The China Shock Revisited: Job Reallocation and Industry Switching in U.S. Labor Markets

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Abstract

Using confidential administrative data from the U.S. Census Bureau we revisit how the rise in Chinese import penetration has reshaped U.S. local labor markets. Local labor markets more exposed to the China shock experienced larger reallocation from manufacturing to services jobs. Most of this reallocation occurred within firms that simultaneously contracted manufacturing operations while expanding employment in services. Notably, about 40% of the manufacturing job loss effect is due to continuing establishments switching their primary activity from manufacturing to trade-related services such as research, management, and wholesale. The effects of Chinese import penetration vary by local labor market characteristics. In areas with high human capital, including much of the West Coast and large cities, job reallocation from manufacturing to services has been substantial. In areas with low human capital and a high initial manufacturing share, including much of the Midwest and the South, we find limited job reallocation. We estimate this differential response to the China shock accounts for half of the 1997-2007 job growth gap between these regions.

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1 Introduction

The rise of China as a manufacturing powerhouse over the past decades is widely regarded as an important reason behind the decline of U.S. manufacturing employment (e.g., Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2016). But concurrently, job creation in manufacturing from new and expanding firms has remained substantial throughout the 2000s, and there has been a significant shift in employment towards services (e.g., Autor and Dorn, 2013; Bernard et al., 2017; Fort et al., 2018), with numerous U.S. companies benefiting from access to cheaper manufactured goods from China.[1]

This paper investigates the extent to which the opposing trends in manufacturing and service sector job growth are related to the "China shock". Specifically, we examine how the China shock affected job creation and job destruction within manufacturing, and to what degree it contributed to the net reallocation of jobs from manufacturing to services. We explore whether this reallocation is the result of within-firm reorganization or new firms replacing those that shut down, and what the characteristics of these firms are. Finally, we investigate whether this reallocation benefited certain areas of the U.S. more than others. By addressing these questions, we seek to provide a more comprehensive analysis of the effects of China's rise on U.S. labor markets, assessing to what extent it created winners and losers across sectors and regions.

Central to our analysis is the Longitudinal Business Database (LBD) of the U.S. Census Bureau, a confidential administrative dataset that links the universe of non-farm private sector establishments in the U.S. to their parent firms. This data offers two crucial advantages over the publicly available statistics such as the County Business Patterns (CBP) used by many other studies in the literature. First, the establishment-level information of the LBD can be used to decompose local job growth in manufacturing and service industries into contributions from job creation and destruction in continuing establishments, entry and exit of establishments, and establishments that switch their primary activity from one industry to another. Furthermore, the parent firm link can be used to analyze how the different margins of adjustment are related to firm and local labor

[1] Take for instance the quote from a 2018 *Wall Street Journal* article: "The phrase on the back of iPhones – Designed by Apple in California. Assembled in China – highlights a key reason for the company's remarkable success[...]" from "Apple Vulnerable in U.S.-China Trade Showdown" by Tripp Mickle and Yoko Kubota, July 24, 2018 https://www.wsj.com/articles/apples-china-ties-make-it-vulnerable-if-trade-fight-gets-worse-1532430003 (accessed September 4, 2024).

market characteristics. This allows us to address the main questions of our investigation on the reallocative effects of the China shock.

Second, the LBD can be used to build local-industry employment from the ground up, based on each establishment's primary activity that is coded to the North American Industrial Classification System (NAICS) in a time-consistent manner. We can thus construct measures of local exposure to industry-level import competition shocks and local employment outcomes that are free of the types of imputation and industry code concordance issues present in the CBP and other publicly available data.[2] Equally, the data allows us to accurately determine the importance of within-firm reallocation from manufacturing to services, and in particular establishments switching their primary activity, in accounting for the negative manufacturing effect of the China shock.[3]

To estimate the impact of Chinese import penetration, we adopt the empirical strategy of Autor et al. (2013) as implemented subsequently by Autor et al. (2014), Acemoglu et al. (2016), and Autor et al. (2021) among others and exploit Commuting Zone (CZ) variations in the exposure to Chinese imports, instrumented by China's exports to other developed countries. In addition, we control for a rich set of local labor market characteristics and local employment growth pre-trends.

The empirical analysis produces three main insights. First, local labor markets more heavily exposed to Chinese import penetration experienced larger reallocation of jobs from manufacturing to services. Indeed, while there is substantial variation across local labor markets, we find that job losses in manufacturing are on average offset by job gains in services.

The reallocation of jobs away from manufacturing is in large part the result of within-firm reorganization; i.e., firms shifting from manufacturing towards services, either by shutting down manufacturing plants and expanding employment in services (not necessarily in the same local labor market), or by switching the primary activity of existing plants from the production of manufacturing goods to the provision of trade-related services (management, research and development,

[2] As described in Section 5 and Appendix B, the CBP changes industry classification after 1997 from the older Standard Industrial Classification (SIC) to the current NAICS. Since there is no one-to-one mapping for many of the industries, this creates important industry concordance issues when computing measures of China shock exposure. Furthermore, due to data confidentiality rules, the CBP only reports employment intervals for some of the local-industry cells. The resulting imputation of actual values creates potentially important measurement error.

[3] We label all of non-manufacturing as "services" for two reasons: (i) mining, agriculture and construction, which produce goods rather than services, remain approximately constant throughout our sample frame, adding up to only about 6-7% of total U.S. employment; and (ii) the remaining non-manufacturing industries associated with services grow from 75% of total U.S. employment in 1990 to 82% in 2007 (these numbers are all computed from the publicly available Business Dynamic Statistics (BDS), which are based on the same source data as the LBD). Hence, all of the relevant structural change outside of manufacturing occurs in services.

and wholesale). The industry switching part accounts for 40% of the total negative effect of the China shock on local manufacturing employment. Furthermore, while switching plants reduce employment on average, by no means all jobs are destroyed. Industry switching therefore contributes to the positive effect of the China shock on local service jobs, although this contribution is relatively small in percentage terms because service employment is on average much larger than manufacturing employment.

These job impacts from the China shock differ from aggregate trends. For manufacturing, about two thirds of the *overall* employment decline from 1997 to 2007 comes from net firm death. In contrast, net firm death accounts for only 25% of manufacturing job loss from the China shock (the rest is mostly due to firm downsizing and plants switching from manufacturing to services). For services, net job creation by existing firms accounts for all of the *overall* job growth from 1997 to 2007. In contrast, net firm creation accounts for 25% of services job growth from the China shock (the rest comes from existing firms). This suggests that the China shock was not the only driver of the increase in manufacturing plant closures during the 2000s, and promoted the entry of new service establishments, including factory-less goods producers (Bernard and Fort, 2015).

Second, the local labor market effects of Chinese import penetration vary substantially by employer characteristics. The bulk of the manufacturing job loss from the shock is accounted for by plants belonging to firms that simultaneously expand employment in services. In contrast, only about a quarter of the service job gains come from establishments belonging to firms that reduce employment in manufacturing. Furthermore, about three quarters of the service job gains come from establishments belonging to large firms (more than 1,000 employees), which suggests that the China shock contributed to the rise of superstar firms in the U.S. (Autor et al., 2020). If we classify plants as high- versus low-wage (relative to their own 6-digit NAICS industry), we find that nearly all of the positive service job effects are in high-paying establishments, suggesting some role of the China shock in shaping between-firm earnings inequality (Song et al., 2019).

