The Impact of Chinese Trade on U.S. Employment: The Good, The Bad, and The Debatable*

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Abstract

Using confidential US Census micro data we find three results. First, there is no evidence that Chinese import competition generated net job losses. In low-human capital areas (for example, much of the South and mid-West) manufacturing saw large job losses, driven by plant shrinkage and closure. But in high-human capital areas (for example, much of the West Coast or New England) manufacturing job losses were limited, with much larger gains in service employment, particularly in research, management and wholesale. As such, Chinese competition *reallocated* employment from manufacturing to services, and from the US heartland to the coasts. Second, looking at the firm-level data we find almost all of the manufacturing job losses are in large, multinational firms that are simultaneously expanding in services. Hence, these large firms appear to have offshored manufacturing employment while creating US service sector jobs. Indeed, we show large publicly traded US firms do not seem to have been negatively impacted by the rise in Chinese imports. Finally, the impact of Chinese imports disappears after 2007 – we find strong employment impacts from 2000 to 2007, but nothing since from 2008 to 2015

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1 Introduction

The spectacular rise in Chinese imports over the past 25 years is widely believed to be an important reason for the decline of U.S. manufacturing employment. The seminal studies of Autor et al. (2013) and Pierce and Schott (2016) estimate that this "China shock" reduced US *manufacturing* employment by around 1.5 million jobs between 1990-2007.[1] At the same time, the U.S. and other high income countries have experienced a large reorganization of production and employment toward *non-manufacturing services* (e.g. Autor and Dorn 2013; Bernard et al. 2017a; Fort et al. 2018). We investigate the extent to which these two developments are related. In particular, how has the China shock led to restructuring in local labor markets and across sectors, thus reshaping the location and organization of economic activity in U.S.?

The heart of our analysis consists of confidential administrative data from the Longitudinal Business Database (LBD) of the U.S. Census Bureau. The data has two key advantages over publicly available data. First, it links the universe of private-sector establishments with their parent firms and follows them over time, allowing us to track the response of economic activity within firms, sectors, and local labor markets to the Chinese import shock. Second, the LBD data is more accurate than public data because public data has to be noise-infused or aggregated at the industry-region level for disclosure avoidance. We also use data up until 2015 to examine the more recent impact of Chinese trade. To estimate the Chinese import shock, we follow the empirical strategy of Autor et al. (2013), and subsequently Autor et al. (2014) and Acemoglu et al. (2016), to exploit regional variations in exposure to Chinese imports, instrumented by China's exports to other developed countries.

Our empirical analysis leads to three key insights. First, there is clear evidence of large job losses in manufacturing, particularly in parts of the country with initially low human capital (primarily the South and the mid-West). Almost all of this negative effect is due to plant shrinkage and closure by continuing firms. These areas also saw declining earnings per worker and little offsetting rise in service jobs. In contrast, we see limited manufacturing job losses in high human capital areas of the country (primarily the West and East Coast), with 50% of this effect driven by

[1] Acemoglu et al. (2016) argue Chinese import competition reduce *total* US employment by around 2m jobs, while Autor et al. (2013) also report a "*highly statistically significant*" negative impact on overall employment/population in Table 5, but do not provide a quantification of this.

industry switching – surviving plants that change their reported industry code from manufacturing to services (particularly research, management and wholesale). This switching reduces measured manufacturing employment, but of course, increases measured service sector employment. In high human capital areas, service sector job growth more than offsets service sector job loss in response to Chinese imports. Hence, Census microdata suggest that imports from China *reallocated* jobs from the manufacturing sector in lower human capital areas to the service sector in higher human capital areas. Since there is no clear evidence of a population migration between these areas, this means the market for labor weakened in low human capital areas relative to high human capital areas due to Chinese trade, exacerbating regional inequality.[2] As such, Chinese trade appears to have transferred jobs and earnings from the U.S. heartland to the coasts.

Second, the negative effect of Chinese imports on manufacturing employment is almost entirely driven by large, high-wage, multinational firms that are simultaneously expanding employment in services. The bulk of manufacturing job destruction occurred through plant closures and downsizing at firms that survived and restructured. We find no evidence that large publicly listed U.S. manufacturing firms suffered from the rise in Chinese imports; their sales, investment and market value are not affected. This suggests that large firms offshored manufacturing employment, presumably exploiting cheap Chinese manufacturing production, and created complementary jobs in U.S. research, design, management, and wholesale activities. U.S. workers in low human-capital areas are relatively worse off, but the firms are not affected negatively on average and potentially even benefited from reducing manufacturing costs by offshoring.

Third, the impact of the China shock disappears after 2007. We find negative employment effects in most overlapping 5 or 10 year differences spanning 1990 to 2007. But after 2007, there is no evidence of regional differences in employment growth caused by Chinese imports. In short,

[2] Bernard et al. (2017b) find a similar reorientation in Danish firm-level data. Aside from well-known high-tech examples of products "designed in the U.S. – manufactured in China", there are many other anecdotes about firms expanding employment in service sectors and adapting operations to the rise of China. For example, Techtronic Industries, the owner of well-known brands Milwaukee Electric Tool, Hoover, and Ryobi among others, manufactures goods in China, but also maintains manufacturing, design, and service operations in Texas, Mississippi, and South Carolina (see "The ups and downs of moving production to China," *CBS MarketWatch,* October 18, 2010, https://www.marketwatch.com/story/the-ups-and-downs-of-moving-production-to-china-2010-10-17; accessed 7/27/2018). In another example, Bernhardt Furniture of North Carolina expanded employment after 2007 where it manufactures custom, high quality furniture, some of which is for export. Bernhardt handles marketing, design, and its global operations in the U.S. (see "In a U.S. manufacturing hub, no illusions about tariffs and jobs," *Reuters*, September 26, 2018, https://www.reuters.com/article/us-usa-trade-jobs-insight/in-a-u-s-manufacturing-hub-no-illusions-about-tariffs-and-jobs-idUSKCN1M60E0; accessed 10/9/2018).

rising Chinese imports were historically responsible for *manufacturing* job losses and *services* job gains in the US, but regional differences in exposure to the China shock have not been a major factor for the last decade.

As such, we characterize our findings as follows:

The Good: The China shock had a significant positive effect on U.S. service sector jobs, particularly in higher human capital areas.

The Bad: The China shock had a significant negative effect on U.S. manufacturing jobs, particularly in lower human capital areas.

The Debatable: We find no evidence for a *net* negative effect on U.S. total jobs. At the same time, *local labor-market level* manufacturing job losses in high human capital areas have been offset by service sector job gains. So, setting aside important general equilibrium issues over extrapolating from local to general employment impacts, there is no evidence for a negative net impact of Chinese trade on jobs.[3]

Our analysis indicates that this reallocation of jobs induced by the China shock is driven in large part by a set of larger, relatively productive firms that successfully adapted to import competition by shrinking manufacturing jobs and simultaneously expanding related services. This structural shift created winners and losers across U.S. local labor markets related to initial human capital levels.[4] These unequal regional effects may be an important force behind the growing regional inequality and political polarization observed in the U.S.

Our work contributes to a large literature estimating, measuring and quantifying the effect of China's rise on the U.S. and global economy. The most closely connected research focuses on labor markets and reorganization. For example, Bernard et al. (2006), Autor et al. (2013), Autor et al. (2014), Pierce and Schott (2016), Acemoglu et al. (2016) and Asquith et al. (2017) all report negative employment impacts of Chinese trade on U.S. employment, particularly for workers in lower-skilled industries. International research shows a similar impact, for example in Europe (Bloom et al.,

[3] At the aggregate level Chinese trade will impact US prices, interest rates, investment, innovation, immigration, etc. Thus we cannot simply add up regional labor market impacts to estimate the net aggregate impact.

[4] The belief that Chinese import competition not only decimated U.S. manufacturing employment but also had a negative effect on U.S. firms is at the center of the current trade dispute between the U.S. and China. See for example Peter Navarro, the Director of the National Trade Council, who opined that "Since China joined the WTO in 2001, over 70,000 American factories have closed [...] Fully half of our annual trade deficit in goods is with [China]. This is causality, not correlation." ("UC Irvine economist who never met Donald Trump is now a key advisor", *Los Angeles Times*, August 17, 2016, https://www.latimes.com/business/la-na-trump-economist-navarro-20160818-snap-story.html; accessed 1/16/2019).

