)	(7.164)
d_trans_ssadis_pc	change in dollar amount SSA disability transfers per worker	8.395***	6.712***	3.841
		(2.205)	(2.160)	(3.373)
d_trans_totmed_pc	change in dollar amount medical transfers per worker	18.270	10.516	18.246
		(11.839)	(13.141)	(23.676)
d_trans_fedinc_pc	change in dollar amount federal income transfers per worker	7.202***	3.128	1.543
		(2.352)	(4.356)	(2.281)
d_trans_othinc_pc	change in dollar amount other income transfers per worker	4.127	3.961*	4.330
		(4.436)	(2.308)	(5.217)
d_trans_totedu_pc	change in dollar amount education assistance transfers per worker	3.709**	2.915	5.480**
		(1.444)	(2.455)	(2.450)
relchg_avg_hhincsum_pc_pw	percentage change in average real household income per adult	-1.476***	0.890	-0.537
		(0.364)	(0.696)	(0.452)
relchg_avg_hhincwage_pc_pw	percentage change in average real household wage income per adult	-2.142***	0.189	-0.862
		(0.585)	(0.686)	(0.535)
relchg_avg_hhincbusinv_pc_pw	percentage change in average real household business income per adult	-0.510	1.762	0.114
		(0.742)	(1.389)	(0.777)
relchg_avg_hhinctrans_pc_pw	percentage change in average real household transfer income per adult	2.119***	3.507**	0.032

		(0.579)	(1.392)	(0.902)
relchg_med_hhincsum_pc_pw	percentage change in median real household income per adult	-1.732***	0.864	-0.575
		(0.381)	(0.639)	(0.442)
relchg_med_hhincwage_pc_pw	percentage change in median real household wage income per adult	-2.320***	-0.028	-0.934*
		(0.513)	(0.768)	(0.543)
d_avg_hhincsum_pc_pw	dollar change in average real household income per adult	-492.636***	102.798	-220.452
		(160.362)	(215.615)	(213.169)
d_avg_hhincwage_pc_pw	dollar change in average real household wage income per adult	-549.332***	-27.924	-260.392
		(169.391)	(147.224)	(188.302)
d_avg_hhincbusinv_pc_pw	dollar change in average real household business income per adult	40.137	69.945	46.134
		(116.689)	(93.174)	(87.740)
d_avg_hhinctrans_pc_pw	dollar change in average real household transfer income per adult	17.317***	29.922***	0.419
		(4.334)	(8.788)	(7.145)
d_med_hhincsum_pc_pw	dollar change in median real household income per adult	-439.868***	91.761	-145.246
		(112.696)	(134.613)	(155.347)
d_med_hhincwage_pc_pw	dollar change in median real household wage income per adult	-476.486***	-80.615	-178.401
		(122.238)	(127.113)	(157.438)

Source: Autor et al. (2013) (ADH) online files. All models include the control variables used in ADH Tables 3-9, including their instrumental variable. These variables are start-of-period measures for manufacturing share of employment, the foreign-born population share, the female share of workers, an index for the share of jobs in routine occupations, index for share of jobs susceptible to outsourcing and census division binary variables. Errors are clustered at the state level. N=1,422 CZs for Column 1 and 722 for Columns 2 and 3.

Appendix Table 2. 2SLS regression of imports per worker on high-level CZ outcomes from 1990 to 2014

	AADHP imports per worker 1999-2011, instrumented	N	R-sq
Employment growth, 1990-2014	0.012	722	0.524
	(0.014)		
Average wage growth, 1990-2014	-0.009	722	0.548
	(0.008)		
Establishment growth, 1990-2014	0.041**	722	0.622
	(0.017)		
Growth in non-manufacturing employment, 1990-2014	0.033*	722	0.436
	(0.020)		
Growth in non-manufacturing establishments, 1990-2014	0.048**	722	0.618
	(0.018)		

Source: QCEW for outcomes, Acemoglu et al. (2016) for imports per worker and instrument, and ADH for control variables. All models include the control variables used in ADH Tables 3-9, including their instrumental variable. These variables are start-of-period measures for manufacturing share of employment, foreign-born population share, female share of workers, share of jobs in routine occupations, share of jobs susceptible to outsourcing and census division binary variables. Errors are clustered at the state level.