Third, the response to Chinese import penetration exposure varies systematically across local labor markets as a function of initial human capital endowments (measured by the share of college-educated population) and initial manufacturing dependence (measured by the share of manufacturing in total employment). In high human capital areas (much of the West Coast and large cities more generally), job reallocation from manufacturing to services is higher than in low human capital areas with high manufacturing dependence (much of the South and the Midwest), primarily because within-firm reallocation and in particular industry switching occurs almost exclusively in high human capital areas. The positive effect on service jobs in high human capital areas robustly outweighs the negative effect on manufacturing jobs, implying a sizable net positive effect on total employment. In low human capital areas with high manufacturing dependence, by contrast, service job gains barely offset manufacturing job losses. Our estimates imply the China shock accounts for half of the one percentage point higher average annual job growth in high human capital areas that we observe in the data. The China shock therefore created winners and losers, not just across workers as documented for instance by Autor et al. (2014) and Pierce et al. (2024), but also across regions by reallocating jobs from the industrial heartland to the coasts and large cities, thereby contributing to the changing geography of jobs in the U.S. (Moretti, 2012).

Our work relates to an extensive literature quantifying the effects of China's rise on domestic labor markets and firm reorganization. Bernard et al. (2006), Autor et al. (2013), Acemoglu et al. (2016), Pierce and Schott (2016), Asquith et al. (2017), Autor et al. (2021) and Pierce et al. (2024) among others all report sizable negative impacts on U.S. manufacturing employment from import exposure to China and other low-wage countries, particularly for workers in lower-skilled industries. International research shows a similar impact, for example in Europe (Bloom et al., 2016), Canada (Murray, 2017) and Brazil (Paz, 2017 and Alfaro et al., 2019). Concurrently, several other studies provide evidence that trade with China and low-wage countries more generally leads to offshoring and creates service sector jobs (e.g., Hummels et al. 2014; Feenstra and Sasahara, 2017; Magyari, 2017; Hummels et al., 2018; or Bernard et al., 2024). One contribution of our work relative to this literature is that we use administrative microdata that (i) has accurate establishment-level employment records for the entire U.S., (ii) includes precise information about industry affiliation; and (iii) can be related to important firm characteristics. This allows us to gain a better understanding of how the China shock led to job reallocation, particularly with regards to industry switching of plants, and reorganization within large multi-sector firms (Holmes and Stevens, 2014; Fort et al., 2018).[4,5] Another contribution of our work is to highlight important geographical differences in the reallocative effects of the China shock as a function of local labor markets' human capital endowment and manufacturing intensity.

An important question is why our results differ from those by Autor et al. (2013), Acemoglu et al. (2016), and Autor et al. (2021), who like us find that local exposure to Chinese import penetration has exerted a sizable negative impact on manufacturing jobs, but who do not find a positive offsetting effect on service jobs. As we describe in the last part of the paper, a final contribution of our work is to carefully document how this difference arises as a function of how local exposure to Chinese import penetration is measured; specifically (i) using NAICS instead of SIC codes to allocate industry import penetration to local labor markets; (ii) calculating import penetration based on domestic absorption instead of employment; and (iii) shifting away from the year 2000 as the starting point of the analysis. While none of these choices are necessarily right or wrong, we believe that in the context of the available data, our choices are natural. First, industry measures of economic activity in the U.S. and elsewhere are classified based on NAICS from 1997 onward, and NAICS represents a conceptual improvement over SIC.[6] Second, weighting Chinese imports relative to initial domestic absorption is the commonly adopted approach in most of the literature because it normalizes the shock by the size of the domestic market, which may not be proportional to the number of workers across sub-sectors. Third, although Chinese import penetration accelerated markedly around China's accession to the World Trade Organization (WTO)

[4]Note that Asquith et al. (2017) attempt a similar decomposition of the manufacturing job growth effects of the China shock using the National Establishment Time Series (NETS). As documented by Crane and Decker (2019), however, the quality of the NETS microdata is subject to important caveats and exhibits business dynamics that deviate importantly from those in official data sources. As a result, the estimates obtained by Asquith et al. (2017) are quite different from ours. Furthermore, they do not consider industry switching.

[5]The fact that establishments and firms change activity due to increased competition is not without precedent. Bernard et al. (2006) document in U.S. Census data that import competition from developing countries induced changes in manufacturing establishment industry affiliation in the 1980s and 1990s. In addition, Bernard et al. (2017) document in Danish data that a non-negligible portion of the net decline in manufacturing employment is due to plants switching industries, and that the switching plants are on average more productive and employ higher skill workers. However, we are to our knowledge the first to document the large role that industry switching plays in accounting for the negative effect of the China shock on local manufacturing employment.

[6]NAICS is a purely production-oriented concept whereas SIC is based on a mixture of demand-based product similarity and the production process. See Office of Management and Budget (2022, 1997), Office of Management and Budget (2022)and Walker and Murphy (2001) for discussion of the development of NAICS relative to SIC and its main classification principles. As a result, neither industry trade flows nor local-industry employment shares used to allocate these trade flows to CZs map consistently from SIC to NAICS or vice versa. Thus, measures of local exposure to Chinese import penetration based on SIC or NAICS basis are highly correlated but far from the same. See Appendix B for details. This difference is relevant not just for measuring local exposure to Chinese import penetration but for any application that uses industry differences in trade flows or employment.

in 2001 and abated around 2010, we focus our analysis on the period 1997-2007 for two reasons. First, industry affiliation of establishments in the LBD (and therefore the CBP and other public use data) is directly measured during Economic Census years, which occur in 5-year intervals (...,1997, 2002, 2007,...), while it is often imputed in intervening non-Census years. Second, starting the analysis in 1997 makes it more likely that we include potential anticipatory effects of China's WTO accession (Alessandria et al., 2021), while ending the analysis in 2007 has the advantage that we avoid attributing potentially confounding effects of the 2008-09 Great Recession, which affected U.S. local labor markets differentially, to the China shock.[7]

Finally, our paper is related to an important strand of research studying the impact of Chinese imports beyond local labor markets. Several studies show that Chinese trade had positive effects in the form of new varieties and lower import prices (Amiti et al., 2020; Handley and Limao, 2017; and Jaravel and Sager, 2018), new US export opportunities (Feenstra and Sasahara, 2017), and supply-side input costs (Wang et al., 2018). Furthermore, a set of recent papers perform welfare analysis in structural general equilibrium models, some of which find positive net welfare effects of China while accounting for structural changes (e.g. Galle et al., 2017; Kehoe et al., 2018; Adao et al., 2019; and Caliendo et al., 2019). Our empirical approach does not allow us to address linkages across geographic labor markets or their interaction in general equilibrium. Nevertheless, our findings of firm reorganization and of differential employment effects across local labor markets as a function of their human capital endowments can inform the patterns that these models should target.