2016), Denmark (Bernard et al., 2018), Canada (Murray, 2017) and Brazil (Paz, 2017 and Alfaro et al., 2019). Second, our work is related to evidence showing Chinese trade transformed U.S. supply chains, creating service sector jobs via input-output chains (e.g. Hummels, Jorgensen, Munch, and Xiang Hummels et al., Feenstra and Sasahara, 2017, and Bernard et al., 2017a), in downstream industries (Wang et al., 2018), and through the reorganization of large-multinationals (Fort et al., 2018). One important contribution of our work is that we use administrative microdata that: (1) has accurate establishment-level employment reports for the entire U.S.; (2) can be linked to important firm characteristics from other Census datasets; and (3) includes precise information about industry affiliation necessary to measure the impact of imports on changes in firm activities.

Another strand of research studies regional impacts of Chinese imports and the effects beyond the labor market. A growing body of work performs welfare analysis in structural GE models, some of which find positive net welfare effects of China's while acounting for structural changes (e.g. Galle et al., 2017, Adão et al. 2019, Kehoe et al. (2018), and Caliendo et al., 2019). Our empirical approach does not address linkages across geographic labor markets or their interaction in general equilibrium. Nevertheless, our findings of firm reorganization and of differential employment and wage effects relative to initial human capital endowments can still inform the policy conclusions that arise in GE models and the patterns in the employment data those models should target. Related empirical work not focused on labor finds evidence that China's WTO accession in 2001 reduced US and global prices (Jaravel and Sager, 2018) and led to welfare gains from new varieties and lower prices on consumer goods and inputs (Amiti et al., 2017 and Handley and Limão, 2017). But on the downside, Chinese competition may have reduced U.S. innovation (Autor et al., 2016a).

The rest of this paper is structured as follows. Section 2 introduces the data, measurement of job flows, import penetration measures, and industry classifications. Section 3 describes our data estimation strategy. Section 4 presents our results on sectoral reallocation. Section 5 provides provides results across geography and between firms. Section 6 concludes.

2 Measurement and Estimation Strategy

A key contribution of our analysis is the detailed decomposition of employment growth into job creation and destruction margins. We describe the data and employment growth margins and then our estimation and identification strategy and how it relates to previous work.

2.1 Microdata Description

We use multiple micro datasets from the US Census Bureau. The primary data on employment outcomes is the Longitudinal Business Database (LBD) which contains more than 7 million establishments across 5 million firms with coverage up to 2015. The LBD is derived from the Census Bureau's Business Register (also known as the Standard Statistical Establishment List) and supplemented with annual firm-level administrative tax records, various surveys, the quinquennial Economic Census and the Survey of Business Organization. The lowest unit of observation is the establishment identified by a unique LBDNUM, a physical location where business is conducted. For each establishment we have data on employment, payroll, the parent firm (if part of a mult-unit operation), and an industry code. Parent firms of establishments are defined based on operational control to link establishment activity to a unique FIRMID. These same data underlie the much more aggregated public-use County Business Patterns (CBP) data used in other studies.

In our primary analysis, we use data from the Economic Census (EC) years (particularly the Census of Manufactures, the CMF) which was collected during years ending in "2" or "7" (e.g. 92, 97, 02, etc). In these years every establishment is required by law to complete a census that requests data on employment, primary industry code, and other activities. Hence, during the EC years we have two measures of employment (the firm-level administrative LBD records and the EC establishment reported data) and updated industry codes. As such, the data in these years is more accurate and we focus on these years in the main results.

To measure industry encoding in a time-consistent manner, we use the Fort and Klimek (2018) (FK) codes, which convert all industry codes to the North American Industry Classification System (NAICS) in 2007. This FK industry coding was designed to provide a continuous industry code for the entire LBD to minimize spurious industry switching. The FK codes remain constant within establishments over time unless the reported industry code changes on administrative records, surveys, or a census that suggests a meaningful change in NAICS industry classification (typically because the plant changes its code in the Economic Census). The FK process uses longitudinal information in the LBD to fill in missing codes. Prior to 1997 when the Census used SIC codes Fort and Klimek (2018) use a detailed concordance to assign NAICS codes to establishments with SIC codes that map uniquely between classifications.[5]

Finally, we estimate the effects of a limited set of worker turnover, skill and other demographic characteristics using the establishment data in the Quarterly Workforce Indicators (QWI), which is part of the Longitudinal Employer-Household Dynamics (LEHD) program. These data cover workers at establishments in a subset of U.S. states that participate in the program. They are derived from state unemployment insurance administrative records, which have a different definition of an establishment but can still be linked to firms in the LBD. As such, we can use these data to estimate heterogeneous effects relative to firm characteristics we measure in the LBD, i.e. industry code switching, and differential impacts across demographic groups of Chinese imports within establishments.

2.2 Employment changes

In our regional analysis, we use the concept of a commuting zone (CZ), which are geographic units for defining local labor markets (Tolbert and Sizer (1996)). Employment growth between year $t-k$ and t in sector i in commuting-zone c, is defined following as

$$g_{ict,t-k} = \frac{E_{ict} - E_{ic,t-k}}{(0.5 * E_{ict} + 0.5 * E_{ict-k})}. \quad (1)$$

This can be decomposed into contributions from job creation and job destruction from continuing establishments, entry, and exit margins between $t-s$ and t as follows

$$g_{ict,t-k} = \frac{(JC_{ict}^{cont}) - (JD_{ict}^{cont}) + \left(E_{ict}^{entry}\right) - \left(E_{ic,t-k}^{exit}\right) - \left(S_{ic,t-k}^{out} - S_{ict}^{in}\right)}{X_{ict}}. \quad (2)$$

Within commuting zone c, we define $JC_{ict}^{cont} = \sum_{e \in cont_{ic}} max(E_{et} - E_{e,t-k}, 0)$ and $JD_{ict}^{cont} = \sum_{e \in cont_{ic}} max(-(E_{et} - E_{e,t-k}), 0)$ as the sum of job creation and destruction and continuing es-

[5] When longitudinal information regarding NAICS industry classification is not available FK codes are assigned randomly to establishment but remain fixed over time. For additional information about the FK codes and their implications for measurements of economic activity please see Fort and Klimek (2018). Using NAICS industry codes rather than SIC is a departure from the previous literature, however we believe this change is warranted give the availability of time consistent FK industry codes and because NAICS industries classifications are defined only based the economic activity of an establishment, whereas many SIC codes are not, due to legacy reasons. Since our main treatment of interest is how competition from imports impacts domestic establishments, we believe NAICS industry affiliation is a more accurate way to measure treatment intensity. Moreover, our baseline sample spans the period from 1992-2012 and NAICS was the applicable nomenclature from 1997 forward for all establishments in the LBD.

tablishments in commuting zone c; E_{ict}^{entry} and $E_{ic,t-k}^{exit}$ are the sum of employment at entering and exiting establishments; and S_{ict}^{in} and $S_{ic,t-k}^{out}$ are the sum of employment at establishments that switch in and out of sector i.

The definition of industry switching merits a careful accounting explanation in the decomposition formula. We focus on broadly defined manufacturing and services sectors and compute growth rates separately across these groups.[6] A non-trivial share of employment between EC years switches from manufacturing to services during our sample (and to a lesser extent, vice versa). To fix ideas, denote the two sectors by $i = M$ for manufacturing and $i = N$ for non-manufacturing services. Consider an establishment in a local area that reports a manufacturing NAICS code at time $t - k$, but also performs other activities, e.g. management or design services, at the same location. If the establishment's primary output and sales activities (not employment share) change by time t to services, e.g. designing and testing products that are manufactured abroad, then the reported industry code and all employment at that establishment will "switch out" of manufacturing and be counted a job loss, $S_{Mc,t-k}^{out}$, in the manufacturing sector. To maintain accounting identities, the same establishment will record their employment at time t in the services sector S_{Nct}^{in}. When adding up within the same sector i, net switching out, $-\left(S_{ic,t-k}^{out} - S_{ict}^{in}\right)$, enters with a negative sign as the final term of (2).