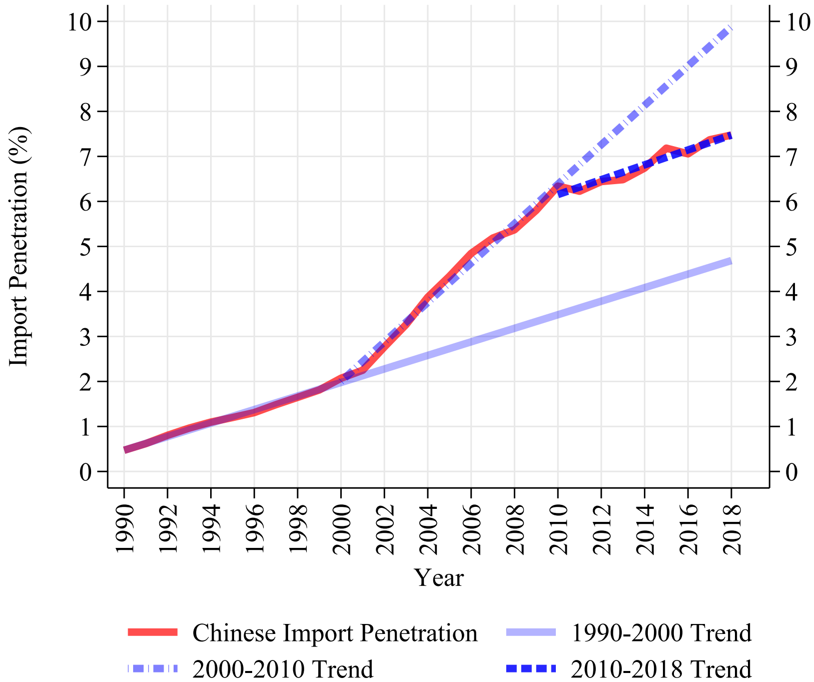
The rest of this paper is structured as follows. Section 2 reviews the basics of the China shock and U.S. employment dynamics. Section 3 describes the administrative employment data from the LBD and the main decomposition into gross job flows, our construction of local exposure to Chinese import penetration, and the estimation strategy. Section 4 presents the results, while Section 5 discusses the importance of measurement for these results. Section 6 concludes.

2 The China Shock and U.S. Employment in Perspective

To motivate our analysis, we start by reviewing the evolution of Chinese import penetration and U.S. employment over the past decades. Figure 1 shows U.S. imports of Chinese manufacturing

[7]Nonetheless, we show in Appendix A that our results are robust to extending the analysis to back to either 1992 or forward to 2012.

Figure 1: Evolution of Chinese Import Penetration in U.S. Manufacturing 1990-2018

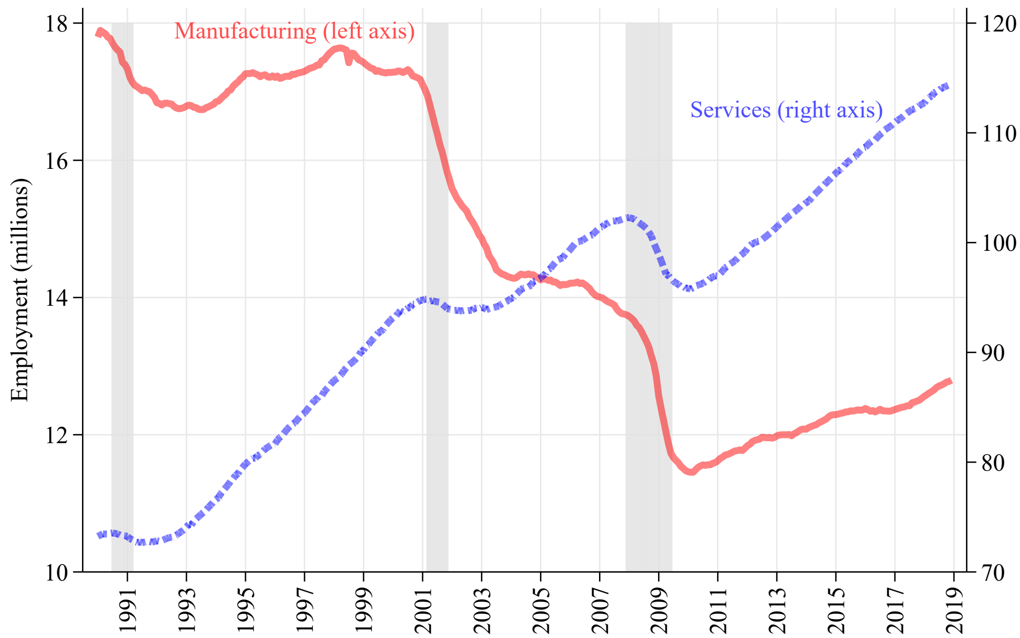


Notes: Import penetration is defined as Chinese manufacturing imports divided by gross output plus imports minus exports. Trend lines are a simple linear fit of import penetration for the specified time period. Manufacturing gross output data are from the Bureau of Economic Analysis (BEA). Manufacturing imports and exports are from U.S. International Trade Commission (USITC) Dataweb. Imports and exports are based on SIC codes until 1996 and on NAICS codes from 1997 to 2018. The same pattern holds if we use NAICS industry coding for all years or if we fix domestic absorption (the denominator in import penetration) to 1991 and compute import growth in real terms as we do in the empirical analysis.

goods as a share of total domestic absorption. Between 1990 and 2000, the ratio grows gradually from about 0.5 percent to about 2 percent. From 2000 onward, the ratio grows twice as fast reaching 6% by 2010, consistent with the timing of the uncertainty reduction in U.S. import tariffs following China's WTO accession (Pierce and Schott, 2016; Handley and Limao, 2017) and the rise in Chinese manufacturing productivity (Autor et al., 2013). After 2010, growth returns to its pre-2000 rate, following the slowdown in productivity growth across nearly all Chinese industrial sectors (Brandt et al., 2022). These differences in growth episodes are clearly apparent from the different trend lines, with the 1990-2000 trend and the 2010-2018 trend statistically indistinguishable from each other.

Figure 2, in turn, shows the evolution of manufacturing and services employment. The manufacturing sector experiences two precipitous declines: a drop of about 3 million jobs from the 2001 recession to 2004, followed by another drop of approximately 2 million jobs during the 2007-2009

Figure 2: Manufacturing and Services Employment, 1990-2018.



Notes: Data are from the Bureau of Labor Statistics. Monthly data. Manufacturing, all employees, seasonally adjusted, series CES3000000001. Services includes all non-manufacturing (services, construction, mining), derived from all employees, private, non-farm, seasonally adjusted, series CES0000000001, less Manufacturing series. Grey bars indicate recessions. See footnote 3for more details on our definition of services employment.

Great Recession. From 2010 to 2019, manufacturing jobs then recover somewhat, similar to the growth in manufacturing jobs after the early 1990s recession. At first sight, the two sudden declines in manufacturing employment seem hard to reconcile with the smooth increase in Chinese import penetration (Bertrand, 2021). These declines may, however, reflect structural changes that manifested themselves in the loss of routine jobs concentrated around recent recessions (Jaimovich and Siu, 2020).

Remarkably, while employment in services shares the business cycle movements around the Great Recession, its evolution for the early 2000s is very different: services jobs remain flat after the 2001 recession and then grow strongly through the end of 2007, adding 7.4 million jobs. A substantial part of this growth is driven by trade-related services – business services, wholesale/retail, and transportation and warehousing – which account for 40% of total services jobs growth.[8]

Given these patterns, it is clear that the main period of the China shock is roughly 2000 to 2010.

[8] The other main contributors to total non-manufacturing jobs growth are healthcare, leisure and hospitality, and finance, insurance and real estate. Mining and construction, by contrast, account for very little of total non-manufacturing jobs growth.

Our baseline analysis in what follows runs from 1997 to 2007 for three reasons. First, 1997 and 2007 are both Economic Census years when the accuracy of the administrative data on establishments, and in particular their industry characteristics and firm affiliations is highest. Second, starting in 1997 makes it more likely that our analysis includes anticipatory effects of China's WTO accession (Alessandria et al., 2021), which could be important for particular industries and locations. Third, we end in 2007 to avoid attributing potentially confounding effects of the Great Recession, which affected U.S. local labor markets differentially, with the effects of the China shock. Nonetheless, we run a series of robustness checks with different start and end points.

3 Data, Measurement, and Empirical Strategy

A key contribution of our analysis is the detailed decomposition of employment growth at the establishment level into various job creation and destruction margins, and connecting these outcomes to firm characteristics. This section describes the data and main decomposition, the measurement of Chinese import competition, and the empirical strategy to identify the local effects of the China shock.

3.1 Establishment- and Firm-level Microdata

We use multiple micro datasets from the U.S. Census Bureau. The primary data on employment outcomes is the Longitudinal Business Database (LBD), which contains the universe of non-farm private employer businesses in the U.S.[9] These same data underlie the much more aggregated public-use County Business Patterns (CBP) data used in other studies. 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 Report of Organization. The lowest unit of observation is the establishment, a physical location where business is conducted. For each establishment, we have annual data on employment, payroll, industry code, and the parent firm (if part of a multi-unit operation) derived from IRS tax-records.[10]

[9] The LBD excludes the self-employed, farms, and government entities.

[10] The parent firm of an establishment is defined based on operational control and may change over time as a result of mergers and acquisitions. There are about 7 million establishments and about 5 million firm observations per year. When decomposing sectoral employment growth by firm characteristics, we attribute establishments to the parent

In our primary analysis, we also use data from Economic Censuses (EC), which is collected during years ending in "2" or "7" (e.g., 1997, 2002, 2007,...). In these years, every establishment is required by law to complete a census that requests data on employment, a primary industry code, and other activities. Hence, during the EC years, the data is more accurate, both in the confidential microdata and the public-use CBP aggregates. We therefore focus on these years and in particular the period 1997-2007, which is the main period of the China shock.

To construct local-industry aggregates from LBD establishments in a time-consistent manner, we use the NAICS industry codes constructed by Fort and Klimek (2018), FK codes henceforth. As described in more detail in Appendix A, the FK coding converts different the SIC and NAICS industry classifications that the U.S. statistical agencies adopted over the years to a time-invariant NAICS code. As a result, the FK codes remains constant for each establishment in the LBD unless the establishment changes its primary productive activity and reports a new industry code as a result (typically during an Economic Census year).

3.2 Employment Growth Decompositions

Following Autor et al. (2013) and many others thereafter, we use the concept of commuting zone (CZ) for defining local labor markets (Tolbert and Sizer, 1996). We base our analysis on the 722 CZs that cover the U.S. mainland. We define employment growth in industry i and commuting-zone c over time period τ as

$$g_{ic\tau} = \frac{E_{ict+\tau} - E_{ic,t}}{0.5\left(E_{ict+\tau} + E_{ict}\right)}. \tag{1}$$

For much of the analysis, we aggregate all manufacturing industries, respectively all services industries into one sector each; so, i typically denotes either manufacturing or services.

Employment growth can be decomposed into contributions from job creation and job destruction from continuing establishments, entry and exit, as well as industry switching between time interval t to $t+\tau$ (mostly 1997 to 2007) as follows

$$g_{ic\tau} = \frac{\left(JC^{cont}_{ic\tau} - JD^{cont}_{ic\tau}\right) + \left(E^{entry}_{ic\tau} - E^{exit}_{ic\tau}\right) - \left(S^{out}_{ic\tau} - S^{in}_{ic\tau}\right)}{0.5\left(E_{ict+\tau} + E_{ict}\right)}, \tag{2}$$

where the sum of job creation by continuing establishments is given by $JC^{cont}_{ic\tau} = \sum_{e \in cont_{ic}} max(E_{e,t+\tau} -$

firm in the end year of the growth interval.

$E_{e,t}, 0)$ and job destruction is $JD^{cont}_{ict} = \sum_{e \in cont_{ic}} max(-(E_{e,t+\tau} - E_{e,t}), 0)$; $E^{entry}_{ic\tau}$ and $E^{exit}_{ic\tau}$ are the sum of employment gains from entering and employment losses from exiting establishments; and $S^{in}_{ic\tau}$ and $S^{out}_{ic\tau}$ are the sum of employment at establishments that switch in and out of industry or sector i. Note that employment gains from entry can be further decomposed according to whether the new establishment belongs to an already existing firm or is part of a firm birth. Vice versa, employment losses from exit can be further decomposed according to whether the closing establishment belongs to a continuing firm or is part of a firm death. Likewise, as discussed in Section 4, each of the terms can be decomposed further by employer characteristics.

Since industry switching is a relatively unknown concept (and is by definition zero in the aggregate), it merits further explanation. As described above, establishments report an industry code in each Economic Census year based on their primary output. As the primary activity of an establishment changes, its industry affiliation may change. To fix ideas, consider our baseline where $i = M$ for establishments in manufacturing and $i = N$ for establishments in services. Consider now an establishment that reports a manufacturing NAICS code in year t, but also performs other activities (e.g., management or design services), at the same location. Suppose now that between t and $t + \tau$, the establishment's primary activity changes to design and testing products because, say, it has outsourced some of its manufacturing production. Then in $t + \tau$, the establishment reports a services NAICS code and its year t employment is counted as part of manufacturing job loss due to "switching out" of manufacturing, $S^{out}_{Mc\tau}$. To maintain accounting identities, the same establishment's employment in year $t+\tau$ is counted as part of services job gain due to "switching in" to services, S^{in}_{Nct}. When adding up within the same sector i, net switching out, $-\left(S^{out}_{ic,t-k} - S^{in}_{ict}\right)$, therefore enters with a negative sign in (2).

3.3 Chinese Import Penetration

Following Acemoglu et al. (2016) and many others thereafter, we define the exposure of CZ c to Chinese import penetration over time interval t to $t+\tau$ as the average change in Chinese penetration across manufacturing industries i, weighted by the initial industry employment shares in that CZ,

$$\Delta IP_{c\tau} = \sum_{i \in M} \frac{L_{ict}}{L_{ct}} \Delta IP_{i\tau}, \tag{3}$$

where $\Delta IP_{i\tau} = \Delta M^{cu}_{i\tau} / (Y_{it} + M_{it} - EX_{it})$ is the change in real imports from China by the U.S. in manufacturing industry i between year t and year $t+\tau$ divided by U.S. initial absorption (U.S. shipments plus imports minus exports $Y_{it} + M_{it} - EX_{it}$), and $\frac{L_{ict}}{L_{ct}}$ is the initial employment share of industry i in CZ c. Differences in CZ exposure to Chinese import penetration therefore stem from differences in initial manufacturing specialization (e.g., textile versus car manufacturing).