2.3 Estimation and Identification Strategy

The estimation strategy follows Autor et al. (2013), estimating a stacked long difference equation of the form

$$\Delta y_{ic\tau} = \alpha + \beta_i \Delta IP_{c\tau} + \boldsymbol{X'}_{c\tau}\gamma_i + \delta_r + \epsilon_{it}, \tag{3}$$

where $\Delta y_{ic\tau}$ is a measure of employment growth in CZ c, sector i, over the period τ. The main coefficients of interests is β_i, which estimates the effect on sector i of changes in local exposure to the change in import penetration, $\Delta IP_{c\tau}$ (detailed below) that we aggregate up from local industry.

[6] The LBD includes the non-farm, private sector employer universe and thus already excludes farms, the self-employed, and government entities (e.g. all of public administration, NAICS 92). So we label all remaining non-manufacturing sectors into "Services" for two reasons: (1) mining, agriculture and construction, which produce goods rather than services, only add up to about 7% of total U.S. employment in the County Business Patterns sample frame (in 2007), and (2) the remaining sectors, which are consistent with the BLS broad categorization of NAICS services, comprise 82% of total employment and thus nearly all employment in non-manufacturing.

The vector $\boldsymbol{X}_{c\tau}$ is a set of commuting zone c specific controls that are used in Autor et al. (2013).[7] Lastly, δ_r is a Census region fixed effect allowing for differential employment trends for each of the nine Census regions.

We define import penetration following Acemoglu et al. (2016) as the change in the level of imports from China over U.S. initial absorption for industry j in 1991,

$$\Delta IP_{j\tau} = \frac{\Delta M^{UC}_{j\tau}}{Y_{j,91} + M_{j,91} - EX_{j,91}}. \tag{4}$$

where $\Delta M^{UC}_{j\tau}$ is the change in U.S. imports from China over period τ , $Y_{j,91}$ is the value of shipments in the NBER-CES Manufacturing Productivity database; $M_{j,91}$ and $EX_{j,91}$ are total U.S. imports and exports in industry j in 1991. All trade flows calculated from the UN Comtrade database. To address concerns over endogeneity we instrument for changes in U.S. import penetration ($\Delta IP_{j\tau}$) with Chinese exports to eight other developed countries[8], while the denominator is the initial absorption in industry j in the U.S. lagged by two years to 1989

$$\Delta IPO_{j\tau} = \frac{\Delta M^{OC}_{j\tau}}{Y_{j,89} + M_{j,89} - EX_{j,89}}. \tag{5}$$

These are industry import penetration shocks and we use a shift-share (Bartik) strategy to allocate the shocks to geographic labor markets based on a local employment share of each industry that is derived from the LBD and lagged by 10 years (i.e. for an import penetration shock over the period 1992-2002

$$\Delta IP_{c\tau} = \Delta IP_{j\tau} \frac{E_{j,t-10}}{\sum_j E_{j,t-10}}. \tag{6}$$

Because $\Delta IP_{c\tau}$ is likely to respond endogenously to other unobserved demand and supply shocks, we estimate this model using 2SLS. We construct $\Delta IPO_{c\tau}$ as in equation (6) using 1982 employment shares and use this measure as an instrumental variable for $\Delta IP_{c\tau}$.

To measure establishment-level industry affiliation as accurately as possible our baseline uses

[7] These include the log average wage in 1991, the change in log real wage (1976 - 1991), the production workers and unionized share of employment in 1991, the capital/value added in 1991, the change in industry share of total employment (1976 - 1991), the routine and offshorable occupation share of employment, the share of female employment, and the shares of the local population with a college degree and that are foreign born.

[8] Specifically, we use Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

5-year long differences from 1992-2012, which aligns with the Economic Census (EC) years of 1992, 1997, 2002, 2007, and 2012. The resulting baseline sample spans a 20 year period with four time period observations per commuting zone, or about 2900 observations. To generate population relevant estimates we weight our estimation by the beginning of period population in each commuting zone.

2.4 Bartik Estimation Concerns

As Borusyak et al. (2018) and Goldsmith-Pinkham et al. (2018) emphasize, Bartik-style identification schemes can be problematic if there are pre-trends correlated with the treatment variable. So to control for potential pre-trends in our baseline specifications we add, relative to Autor et al. (2013), a set of controls for manufacturing, services, and total CZ job growth over the 1980-90 period. We do see some variation in coefficients, particularly in services, highlighting the challenges of estimating the aggregate impact of Chinese trade on US labor markets. To remain conservative, we include these pre-trends and note that without them, the service sector estimates shown below would in fact be stronger.

A second issue raised recently by Jaeger et al. (2018) is that when the impact of treatment variables take many years to arise, estimating shorter-difference specifications can conflate short- and long-run impacts. To address this, we also estimate specifications with 10-, 15-, and 20-year differences and again see similar qualitative results.

Finally, as Adão et al. (2018) emphasize when using Bartik estimators, standard errors may be under-estimated due to the correlations in industry level shocks across commuting zones induced by the weighting scheme. In our approach, since the number of industries is around 400 and the number of commuting zones is over 700, this issue is not a major concern (indeed Adão et al. (2018) discuss this for the original Autor et al. (2013) paper), but nevertheless, we calculate standard-error robust results.

3 The Impact of the China Shock on Sectoral Reallocation

We begin by laying out our baseline estimates for the period 1992-2012 in manufacturing, services, and total CZ employment and then comparing them to previous estimates. We then decompose the effect of Chinese imports across job reallocation margins within the manufacturing and service sectors: job creation and destruction, entry and exit, and industry switching.

3.1 Employment Effects of Chinese Import Penetration

In Table 1, we estimate a negative and significant effect of Chinese import penetration exposure on manufacturing job growth. When we check for heterogeneity across time in column (2), we find no evidence of a negative effect for the 2007-2012 period (the post 2007 point-estimate is $8.458 = -4.292 + 12.750$). Turning to services job growth in columns (3-4), we find a positive and weakly significant effect from 1992-2012 that reamains when we break out 2007-2012 separately. These positive effects are small relative to the total number of service jobs. But because services is more than three times as large as manufacturing by employment, these positive effects more than offsets the negative manufacturing effects, resulting in a positive but insignificant overall impact on total CZ jobs in columns (5) and (6).

A potential concern with our baseline sample frame is that the dates of the Economic Census may correspond to particular demand and supply shocks that drive these differential patterns across manufacturing and services. To check for this possibility, we report in Appendix Table A1 the estimates from stacked regressions over all 5-year differences from 1991-2014 (i.e. 19 sets of 5-year samples spanning 24 years of data). We cluster at the CZ level to account for the correlated errors from overlapping years. All the the quantitative results from Table 1 continue to hold up. Indeed, we find a somewhat more negative effect on manufacturing job growth, a positive, somewhat larger, and more significant effect on service job growth, and a positive but insignificant effect on overall CZ job growth. When we allow for a separate estimated effect post-2007, we continue to find a positive service job growth but this effect is significant only for the 2007-2014 years. Moreover, the post-2007 interaction generates a negative but insignificant coefficient of Chinese imports on total CZ that turns strongly positive after 2007. This may reflect a more robust recovery in employment following the 2008-9 recession and financial crisis after 2012. Given the general robustness of the estimates with respect to samples, we continue our analysis with our baseline sample that consists of the four, non-overlapping, 5-year Economic Census windows from 1992 to 2012.

One immediate question is why our results differ from those in Autor et al. (2013), who like us report a negative impacts of Chinese trade on manufacturing employment, but do not find a positive impact on services. Table 2 provides answers. Column (1) starts with the estimates from Autor et al. (2013).[9] Column (2) replicates these results with our LBD data using exactly the same regression specification and control variables as Autor et al. (2013). The slight difference in results is most likely due to Autor et al.'s measure of employment based on worker counts from CIPUMS and the ACS instead of job counts from the LBD. But this difference does not affect their main conclusion: the change in Chinese imports had a large and significant negative effect on local manufacturing employment; a slightly negative but insignificant effect on local service sector employment; and a larger negative but still insignificant effect on total CZ employment.[10]

Column (3) replaces the SIC industry definitions that Autor et al. (2013) use with our NAICS industry definitions – which are the codes directly reported by the establishments in our sample for every year except 1992 – and changes the definition of IP from the employment-based one to the absorption-based one that is common in more recent studies, e.g. Autor et al. (2014) and Acemoglu et al. (2016). The two changes result in a more negative estimate for local manufacturing employment while the estimate for service sector employment changes sign and becomes positive, but remains insignificant. We believe the results are somewhat sensitive to industry codes because of the importance of a few large industries in driving the results, particularly electronics and computing equipment (as highlighted by Goldsmith-Pinkham et al. (2018)), whose classification was updated in the move from SIC to NAICS.