All trade flows are sourced from the UN Comtrade database and allocated to industries using a trade-weighted concordance from the 6-digit level of the Harmonized System (HS6) to the 6-digit NAICS level. As described in Appendix A, this concordance is built in the same way as the one by Autor et al. (2013), based on the HS10-to-NAICS6 concordance by Pierce and Schott (2012) and HS10 trade flows for the U.S. from the U.S. International Trade Commission (USITC). Initial U.S. shipments $Y_{j,t}$, in turn, are obtained from the NBER-CES Manufacturing Industry database.

Table 1, Panel A reports population-weighted summary statistics for CZ import penetration for 1997-2007. There is substantial dispersion in IP across CZs, ranging from 0.055 per year at the 25th percentile to 0.112 per year at the 75th percentile. Appendix B provides further detail with regards to the the top CZs by shock and the geographic distribution of the shock.

Panel B shows the same population-weighted summary statistics for annual CZ employment growth. Consistent with the aggregate BLS data from Figure 2, manufacturing employment declined on average by about 20% from 1997 to 2007, or 2% per year, whereas services employment increased on average by about 18% or 1.8% per year. There is substantial dispersion in these growth rates across CZs, ranging from -3.1% at the 25th percentile to -1.2% at the 75th percentile for manufacturing and ranging from 1.3% at the 25th percentile to 2.5% at the 75th percentile for services.

3.4 Empirical strategy

To estimate the impact of Chinese import penetration on local labor market outcomes, we follow Autor et al. (2013) and many others thereafter and estimate long difference regressions of the form

$$\Delta y_{ic\tau} = \alpha_\tau + \beta_i \Delta IP_{c\tau} + \boldsymbol{X'_{c\tau}} \gamma_i + \epsilon_{it}, \tag{4}$$

where $\Delta y_{ic\tau}$ is a measure of employment growth in CZ c, industry i, over time interval τ. The main coefficients of interest is β_i, which estimates the effect of local exposure to Chinese import penetration, $\Delta IP_{c\tau}$. The vector $\boldsymbol{X}_{c\tau}$ contains the set of CZ-specific start-of-period controls from Autor et al. (2013), Census region fixed effects allowing for differential employment trends for each of the nine Census regions, as well as CZ-level pretrend controls (see below).[11] The regressions are weighted by CZ working age population in 1991 and standard errors are heteroscedasticity-robust.[12]

For causal identification, we follow Acemoglu et al. (2016) and instrument local exposure to Chinese import penetration to the U.S. with Chinese import penetration to eight other developed countries[13]

$$\Delta IP_{c\tau}^{IV} = \sum_{i \in M} \frac{L_{ic0}}{L_{c0}} \Delta IP_{i\tau}^{co}, \tag{5}$$

where $\Delta IP_{i\tau}^{co} = \Delta M_{i\tau}^{co} / \left(Y_{i0} + M_{i0} - EX_{i0}\right)$ is the change in real imports from China by the other countries in manufacturing industry i between year t and year $t + \tau$, divided by initial absorption in some base year prior to year t; and $\frac{L_{ic0}}{L_{c0}}$ is the employment share of industry i in CZ c in that same base year.[14]

As Borusyak et al. (2018) and Goldsmith-Pinkham et al. (2018) emphasize, the type of Bartik-style identification schemes used here can be problematic if there are pre-trends correlated with the treatment variable. To control for potential pre-trends, we therefore add CZ manufacturing and services employment growth (relative to total CZ employment) over the 1982-92 period as additional control variables (we use this as the most recent prior Economic Census year data). As shown in Appendix A.4, we do see some attenuation in coefficient estimates relative to regressions without these pre-trend controls, highlighting the challenges of estimating the impact of Chinese trade on U.S. local labor markets. To remain conservative, we include these pre-trends and note that without them, the magnitude of estimates for services and total CZ employment growth shown below would be even stronger.

[11] The CZ-specific controls from Autor et al. (2013) are the share of manufacturing employment, the share of college-educated population, the share of foreign-born population, the share of employment among women, the share of employment in routine occupations, and an offshorability index of occupations. All of these controls are computed for 1990, the start year of Autor et al. (2013)' s investigation. See Autor et al. (2013) for further discussion of these controls.

[12] For regressions that stack CZs over several time intervals, we cluster the standard errors at the CZ level.

[13] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

[14] Following Acemoglu et al. (2016), we use 1988 as the employment base year for all of our regressions. Results are robust to using other base years.

Furthermore, as Adao et al. (2018) emphasize when using Bartik estimators, standard errors may be under-estimated due to the correlations in industry level shocks across geographical areas 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 should not be a major concern (indeed, Adao et al., 2018 discuss this for the original Autor et al., 2013 paper).

Our main specification considers one single time period from 1997 to 2007. As discussed above, this choice is motivated on the one hand, by our focus on the main period of the China shock and, on the other hand by our objective to measure industry affiliation of establishments as accurately as possible while including potential anticipatory effects. The resulting sample therefore contains about 700 (rounded) observations (commuting zones) of 10-year growth rates.

An alternative specification that is also based on Economic Census years and covers the same time period would stack the two 5-year periods 1997-2002 and 2002-2007. For most of our analysis, we prefer the single 10-year period as our baseline because our main goal is to evaluate the longer-run impacts of the China shock. As argued for example by Jaeger et al. (2018) and Autor et al. (2021), the impact of treatment variables may take several years to arise and thus, estimating shorter-difference specifications can conflate short- and long-run impacts. Furthermore, in Section 4 and Appendix A.4, we discuss how the estimates change when we extend the analysis back to 1992 or forward to 2012. In short, we find that all of our results are robust to these changes; and for some of the outcomes, the results are even stronger.

4 Results

We begin by presenting the baseline estimates of the local net employment growth effects of the China shock, followed by decompositions into job reallocation margins and by employer characteristics. Finally, we explore differences in outcomes by CZ characteristics.

4.1 Local Employment Effects and Sectoral Job Reallocation

Table 2 reports our baseline estimates for the effect of local exposure to the China shock on manufacturing, services and total job growth for the period 1997-2007. As shown in columns (1) and (2), we find a negative effect on manufacturing job growth of -6.32 (t-statistic of -2.05), while for services job growth, we find a positive effect of 4.67 (t-statistic of 2.86). Hence, local labor markets more heavily exposed to Chinese import penetration experienced on average a significantly larger reallocation of jobs from manufacturing to services. Although in absolute value the positive effect on services job growth is smaller than the negative effect on manufacturing job growth, the positive services effect more than offsets the negative manufacturing effect because services employment is on average more than three times as large as manufacturing employment, resulting in a positive overall estimate for total CZ job growth of 2.17 (t-statistics of 1.39). This is illustrated by columns (3) – (5), which show the estimated effects of the China shock on manufacturing, services and total CZ employment as a share of total average CZ employment. While the total CZ employment effect is insignificantly different from zero at standard confidence level, we can rule out that the China shock had a sizable negative effect on total CZ employment.

Given the annual increase in Chinese import penetration of 0.087 across CZs over the 1997-2007 period (Table 1), the point estimates in columns (1) and (2) imply that the China shock reduced manufacturing employment growth by -0.55 ($= -6.234 \times 0.087$) percent per year, or about 25% of the aggregate annual decline of -2.15 percent. For services, the implied average effect is 0.40 ($= 4.667 \times 0.087$) percent per year, or about 22% of the aggregate annual increase in services employment of 1.81 percent.[15] These calculations abstract from general equilibrium effects. Nonetheless, they suggest that the China shock, while important, was not the main source of the decline in manufacturing employment during the 2000s.

One potential concern with these estimates is that the China shock may have had important short-run effects that are disguised by the 10-year interval over which we estimate the regressions. Alternatively, the full effects of the China shock may have taken longer than 10 years to materialize. In Appendix A.4 and Table A.1, we therefore perform the same regressions both for stacked 5-year periods (1997-2002 and 2002-2007 as well as 1992-1997, 1997-2002, 2002-2007) and the 15-year period 1997-2012. Overall, we find similar estimates that, if anything, point to even stronger reallocative effects. We therefore leave the discussion of these robustness checks to the appendix

[15] Similarly, the estimates imply that CZs with local China shock exposure around the 75th percentile experienced -0.36 percentage points ($= -6.234 \times (0.112 - 0.055)$) lower manufacturing employment growth per year than CZs with local China shock exposure around the 25th percentile. Vice versa, CZs with local China shock exposure around the 75th percentile experienced 0.26 percentage points ($= 4.667 \times (0.112 - 0.055)$) higher services employment growth than CZs with local China shock exposure around the 75th percentile. These calculations assume homogenous effects of local China shock exposure across CZs. As discussed in Section 4.4, this is not the case. We will therefore analyze differences in the effects of local China shock exposure by different CZ characteristics.

and continue the analysis with the baseline 1997-2007 period.

One immediate question is why our results differ from those in Autor et al. (2013), Acemoglu et al. (2016) or Autor et al. (2021), who like us report a negative impact of Chinese imports on manufacturing employment, but do not find a positive offsetting impact on services employment and therefore a net negative effect on total CZ employment. As discussed in the introduction, this difference in results is due to how local exposure to Chinese import penetration is measured. We refer to Section 5 for an in-depth analysis of the importance of measurement and why we believe our choices are natural in the context of the present data.

4.2 Within-Sector Job Reallocation and Industry Switching

Our results so far imply that areas exposed more heavily to the China shock experienced, on average, stronger sectoral reallocation of jobs from manufacturing to services. To investigate the sources of this reallocation, we decompose net employment growth for each CZ and sector into gross job flows margins and industry switching as described in equation (2) and regress the different components on the local import penetration shock.

Before discussing the estimation results, it is worth considering the aggregate patterns of within-sector reallocation and industry switching. As shown in Table 3, 84% of the negative net job growth in manufacturing of -2.15 percent per year is due to negative net entry of establishment (i.e., the contribution from establishments ceasing operations exceeds the contribution from newly opened establishments), with most of it due to net firm death and the rest from net closings of establishments by continuing firms.[16] The remaining 16% come from continuing establishments that on net reduce jobs. For services, in turn, almost two thirds of the positive net job growth of 1.81 percent per year is from net entry of establishments, with all of it accounted for by net openings of new establishments by existing firms, while the remaining one third is from net job creation of continuing establishments. For both sectors, the contribution of net switching to/from the other sector is negligible on average, but as we will see below, this is not the case for the estimated response to the China shock.[17]

Turning to our local China shock estimates, Table 4 reports the effect on the job reallocation

[16] Employment growth due to total net entry of establishments is -1.80 percent per year, of which -1.40 ($= 1.20 - 2.60$) percent per year or 65% of the total negative job growth of -2.15 percent per year is from net death of firms and -0.40 ($= 0.84 - 1.24$) is from net closings of establishments by continuing firms.

[17] Ding et al. (2022) also find that the contribution of net switching in and out of manufacturing is small in the aggregate.

margins.[18] In short, the shock has heterogeneous effects on the different margins that diverge substantially from the aggregate trends, and for manufacturing these effects are not uniformly negative. As shown in Panel A, only about one fourth of the total manufacturing job loss effect of the China shock (-6.23 in column 1) is due to increased net death of firms ($0.79 - 2.34$ in column 5 and column 7), and the effect on net job creation at continuing establishments is even positive ($1.13 - 0.51$ in column 2 and column 3). Indeed, the China shock increased gross job creation from continuing establishments (1.13 in column 2) as well from firm birth (0.79 in column 4). The bulk of the total job loss effect comes instead from firms that continue operations but reduce employment through lower new establishment openings (-0.48 in column 4), higher establishment closings (-2.37 in column 6), or switching the primary activity of establishments from manufacturing to services (-2.46 in column 9). While all the other margins are imprecisely estimated, the net negative effect from switching ($-0.09 - 2.46$ in columns 8 and 9) is highly significant and accounts for 40% of the total manufacturing job loss from the China shock.

For services, Panel B shows that over 40% of job gain effect from the China shock is due to increased job creation and reduced job destruction among continuing establishments (0.95 and 1.09 in columns 2 and 3). While other margins are less precisely estimated, they are all positive. The effects on net entry (columns 4 through 7) account for over 50% of the total effect. Industry switching *into* services from manufacturing (0.28 in column 8) is the flip-side of the negative industry switching effect of plants switching out of manufacturing in Panel A. The contribution of industry switching to services employment is precisely estimated, but the effect is small because total services employment is substantially larger than manufacturing. Furthermore, establishments switching out of manufacturing in response to the China shock reduce employment somewhat on average, although by no means all jobs are destroyed.

Table 5 provides a more detailed analysis of the industry switching patterns out of manufacturing. The bottom-right element (row 4, column 4 of the matrix), replicates the estimated coefficient for the overall contribution of switching out of manufacturing (2.46 in absolute value), that appears in Panel A, column 9 of Table 4. We break this estimate down into additive sub-components by

[18] Column (1) starts by replicating the average impact on manufacturing jobs (panel A) and services jobs (panel B) from Table 3. Columns (2) - (9) show the estimates for the different components. Since these components add up exactly to net employment growth for each CZ and sector, the sum of the estimates in columns (2) - (9) for each panel equal the estimates in column (1).

manufacturing industry from which the switching establishments originate (going down the rows) and the services industries to which these establishments switch (going across the columns). The estimates are signed in terms of their contribution to job losses in manufacturing in response to the China shock.

Looking across the columns, the total effect of switching out of manufacturing is driven almost entirely by establishments that switch into wholesale trade (column 1) or professional services and management (column 2) even though these industries account for only about 15% of total services employment. Looking down the rows, nearly all of the industry switching effect originates from establishments formerly operating in metal, machinery, computers, electronics and electrical manufacturing (row 3), which accounts for about 55% of total manufacturing employment. Hence, a typical industry switch would be a plant producing electrical goods that switches to primarily designing, marketing and wholesaling them, perhaps as a factoryless producer.

It is important to re-emphasize that switching establishments are continuers – they do not shut down. This suggests that industry switching arises from manufacturing plants being repurposed toward designing, developing, managing and wholesaling of goods in response to competition or new opportunities created from rising Chinese manufacturing competitiveness. Although others have noted the transition of former manufacturers into multi-sector operations (Fort et al., 2018), our results provide evidence that this transition was strongest in labor markets more exposed to the China shock.[19]

Finally, while the role of industry switching for the negative manufacturing impact of the China shock is a striking result, it does not imply that the remaining jobs in switching plants that were formerly attributed to manufacturing are simply relabeled as services jobs. Examining whether these plants experience higher worker turnover and what types of new workers replace previously employed workers would be interesting. Since such an examination requires worker-firm matched data to which we do not have access, we leave this for future research.