Column (4) keeps the regression specification of column (3), but changes the long-difference windows from 1990-2000 and 2000-2007 to the five year long differences aligned with the Economic Census years: 1992-1997, 1997-2002 and 2002-2007. Somewhat surprisingly, this change also reduces the negative effect on manufacturing employment slightly and more than doubles the services coefficient such that it becomes significantly positive. Column (5) reports the estimates over all overlapping 5-year differences from 1991-2014 (our full window of data) revealing similar results.[11] Hence, the results from the 91-00 and 00-07 differences in Autor et al. (2013) are particular to those

[9] The headline results in Autor et al. (2013) pertain to changes in the ratio of employment to working-age population instead of employment growth. For comparability with our results, we show their results for employment growth defined as changes in log level; Table 5, Panel A, columns (1) and (2) of their AER publication. That table does not report the estimate for total CZ employment growth, but we were able to estimate it from their replication code and data.

[10] As Autor et al. (2013) note in their paper, the effect on the total CZ employment-to-population rate is negative and highly significant. We confirm this with their replication code.

[11] Results are quantitatively similar using longer overlapping windows in unreported results.

years, possibly because they are not all at the same point in the business cycle.[12]

Column (6) extends the sample to include the most recent available Economic Census year of 2012, with similar results. Column (7) adds pre-trends for 1980-1990 manufacturing or services employment growth, which are important to address Bartik instrument concerns, with little impact on the manufacturing estimates but somewhat smaller services estimates.[13]

In summary, we confirm the result in Autor et al. (2013) that Chinese imports have a robust negative impact on U.S. manufacturing employment in the regions most exposed to the shock. However, we find evidence for a positive impact on services, which offsets the negative manufacturing effect and results in a positive, but insignificant total CZ effect. This difference follows from using NAICS rather than SIC industry identifiers and from shifting away from the two long difference periods of 1991-2000 and 2000-2007. We think both of these changes are natural in the context of the data. The Census data is classified from 1997 onward based on NAICS codes, so using these industry codes seems like a clear choice; and our Census year anchoring yields results that are similar to using all possible combinations of 5 year differences.[14]

3.2 Employment growth margins, sectoral reallocation, and industry switching

Our results so far suggest there are job gains in the service sector that offset the job losses in manufacturing. To investigate this in more detail we decompose gross job creation and destruction within and across sectors and regress these measures on Chinese import penetration.

We find significant heterogeneity across job flow margins that strong suggests firm restructuring drives job losses. Table 3 starts in column (1) by replicating the overall impact of Chinese trade on manufacturing (panel A) and non-manufacturing (panel B). In columns (2) to (9), we use the decomposition described in equation (2) and find two key results for manufacturing. First, manufacturing job losses are driven by three key components: job destruction at continuing plants (column 3), industry switching (column 4) and plant-closure at continuing firms (column 7). Second, plant closures from firm death (column 9) do not play a major role in driving manufacturing job losses,

[12] Using NBER business cycle dates, 1991 was during the 1990-91 recession; 2000 was before the 2001 recession; and 2007 was the peak just before the 2008-09 recession.

[13] We report the robustness of our results to alternative controls in Appendix Table A2.

[14] The industry encoding differences also highlight another advantage of using Census microdata. Even though NAICS-based industry codes were collected in the 1997 Economic Census, the public-use County Business Patterns database for 1997 reports employment on a SIC-basis because the production release was scheduled before the updated codes were available.

and indeed are insignificant. This highlights the role of firm restructuring driving manufacturing employment decline caused by Chinese imports. The large majority of job loss in manufacturing arises either from plants that are switching into services or firms that are continuing but closing down plants. In services (Panel B), we see a large fall in job destruction (column 3), and significant contribution of industry switching in job creation (column 4) which is the flip-side of the negative industry switching coefficient for manufacturing in panel A.

The prominence of industry switching in driving the impact of Chinese trade is remarkable – it accounts for about 1/3 of the total job losses in overall manufacturing employment. In Table 4 we investigate this further. The regression coefficients on Chinese trade for overall gross industry switching into all of services is 1.717.[15] We break this down into additive sub-components in Table 4 by the industry that employment is switching from (going down the rows) and the industry employment is switching into (going across the columns).

We find in the top row that total switching from manufacturing in response to Chinese trade is heavily driven by plants that switch into professional services (NAICS 54), management (NAICS 55) and wholesale trade (NAICS 42). These activities account for only 14% of service employment, but they are 85% of plant employment that switches out of manufacturing in response to Chinese trade. The estimates imply that industry switching arises from manufacturing plants being repurposed toward developing, designing, managing and wholesaling goods (which are now possibly made in China). Looking down the rows we see the huge majority of industry switching is driven by plants in metal, machinery, computers, electronics and electrical. Indeed, this is the "West Coast story" whereby electronics companies have generated tremendous service sector growth around research, design, management and wholesale activities for products now produced in China. While others have noted the transition of former manufacturers into multi-sector operations (e.g. Fort et al. (2018)) our results provide evidence that this transition was strongest in labor markets more exposed to the China shock, suggesting Chinese trade accelerated this process.[16]

One potential concern with our switching results is the accuracy of industry code reporting. To address this, we first note the Census derives industry codes from multiple sources. When

[15]In table 2 the net value of 1.111 comes from a switch-out of 1.717 less a switch in coefficient of 0.606 (noting $1.111 = 1.717 - 0.606$).

[16]The fact that establishments and firms change activity due to increased competition is not without precedent. Bernard et al. (2006) documented that import competition from developing countries induced changes in establishment industry affiliation in the 1980s and 1990s.

an establishment is born, the first source is usually the Internal Revenue Service, with a second source provided by the Social Security Administration. In addition, the Census Bureau also collects industry information from Economic Censuses every five years, which requires establishments to report information on the principal business or activity, including class of customer and details of sales, shipments, receipts, or revenues in order to assign an accurate and complete NAICS code. Importantly, NAICS assignment is process-oriented and based on output and sales activity, rather than employment. Discrepancies for larger plants are followed-up by Census personnel, with the Census records typically being taken as the most reliable source of industry information. In addition, we also show in Appendix Table A3 that establishments that switch industries also see significantly higher worker additions and separations – industry switching is accompanied by an almost doubling of workers flows.

4 The Impact of the China Shock on Regional Reallocation

Our results from above indicate that Chinese import penetration led firms to reallocate jobs away from manufacturing towards management, marketing, research and wholesale activities. Since many of these activities are skill-intensive, we investigate whether this reallocation benefited local labor markets with high human capital relatively more than local labor markets with low human capital.

To do so, we split the approximately 700 CZs in our sample into two groups depending on whether the share of population with a college degree in 1990 (i.e. prior to the China shock) is higher or lower than the median share. Figure 1 shows that the resulting high human capital CZs are located primarily on the coasts, and around major cities. These CZs account for about 80 percent of total employment. In contrast, the low human-capital CZs are mainly located in the Midwest and South, an area of the U.S. often called the Heartland.

We re-estimate our employment regressions separately for low human capital (LHC) and high human capital (HHC) areas. Table 5 reports the results for the manufacturing sector. Column (1) shows the effect of import penetration on net employment growth. The impact of Chinese imports is negative in both areas, but the coefficient for HHC areas of -3.108 is one third smaller and not significant compared to the estimate for LHC areas of -4.527, which is significant. This suggests that manufacturing jobs in areas with lower initial levels of education were impacted more severely.[17] This pattern of results is consistent with Eriksson et al. (2019) who also find that the local effect of import competition depends critically on demographic characteristics, including the education of the workforce.

Column (2) reports the estimate for net switching to services. In HHC areas, the effect is large and significant, accounting for about 50% of the total negative effect on manufacturing jobs ($-1.64/-3.108 = 0.53$). In LHC areas, in contrast, this effect is much smaller and not significant. Hence, the effect of Chinese imports on establishment switching from manufacturing to related services discussed above is concentrated primarily in HHC areas.[18]

Column (3) reports the difference between the effect on net employment growth and net switching, which we define as the effect on "conventional employment growth," i.e. the change in manufacturing jobs that *excludes* apparent manufacturing job losses due to continuing establishments switching, on net, to service industries. For HHC areas, this conventional effect is small and insignificant. But in LHC areas, the conventional job loss effect is three times larger and significant. As discussed earlier, these estimates do not tell us whether on net, establishments switching out of manufacturing shrink employment and/or have substantially larger job turnover. Nevertheless, the difference between HHC and LHC areas in this respect is remarkable.

Given that switching out of manufacturing is associated in large part with relatively high skilled activities (professional services including R&D and management), it is perhaps not surprising that this switching occurs primarily in areas with high education levels whereas in areas with low education levels, manufacturing establishments may just shrink or close. Columns (4) - (6) confirm this point. In HHC areas, the effects on job creation and job destruction in continuing establishments essentially cancel each other out; and the effects on net entry are negative, driven in large part by lower entry of new establishments. In LHC areas, the picture is quite different. There are large negative effects on both job destruction at continuing establishments and net entry of new

[17] While we cannot reject statistical equality across regions for net growth, we make three important observations: (1) there is substantial heterogeneity by region in the growth margin contributions in the remaining columns; (2) the HHC coefficient is imprecisely estimated and suggests much of the identifying variation for a negative manufacturing effect comes from LHC regions; and (3) we do find highly significant differences in our subsequent wage results. All of which suggest a constrained regression, such as the baseline in Table 3, masks important regional variation in employment reallocation.

[18] Closer inspection reveals that essentially all of the estimate of -1.64 on net switching is accounted for by establishments switching out of manufacturing into services and almost nothing by establishments switching from services into manufacturing.

establishments that together account to almost equal parts for the manufacturing job losses.

To further investigate these differences in manufacturing jobs losses across regions, we estimate the impact on overall employment growth and average earnings per worker by sector. As reported in Table 6, the differences are equally important if not more important. Column (1) shows a positive effect on total employment growth for HHC areas and a negative effect for LHC areas. Both of these estimates are quite imprecise but the net difference in total CZ employment growth between HHC and LHC areas is -2.7 and significant at the 10% level. Hence, in HHC areas, the negative effect on manufacturing jobs is offset by positive effects on service jobs whereas in LHC areas, this offsetting effect largely did not occur.

Columns (2) - (4) show the effects on average earnings per worker (measured as total payroll divided by total jobs) for all jobs, manufacturing jobs, and service jobs. In HHC areas, the effects are mildly positive but not significant for overall employment and services, and more strongly positive and weakly significant for manufacturing. The positive manufacturing effect is possibly due to a change in composition towards higher skill manufacturing jobs. More importantly, the absence of a negative effect on earnings in services suggests that the positive effect in services in these areas did not come in the form of lower pay and/or lower hours jobs. In LHC areas, in contrast, the effects on earnings per worker are substantially negative. There is a large overall drop in average earnings per worker with a significant coefficient of -5.172. In manufacturing, the impact is smaller, -2.332, and insignificant (again, possibly due to compositional changes towards higher skill jobs). But for services, the effect is even larger, -6.7 and highly significant. All of these negative earnings effects in LHC areas are statistically different from the positive effects in HHC areas.

Taken together, these results are quite striking. The loss of manufacturing jobs in high human capital areas is predominantly driven by establishments switching their industry codes from manufacturing to services between 5-year Census intervals. In low human capital areas the loss of manufacturing jobs is instead entirely accounted for by conventional downsizing of existing plants and net exit. In addition, these conventional employment losses in manufacturing are accompanied by large reductions in average earnings per worker, but only in low human capital areas.

5 Firms and the employment impact of Chinese trade

To gain further understanding of the mechanisms driving employment reallocation, we step back from regional differences in human capital and investigate differences in firms–such as size and trade status–and establishment characteristics including average earnings. We find most of the negative manufacturing impact is driven firms that are expanding services employment, importers, and large firms.

5.1 Decompositions by firm characteristics

We decompose net employment growth into binary categories based on the parent firm's activity and characteristics. To do so, we exploit the detailed information we have on firm activity within and outside the same CZ. We focus on the contribution of the operative characteristics (e.g. expanding, importing, etc.), each of which are a significant share of the total effect. The residual component and contribution across additional margins are available on request.

In Table 7, column (1) we repeat the manufacturing and services estimates from our baseline in Table 3. When then report the contribution to net growth by different firm-level margins. We start by computing the contribution to manufacturing employment growth by firms that are expanding in services (either in the same CZ or nationally) in column (2). We estimate a coefficient of -2.6, which is more than 70% of the net negative effect on manufacturing growth. We find that expanding firms account for all of increased job destruction at continuing establishments.

We then breakout firms that are importers at the beginning and end of each stacked difference in both year $t-k$ and t., i.e. stable importers.[19] We measure import participation by linking the LBD to the LFTTD firm-level trade data. In column (3), we see that establishments belonging to importing firms account for more than 100% of the total negative effect on local manufacturing employment, whereas establishments belonging to non-importing firms make a small, insignificant contribution. Local services growth employment at importers mirrors the manufacturing impact. Services employment growth responds positively, a coefficient of 1.053 that is strongly significant, and explains over 70% of the net services effect. While we don't break out this effect into industry detail, the latter is consistent with an offshoring story where importers require engineering and

[19] Results are not quantitatively different if we use importer-exporters or drop the requirement that firm imports in both $t-k$ and t.

design services employment to develop products and retail, wholesale, and logistics services to bring them to market.

Perhaps not surprisingly, we most of the negative manufacturing impact and all of the services growth in local employment is from establishments that belong to large firms. We define large firms as operations with more than 1,000+ employees across all industry activities.[20] Establishments at large firms contribute to about 3/4 of the negative manufacturing employment effect in column (4). This is primarily because these firms are large. They account for more than 100% of job destruction in continuing establishments, a large part of establishment exits, and most of the establishment switching (in unreported coefficients). Turning to services growth, establishments at large firms contribute to nearly all of the *positive* impact of Chinese imports.

5.2 Decomposition by Establishment Earnings Per Worker

Rather than splitting our sample by geography or firm characteristics, we can also examine the distributional effects of the China Shock by investigating the differential effect of trade on establishments according to whether they are above or below the median earnings per worker.

For this exercise, we estimate (3) while splitting each decomposition term into two groups: employment growth from establishments above and below the median of within industry earnings. We compute median earnings within narrow 6 digit NAICS industry codes across the entire LBD.[21] To fix ideas, we measure local job creation in CZ c accounted for by high average earnings (HAE) establishments in sector i over the period years $t-k$ and t, as follows

$$JC_{ict}^{cont,HAE} = \sum_{e \in cont_{ic}} max(E_{et} - E_{et-k}, 0) * 1(AE_{eit-k} \geq AE_{it-k}^{median})$$

where AE_{eit-k} is the average earnings per worker of establishment e a in industry i and CZ c, AE_{eit-k}^{median} is the median average earnings per worker within industry i and year t, and $1(AE_{eit-k} \geq$

[20]Firm size is measured in the end year of the long difference. None of the results would change if we measured firm size instead in the beginning year. Approximately 50 percent of total manufacturing employment is accounted for by firms with more than 1,000 employees.

[21]We construct our measure of average earnings at the establishment-level using total payroll and employment derived from the LBD. For all existing establishments in time $t-k$ we compute the median average earnings in that year by 6-digit industry and classify all establishments below the median as low average earnings establishments and all with median or above average earnings as high average earnings establishments. For all establishments that enter the sample between $t-k$ and t we classify them as high or low earnings establishments based on their average earnings relative to the within-industry earnings distribution in year t.

AE^{median}_{it-k}) is a binary indicator function. We construct the same variables for job destruction, entry, exit and net switching.