[19] One potential concern one may have with our switching results is that establishments change industry affiliation at random. However, if industry measurement error was important, we should not observe such precise results with regards to switching from one particular manufacturing industry to three particular (and small) services industries. It should also not be correlated with the China shock. Furthermore, as described in Appendix A, the U.S. Census Bureau goes through great efforts to determine industry affiliation during Economic Census years and indeed, most industry switching occurs during those years.

4.3 The Role of Employer Characteristics for Job Reallocation

The results from the decompositions above indicate that firm birth and death are not the main drivers of the observed local job reallocation effects of Chinese import competition. Instead, the results—in particular with regards to industry switching—-are suggestive of *within-firm reallocation* of jobs. To investigate the importance of this mechanism, we exploit the establishment-firm linkage of the LBD further and quantify the extent to which the China shock leads to local manufacturing job loss and services job gains within the same firms.

Specifically, we decompose net employment growth based on firm-level activity in the other sector; i.e.,

$$g_{ic\tau} = \frac{\triangle E_{ic\tau}^{expand(-i)} + \triangle E_{ic\tau}^{contract(-i)} + \triangle E_{ic\tau}^{none}}{0.5\left(E_{ict+\tau} + E_{ict}\right)}. \tag{6}$$

The term $\triangle E_{ic\tau}^{expand(-i)} \equiv \sum_{e\in\mathcal{E}_{ic}^{expand_{-i}}} \left(E_{et+\tau} - E_{et}\right)$ is the net employment change of the set of establishments $\mathcal{E}_{ic}^{expand(-i)}$in sector i and CZ c that belong to firms expanding employment in the other sector $(-i)$; the term $\triangle E_{ic\tau}^{contract(-i)} \equiv \sum_{e\in\mathcal{E}_{ic}^{contract(-i)}} \left(E_{et+\tau} - E_{et}\right)$ is the net employment change of the set of establishments $\mathcal{E}_{ic}^{contract(-i)}$ in sector i and CZ c that contract employment in the other sector $(-i)$; and the term $\triangle E_{ic\tau}^{none} \equiv \sum_{e\in\mathcal{E}_{ic}^{none}} \left(E_{et+\tau} - E_{et}\right)$ is the net employment change of the set of establishments belonging to firms with no presence in the other sector $(-i)$. These three terms are mutually exclusive. Necessarily, for a firm to expand in the other sector, it needs to own more than one establishment.[20] Whether such multi-establishment firms expand in the other sector is then calculated across all of its establishments, independent of whether they are located in the same CZ, c, or in other CZs.

Aside from the decomposition with respect to firm activity in the other sector, we implement a similar decomposition based on firm size; i.e., whether the establishments in a sector and CZ belong to firms with more than 1,000 employees or firms with less than 1,000 employees across both sectors and all CZs. Furthermore, we decompose sector-CZ net job growth into establishments with high versus low average earnings per worker relative to median earnings in the establishment's 6-digit NAICS industry code.[21]

[20] For establishments that change firm ownership between t and $t+\tau$, we use the firm characteristics in $t+\tau$.

[21] Specifically, average earnings per worker at the establishment-level is constructed by dividing total payroll with employment, both from the LBD. For all existing establishments in year t, we compute the median average earnings 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

Panel A of Table 6 reports the results. As shown by columns 2 to 4, the local employment effects of the China shock for manufacturing and services by firm activity in the other sector are nearly a mirror image of each other. About 80% of the negative manufacturing effect is from establishment belonging to firms that expand in services (Panel A, column 2), with the remainder accounted for by establishments belonging to firms that either contract in services or do not have a presence in services (Panel A, columns 3 and 4). In contrast, over 60% of the positive services effect comes from establishments belonging to firms with no manufacturing presence (Panel B, column 4), and about 10% of services gains are from establishments belonging to firms that expand in manufacturing (Panel B, column 2).

As the remainder of Table 6 shows, the negative manufacturing effect of the China shock is split about 60/40 between large and small firms (Panel A, columns 5 and 6), but only the small plant growth contribution is marginally significant.[22] In contrast, most of the positive effect of the China shock on services employment comes from large firms (Panel B, columns 5 and 6). This is interesting since large firms account on average account for only about half of total services employment.

There is a similar split in the contribution of job losses at high and low wage plants in manufacturing, with 60% accruing to higher wage plants (Panel A, columns 7 and 8). These estimates are, however, again surrounded by considerable uncertainty. As with firm size, the results are much clearer for services: most of the job gains effect of the China shock are in establishments that pay high wages relative to their own industry (Panel B, columns 7 and 8).

The LBD data does not track job-to-job worker flows, so we cannot determine if job losses at high-wage manufacturing plants within a given CZ were compensated by service job gains with equally high or even higher wages. However, we do know that industry switching plants are disproportionately concentrated toward professional and technical services (Table 5). So it is likely that at least some of the job gains were for high-wage (and thus high-skill) service sector workers that had different skills than workers that lost manufacturing jobs. Similarly, our data do not allow us to know whether the workers that lost manufacturing jobs obtained work in service sector jobs

sample between t and $t + \tau$, we classify them as high or low earnings establishments based on their average earnings relative to the within-industry earnings distribution in year t.

[22] The larger negative effect for firms with over 1,000 employees is consistent with Holmes and Stevens (2014), who argue that larger plants (not firms specifically) operate at scale by producing more standardized goods with low-skilled labor that is more vulnerable to import competition. We reemphasize, however, that the estimates are surrounded by considerable uncertainty.

in the same CZ and if so, whether pay in those service sector jobs was higher or lower than in the previous manufacturing jobs. More evidence on these dynamics can be found in the matched employer-employee data analyzed by Pierce et al. (2024). They show workers initially employed in services have wage gains, while manufacturing workers have persistent negative effects from import competition. In Appendix A.4 and Table A.2, we provide additional results on average earnings per worker and payroll in services and manufacturing and compare them with the results in Pierce et al. (2024).

4.4 A Tale of High Versus Low Human Capital Labor Markets

Our finding that in response to the China shock, firms reorganize away from manufacturing towards services, especially in professional services, management, and wholesale (Tables 4 and 5), and that these service job gains tend to be in higher-wage establishments (Table 6) suggest that job reallocation has occurred disproportionately in local labor markets with relatively high human capital and therefore more highly paid workers. To evaluate this conjecture, we approximate human capital by college education and sort CZs according to whether their share of population with a college degree in 1990 is above or below the (population-weighted) median. In addition, motivated by Gagliardi et al. (2023)'s finding that for local labor markets with low human capital, the manufacturing share of employment at its peak negatively predicts subsequent employment growth, we further split the CZs with below median share of college-educated population into whether their 1990 share of manufacturing employment is above or below the (population-weighted) median. This yields a three way split: high-human capital, low-human capital and high-manufacturing and low-human capital and low manufacturing CZs.[23]

The resulting group with high human capital (HHC) contains 143 CZs, the group with low human capital and low manufacturing share (LHC-LMS) contains 254 CZs, and the group with low human capital and high manufacturing share (LHC-HMS) contains 325 CZs. As shown in Figure 3 in the Appendix, the HHC areas are located primarily on the coasts and around major cities. In contrast, the LHC-LMS areas are located primarily in the Mountain and West Central states (Montana to Texas) while the LHC-HMS areas are concentrated in the Midwest and South (an area

[23] We refrain from dividing the CZs with above-median human capital into low and high manufacturing share subgroups because this would present disclosure and sample size issues.

of the U.S. often called the Heartland) as well as the parts of the Pacific West. As shown in Table A.3 in Appendix A.6, the growth in exposure to Chinese import penetration is on average about twice as large in LHC-HMS areas as in LHC-LMS and HHC areas (0.134 versus 0.055, respectively 0.079), whereas employment growth is on average only about one third as large in LHC-HMS areas as in LHC-LMS and HH areas (0.538 versus 1.539, respectively 1.523).