Most of the job loss in manufacturing are in low earnings establishments and nearly all the gains in services are in high earnings establishments. In column (5) of Table 7 we find a negative, insignificant contribution of high earnings establishments to within CZ employment losses in manufacturing. In contrast, 2/3 of the impact of Chinese imports comes from low wage manufacturing job losses in column (6). We omit the coefficients, but also find the majority of manufacturing job loss in high earnings establishments is from industry switching, with no significant impact from "conventional" jobs loss excluding switching. In contrast, low earnings establishments see a significant "conventional" job loss from establishment job destruction and closure, with no significant impact of next switching. We see the opposite story play out for services in Panel B. Over 90% of the contribution of local services job growth is in high earnings establishments in areas with high Chinese imports. In column (6), we find no evidence that Chinese imports increased low wage services job growth.[22]

Collectively, these results are suggestive of the offshoring of manufacturing jobs. Large, multinational firms (importers) contribute to most of the local labor market job losses in manufacturing. Moreover, the job losses are larger in areas where parent firms are expanding services employment. These firms presumably benefit from the provision of cheaper manufacturing of goods whose production is offshored to China, suggesting complementarities with the job gains in service operations concentrated in high wage establishments and high human capital labor markets.

5.3 Firm-level Effects

Our final investigation into reorganization and firm adaptation examines the impact of Chinese trade on publicly listed US manufacturing firms.

We construct a firm-level measure of exposure to Chinese import penetration we use the Compustat Segments database, which reports firm sales by line of business.[23] The Segments database allows us to construct a firm specific profile of average sales over the period 1987-1992, prior to rise

[22]However, its important to note that the services jobs are high wage relative to own industry medians. It still possible that the low wage manufacturing jobs that were destroyed paid higher wages than any new service sector jobs.

[23]Each line of business is associated with an industry code and in many cases a secondary industry code reported at the 4-digit SIC. Following Bloom et al. (2013), for lines of business with two codes listed, we allocate 75 percent of the line's sales to the primary industry and 25 percent to the secondary industry

of Chinese import penetration. We use these average sales to construct a firm-specific measure of import penetration based on each firms exposure to industry level import penetration as follows:

$$\Delta IP_{f\tau} = \Delta IP_{j\tau} \frac{\overline{S}_{fj,87-92}}{\sum_j \overline{S}_{fj,87-92}} \tag{7}$$

where $\Delta IP_{j\tau}$is the change in imports in industry j over the period τ, as defined previously, and $\overline{S}_{fj,87-92}$ is firm $f's$ average sales in industry j over the period 1987 to 1992. We construct an instrument for supply driven shocks to import penetration using $\Delta IPO_{j\tau}$ in the same way as for our local import penetration measure.

We continue to employ our baseline long difference regression specification at the firm-level to estimate the effect of growth in $\Delta IP_{f\tau}$ on global employment, sales, investment or market value over a period of τ years. We include industry and period fixed effects controlling for industry- and period specific-trends. Having established that the China Shock appears to have stopped impacting local employment around 2007 and in an effort to avoid contamination from the Great Recession, we restrict the sample for these regressions to the period 1992-2007. We utilize all 5-year long difference periods over this period in order to minimize the impact of any individual sample year. In order to correct for an inflated observation counts from rolling periods, we cluster our standard errors at both the firm and industry level.[24]

We find a weak relationship with Chinese trade growth across multiple firm performance measures in Table 8. Panel A includes unweighted regressions showing a small negative impact of Chinese imports on the average firm. Only sales and profits have a negative response to the China shock. In Panel B we weight by initial firm employment to be more consistent with our baseline estimation using the LBD. Firm-level Chinese imports have a positive, insignificant effect on all measures. We interpret this finding as evidence that adjustment and reorganization did not occur without some firms enduring losses. But large, publicly listed firms do not respond negatively to Chinese import growth.

[24]For additional information about the data and empirical strategy see Appendix B.

6 Conclusion

We evaluate the effects of China's growing importance in the global economy on the location and organization of economic activity within the U.S. during from 1990-2014. We use disaggregated, establishment-level micro-data from the U.S. Census micro data to analyze job creation and destruction margins of local labor markets. We find that the impact of Chinese import competition on US manufacturing had a striking variation in the contribution of job growth margins, across initial human capital endowments, and firm characteristics.

In high human capital areas (for example, much of the West Coast or New England) most manufacturing job losses came from establishments that switched activities from primarily manufacturing into services. The establishment remained open but changed to research, design, management or wholesale services. In low human capital areas (for example, much of the South and mid-West) manufacturing job losses came from plant closure without much offsetting gain in service employment. Indeed, when examining firm we find these Chinese trade manufacturing job losses came mainly from large multinationals that were simultaneously expanding US service sector employment. Hence, our evidence suggests Chinese trade redistributed jobs from manufacturing in lower income areas to services in higher income, high human capital areas. These differential patterns are consistent with skill-biased technical change from globablization suggested in the theoretical literature (Acemoglu (2003); Thoenig and Verdier (2003)). Finally, the impact of Chinese imports appears to have disappeared after 2007 – we find strong employment impacts from 2000 to 2007, but nothing from 2007 to 2015.

On net, we provide evidence of significant reorganization of economic activity in response to the import penetration both within and across establishments, firms, industries and local economies. This new evidence puts the measured decline in manufacturing employment and its contrast with services employment in a broader context and highlights the consequences for regional inequality and polarization of economic opportunity.

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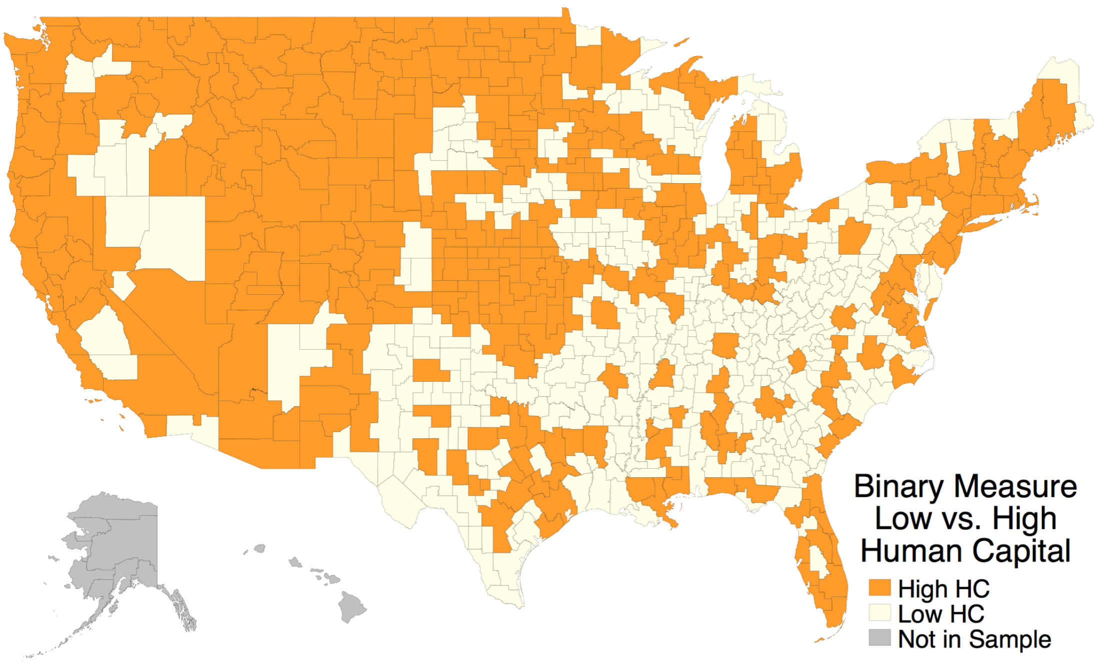
7 Figures

Figure 1: High versus Low Human Capital Commuting Zones



Note: The above figure plots commuting zones above and below the median level of human capital in 1990, where human capital is defined as the share of the population with a college degree computed using the decennial census.

Appendix

7.1 Firm-Level Compustat Data Construction and Methods

This paper provides evidence that the decline in local manufacturing employment in response to Chinese import competition was driven primarily by large, importing firms reallocating jobs towards service sector activities. One limitation of our Census micro-data is that it only covers the domestic activities of firms. Given that multinational firms account for a large and growing portion of total U.S. employment, we also wish to investigate how import penetration effects total global employment of firms as well as other firm attributes. In this appendix we address this question by utilizing data on global firm employment, sales, investment and market value from Compustat and follow a similar empirical strategy as laid out in section 3 to identify the causal effect of import penetration on firms rather than local economies. Using the Compustat database we first construct a firm-level measure of exposure to Chinese imports and then estimate the effect import exposure on employment, sales, profits, and market value. Section B.1 describes our measure of firm import exposure and performance as well as our empirical strategy and section B.2 presents our empirical results.

Data description and Empirical Strategy

In order to augment our Census micro data for this purpose, we use data on publicly traded firm listed on the North American stock markets from Compustat, which allows us to measure exposure to Chinese trade at the firm-level by providing information regarding firms sales by product type. We use the Compustat Segments database, which reports reports firm sales by line of business. Each line of business is associated with an industry code and in many cases a secondary industry code reported at the 4-digit SIC. Following Bloom et al. (2013), for lines of business with two codes listed, we allocate 75 percent of the line's sales to the primary industry and 25 percent to the secondary industry. The Segments database allows us to construct a firm specific profile of average sales over the period 1987-1992, prior to rise of Chinese import penetration. We use this sales average to construct a firm-specific measure of import penetration based on each firms exposure to industry level import penetration as follows:

$$\Delta IP_{f\tau} = \Delta IP_{j\tau} \frac{\overline{S}_{fj,87-92}}{\sum_j \overline{S}_{fj,87-92}} \tag{8}$$

where $\Delta IP_{j\tau}$is the change in imports in industry j over the period τ, as define previously, and $\overline{S}_{fj,87-92}$ is firm $f's$ average sales in industry j over the period 1987 to 1992. We construct an instrument for supply driven shocks to import penetration using $\Delta IPO_{j\tau}$ in the same way as for our local import penetration measure. In addition to allowing us to measure firm-level exposure to import penetration, the

Turning to our measure of global firm performance, Compustat allows us to measure the following: employment, sales, profits, investment and market value.[25] Employment is measure by the variable "emp," which measures annual global employment for each firm. Firm sales are measured by the variable "sale" which measure sales net of turnover. The firm investment rate is defined as the firms real capital expenditures divided by the capital stock in year t-1. Profits are defined quite broadly as sales minus cost of goods (cogs). Lastly, the market value of the firm is measure utilizing information on the monthly total return of the firm (trt1m). All measures are winsorized and we then construct long difference of all measure. DHS growth rates are employed for all outcomes that are measured in levels (employment, sales, profits and market value), while for investment our outcome is measured in changes in the investment rate.

Having constructed our measure of firm-level performance and firm-level import exposure we now turn to our baseline firm-level regression specification, which takes the form

$$\Delta x_{fj\tau} = \alpha + \beta \Delta IP_{f\tau} + \delta_j + \delta_\tau + \epsilon_{it} \tag{9}$$

where $\Delta x_{fj\tau}$ is the firm-level growth rate of either employment, sales, investment or market value over a period of τ years; $\Delta IP_{f\tau}$ is our measure of firm-level import penetration as defined in equation (8); and δ_j and δ_τ are industry and period fixed effects controlling for industry- and period specific-trends. Having established that the China Shock appears to have stopped impacting local employment around 2007 and in an effort to avoid contamination from the Great Recession, we restrict the sample for these regressions to the period 1992-2007. We utilize all 5-year long

[25]Employment and sales correspond to the global rather than domestic activities of the firm. Profits are measured as sales minus cost of goods, which excludes depreciation. Investment is measured as a percent of the lagged capital stock. Market value is measured based on the firm's stock price.

difference periods over this period in order to minimize the impact of any individual sample year. In order to correct for an artificially inflated number of observations, we cluster our standard errors at both the firm and industry level. The empirical strategy for these firm-level regressions is similar to that of Autor et al. (2016b), who employ the Compustat database along with the U.S. Patent and Inventor Database to measure the effect of increased firm import penetration on innovation. Although our strategy is similar, it deviates in several key ways. First, Autor et al. (2016b) do not use a rolling window of long difference periods and instead use the periods 1991-1999 and 1999-2007. Second, they weigh their regressions by the number of patents that firms file in order to produce a representative sample of innovating firms, and third – and perhaps most importantly – they utilize an industry- rather than firm-level measure of import penetration. Employing the Segments information in Compustat allows us to construct our firm specific measure of Chinese import penetration as defined by equation (8), which attributes Chinese imports to firms according to products they sold prior to the increase in Chinese trade rather than their industry affiliation. Using our firm-level measure also allows us to include industry fixed effects to control for trends, even within detailed 4-digit SIC industries, restricting our variation to differences in trade exposure across firms within the same industry.

Table 1: The Local Employment Effect of Chinese Import Penetration

Dep Var. Change in Employment (Δln)	Manufacturing		Services		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Annual Δ in China IP	-3.558**	-4.292***	1.460*	1.356*	0.598	0.318
	(1.674)	(1.344)	(0.823)	(0.818)	(0.813)	(0.800)
Annual Δ in China IP x Post 2007		12.750		1.811		4.874
		(14.910)		(6.213)		(6.012)
Observations (rounded)	2900	2900	2900	2900	2900	2900

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 2: Comparison of Results to Autor, Dorn and Hanson (2013)

Dependent variables: annualized change in sectoral CZ employment	Autor, Dorn and Hanson (2013)	ADH Replication with LBD data	NAICS industries & ΔIP as in Acemoglu et al.	Census 5-year diffs 1992-2007	All 5-year diffs 1991-2014	Census 5-year diffs 1992-2012	**Baseline:** Census 5-year diffs 1992-2012 and pretrends
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Manufacturing sector							
Annual Δ in China IP	-4.231***	-5.584***	-6.694***	-4.256***	-5.168**	-3.687***	-3.558**
	(1.047)	(1.384)	(1.845)	(1.406)	(2.470)	(1.690)	(1.674)
Panel B: Services sector							
Annual Δ in China IP	-0.274	-0.230	0.977	2.201**	2.932***	2.304**	1.460*
	(0.651)	(0.878)	(1.074)	(0.383)	(1.097)	(0.955)	(0.823)
Panel C: Total	-1.184[(a)]	-1.432	-0.864	1.053	0.929	1.26	0.598
Annual Δ in China IP	(0.764)	(0.924)	(1.093)	(0.916)	(1.018)	(0.931)	(0.813)
Stacked long differences	90-00 00-07	90-00 00-07	91-00 00-07	92-97, 97-02 02-07	All 5-year stacks from 1991 to 2014	92-97, 97-02 02-07, 07-12	92-97, 97-02 02-07, 07-12
Pre-trend Controls	No	No	No	No	No	No	Yes
Observations (rounded)	1400	1400	1400	2200	13500	2900	2900

Notes: Each stack contains (rounded) 700 CZs. All regressions include the original ADH controls and Census division dummies. In columns (1) and (2), coefficients estimates are weighted by start-of-period CZ national population share and robust standard errors in parenthesis are clustered at the state level (as in ADH). In columns (3) to (7), coefficients estimates are weighted by 1991 CZ population (as in AADHP). Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%. (a) This coefficient is the authors' estimate from ADH replication data archive and

Table 3: Employment Growth Decomposition of the Impact of Chinese Trade

Dep var. contribution to sectoral employment growth	Net Employment Growth	Continuing Establishments (conventional and switching)			Entry of Establishments		Exit of Establishments	
		Job Creation	Job Destruction	Net switching	by Firm Continuers	by Firm Birth	by Firm Continuers	by Firm Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effect on CZ employment growth component in Manufacturing sector								
Annual Δ in China IP	-3.558**	0.414	-0.842	-1.111***	-0.285	0.854	-1.593*	-0.995
	(1.674)	(0.686)	(0.818)	(0.191)	(0.532)	(0.598)	(0.832)	(0.882)
Panel B: Effect on CZ employment growth component in Services sector								
Annual Δ in China IP	1.460*	0.001	0.666**	0.141***	-0.033	-0.063	0.611**	0.137
	(0.823)	(0.315)	(0.285)	(0.060)	(0.318)	(0.419)	(0.287)	(0.329)

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 4: Impact of Chinese Imports on Industry Switching out of Manufacturing

Dependent variables: contribution to CZ manufacturing employment growth	All Services	NAICS 54/55 (Professional Services & Management)	NAICS 42 (Wholesale)	Other Services
	(1)	(2)	(3)	(4)
All Manufacturing	1.717***	1.086*	0.490**	0.140
	(0.595)	(0.577)	(0.197)	(0.169)
NAICS 31 (Food&Bev, Textile mills, Apparel, Leather)	0.140	0.040	0.140	-0.040
	(0.164)	(0.050)	(0.095)	(0.113)
NAICS 32 (Wood, Paper, Petro, Chem., Plastics & Rubber, Nonmetal)	-0.028	-0.127	0.036	0.062
	(0.141)	(0.094)	(0.035)	(0.081)
NAICS 33 (Metal, Machinery, Electronics, Transport Equip, Furniture)	1.605***	1.172**	0.314**	0.118
	(0.622)	(0.594)	(0.148)	(0.087)

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 5: Impact of Chinese Imports on Manufacturing Employment by Region

	Net Employment Growth	Net Switching to Non-Mfg	Conventional Emp. Growth (1) - (2)	Job Creation by Continuing Establishments	Job Destruction by Continuing Establishments	Net Entry and Exit of Establishments
	(1)	(2)	(3)	(4)	(5)	(6)
Annual Δ in China IP× 1(HHC)	-3.108	-1.640**	-1.468	0.932	-0.668	-1.732
	(2.056)	(0.803)	(1.949)	(0.923)	(1.040)	(0.840)
Annual Δ in China IP× 1(LHC)	-4.527**	-0.528	-3.999**	-0.100	-1.770**	-2.129***
	(1.835)	(0.528)	(1.665)	(0.564)	(0.853)	(0.860)
P-values: HHC = LHC	0.496	0.117	0.187	0.195	0.247	0.000

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 6: Impact of Chinese Imports on Overall Employment Growth and Earnings

	CZ Total Employment Growth	Nominal Average Earnings Growth		
		CZ Total	Manufacturing	Services
	(1)	(2)	(3)	(4)
Annual Δ in China IP x 1(HHC)	0.913	0.635	3.887*	0.466
	(1.085)	(1.245)	(2.227)	(1.301)
Annual Δ in China IP x 1(LHC)	-1.684	-5.172***	-2.332	-6.695***
	(1.134)	(1.243)	(1.517)	(1.647)
P-value: HHC = LHC	0.098	0.001	0.021	0.001

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 7: Impact of Chinese Imports by Firm and Establishment Characteristics

Panel A: Manufacturing

	Manufacturing Employment Growth (1)	Contribution by Firms Expanding in Services (2)	Contribution by Importing Firms (3)	Contribution by Firms with 1000+ Employees (4)	Contribution by Estabs with High Earnings per Worker (5)	Contribution by Estabs with Low Earnings per Worker (6)
Annual Δ in China IP	-3.558**	-2.600**	-3.896***	-2.791**	-1.249	-2.306**
	(1.674)	(1.014)	(1.365)	(1.398)	(1.300)	(0.911)

Panel B: Services

	Services Employment Growth	Contribution by Firms Expanding in Mfg	Contribution by Importing Firms	Contribution by Firms with 1000+ Employees	Contribution by Estabs with High Earnings per Worker	Contribution by Estabs with Low Earnings per Worker
Annual Δ in China IP	1.460*	0.471**	1.053***	1.403***	1.376**	0.083
	(0.823)	(0.217)	(0.366)	(0.487)	(0.590)	(0.479)

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 8: Impact of Chinese Trade on Publicly Traded Manufacturing Firms

Dep Var. Change (Δln) in:	Employment	Sales	Profits	Investment	Market Value
	(1)	(2)	(3)	(4)	(5)
Panel A: Manufacturing Firms w/ Trade Exposure					
D in Firm-Level China IP	-0.209	-0.345*	-3.014**	-0.110	-0.134
	(0.172)	(0.186)	(1.514)	(0.130)	(0.182)
Observations	11835	11908	11922	11964	10967
Panel B: Manufacturing Firms w/ Trade Exposure, Employment Weighted					
D in Firm-Level China IP	0.334	0.312	0.263	0.120	-0.472
	(0.423)	(0.275)	(0.533)	(0.078)	(0.353)
Observations	10429	10439	10451	10493	9604

Notes: Import penetration measure in all regressions is the five year change in Chinese imports / absorption attributed tc firms based on their average sales over the period 1987 to 1992. Estimation is performed on a rolling window of stackec five-year long differences spanning 1992-2007. All regressions include industry and year fixed effects. In Panel B coefficients estimates are weighted by initial firm employment. Robust standard errors reported in parenthesis are clustered at firm and industry level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table A1: All 5-year long differences from 1991-2014

Dep Var. Change in Employment	Manufacturing		Services		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Annual Δ in China IP	-5.147**	-5.591**	2.311**	1.305	0.419	-0.242
	(2.450)	(2.727)	(0.939)	(0.978)	(0.901)	(0.987)
Annual Δ in China IP x Post 2007		4.466		10.120***		6.652**
		(7.258)		(3.574)		(3.037)
Observations (rounded)	13700	13700	13700	13700	13700	13700

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportionec to CZs using NAICS-based employment weights. Each regression is performed for all stacked five-year long differences from 1992-1997 to 2009-2014 and includes the original ADH controls and Census division dummies as well as 1980-90 employment growth pretrends. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table A2: Alternative pretrend controls

Dep Var. Change in Employmet (Δln)	No pretrends	1980-90 sectoral employment growth pretrends	1980-90 sectoral employment share pretrends
Panel A: Manufacturing empl	-3.697***	-3.558**	-4.091***
Annual Δ in China IP	(1.675)	(1.674)	(1.701)
Panel B: Services employmen	2.922***	1.460*	1.689**
Annual Δ in China IP	(0.945)	(0.823)	(0.807)
Panel C: Total CZ employmer	1.238	0.598	0.651
Annual Δ in China IP	(0.924)	(0.813)	(0.801)
Observations (rounded)	2900	2900	2900

Notes: The import penetration measure in all regressions is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression is performed for stacked five-year long differences 1992-1997, 1997-2002, 2002-2007, and 2007-2012 and includes the original ADH controls and Census division dummies. Coefficients estimates are weighted by 1991 CZ population. Robust standard errors in parenthesis are clustered at the CZ level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table A3: Firm-by-State Job Reallocation, Switching Employment Share, and Chinese Imports

Panel A: Job Reallocation Measures vs Firm Emp. Share of Estabs. Switching to Services

Dependent variables: Firm-by-State Job Reallocation Measures	Job Reallocation (Job Creation + Job Destruction)	Job Turnover (Hires + Seperations)	Job Churn (Hire - Creation + Seper - Destruction)
	(1)	(2)	(3)
Employment Share of Switching Estabs.	0.070***	0.146***	0.076***
	(0.008)	(0.014)	(0.011)
Y Mean	0.069	0.168	0.099
R Squared	0.114	0.053	0.019
Observations	5500	5500	5500

Panel B: Impact of Firm-Level Chinese Imports on Emp. Share of Estabs. Switching to Services

Dependent variables: Firm-by-State Labor Force Dynamics Measures	Emp Share Switching Estab.	Emp Share Switching Estab.	Emp Share Switching Estab.
	(1)	(2)	(3)
Annual Δ in Firm-level China IP	0.004***	0.008***	0.033**
	-0.001	(0.002)	(0.015)
Model	OLS	IV	IV
R Squared	0.529	0.528	0.386
Observations (rounded)	5500	5500	5500

Notes: The sample includes all firms observed in the QWI (for the states where we have access to micordata) that also have estabishments that switch from manufacturing to services between Economic Census years (1997-2002, 2002-2007, 2007-2012). In panel A, the coefficients estimates are weighted by initial firm size. In panel B, columns (1) and (2) are unweighted. Column (3) is weighted by initial firm size. Robust standard errors in parenthesis are clustered at the firm level. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.