When we re-estimate the baseline employment regressions in (4) separately for each of the three groups, we find large differences in the local labor market responses to the China shock. Table 7 reports the results for the HHC (West coast and cities) group and the LHC-HMS (Heartland) group, together with p-values for a test of equal coefficients (the estimates for the LHC-LMS group look similar to the HHC group but are surrounded by considerably more uncertainty).[24] Interestingly, as shown in column 1, the effect of local exposure to Chinese import penetration on manufacturing job growth is estimated to be more negative in HHC areas (-15.8 with t-statistic of -2.23) than in LHC-HMS areas (-5.67 with t-statistic of -2.41). For services job growth in column 2, by contrast, the estimated effect is much more positive for HHC areas (11.06 with t-statistic of 3.11) than for LHC-LMS areas (2.62 with t-statistic of 2.02), and the estimates are significantly different from each other. As a result, the rate of job reallocation from manufacturing to services is substantially higher in HHC areas and the larger positive services effect more than offsets the larger negative manufacturing effect, implying a positive effect on total CZ employment that is statistically significant (6.74 with a t-statistic of 2.09). In contrast, in LHC-HMS areas, the estimated effect on total CZ employment is close to zero and insignificant (0.6 with a t-statistic of 0.51).

As shown in Table A.5 in the Appendix, the larger negative effect of the China shock on manufacturing jobs and the larger positive effect on services jobs in HHC areas versus LHC-HMS areas is primarily due to within-firm reallocation. Industry switching out of manufacturing occurs almost exclusively in HHC areas, accounting for half of the larger negative effect on manufacturing jobs in HHC areas. The rest is due to *continuing firms* in HHC areas shutting down more manufacturing plants and opening fewer new manufacturing plants, whereas in LHC-HMS areas manufacturing job losses are primarily driven by firm death and job destruction at continuing plants. In turn, the

[24] We defer the results for the LHC-LMS group (the 250 CZs that are both low human capital and low manufacturing share) to Table A.4 in the Appendix. The signs of the coefficients have the same pattern as those in Table 8, but none of the coefficients are significant. Essentially, because the manufacturing base and human capital are both low in these CZs, there is less exposure to the shock and no high skill employment base that reallocates toward services.

larger positive effect on services jobs in HHC areas occurs in large part because of expansion by existing firms (net job creation at continuing establishments and openings of new establishments) and fewer job losses due to firm death. Together, these results point to an important role of local human capital for within-firm reallocation from manufacturing to services and why HHC areas see significantly more business dynamism in response to the China shock.[25]

To understand how the China shock impacts total CZ employment across these two groups of CZs, we need to take into account that the manufacturing share of employment in HHC areas is, on average, substantially lower than in LHC-HMS areas.[26] Columns 3 and 4 of Table 7 therefore reports the estimates of local exposure to the China shock on the decomposition of total CZ job growth into manufacturing and services. As with the sector-specific growth rates, the difference in estimated effects for services is statistically different across the two areas and large (2.15 versus 9.43), whereas the difference in estimated effects for manufacturing is not statistically different and much smaller in magnitude (-1.55 versus -2.69), reflecting the difference in manufacturing shares of employment. The sum of the two estimates equals the effect on total CZ employment. As shown in column 5, this effect is more than ten times larger in HHC areas than in LHC-HMS areas (6.74 versus 0.60).

When comparing these differential employment effects, it is also important to note that the LHC-HMS areas were, on average, exposed to import penetration shocks that are almost twice as large as in HHC areas (as shown in Table A.4, the average annual shocks was 0.134 in LHC-HMS areas and 0.079 in HHC areas). To interpret the economic significance of these employment effects across the two areas, we focus again on the contributions of manufacturing and services job growth relative to total CZ jobs in columns 3 and 4 of Table 7 and compute the employment effect implied by the average import penetration shock in each of the areas. For both LHC-HMS and HHC areas, the resulting negative employment effect from manufacturing is about -0.21 percent per year on average ($= -1.55 \times 0.134$ for LHC-HMS areas and $= -2.67 \times 0.079$ for HHC areas). In contrast, for LHC-HMS areas, the positive employment effect from services is only about 0.29 percent per year on average ($= 2.15 \times 0.134$), barely offsetting the negative effect from manufacturing, while for

[25] 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.

[26] Over the 1997-2007 period, the average manufacturing share of employment is 13.1% in HHC areas and 22.4% in LHC-HMS areas. See Table A.4 in the Appendix for details.

HHC areas, the positive employment effect from services is about 0.74 percent per year on average ($= 9.43 \times 0.079$), implying a positive overall effect of 0.53 percent per year. Our estimates thus imply that the China shock accounts for about half of the 1 percentage points difference in mean annual job growth between LHS-HMS and HHC areas.

5 The Role of Measurement

As discussed in Section 4, our results differ from those in Autor et al. (2013), Acemoglu et al. (2016) or Autor et al. (2021), who like us report a negative impact of local exposure to Chinese import penetration on manufacturing employment, but do not find a positive impact on local services employment, and therefore a net negative impact on total CZ employment. Here, we connect their results to ours and highlight the importance of measurement. Our objective is to demonstrate, using this particular application, how differences in results can arise as a function of a researcher's choice to use public use survey data and administrative aggregates versus confidential microdata.

Row (1) of Table 8 shows the estimates reported in Autor et al. (2013).[27] These estimates are based on the same instrumental variables regression of (4), including the same controls except for employment growth pre-trends (which is not important for the difference in result). Relative to our baseline, Autor et al. (2013) define industry import penetration as thousands of dollars in increased imports from China per U.S. worker and use SIC-based employment shares constructed from the publicly available CBP to apportion industry-level import penetration to CZs. Furthermore, they estimate their regressions over two stacked intervals, 1990-2000 and 2000-2007. We instead define import penetration as the change in Chinese imports relative to domestic absorption, use NAICS-based employment shares to apportion the industry shocks to CZs, and estimate our regressions over Economic Census years, in particular 1997-2007 (although as shown in Appendix A, results are robust to other Census year intervals).

In what follows, we show that these differences in measuring local exposure to the China shock account for essentially all of the differences between Autor et al. (2013)'s results and our results.

[27] 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 published version. 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. We return to results for changes in the employment-population ratios below in Section 5.2.

Then we consider how our results change depending on whether local employment is measured by jobs (as is typically the case in administrative data such as the LBD) or resident work status (as is typically the case in household survey data). While this choice is unimportant for Autor et al. (2013)'s results, it turns out to matter with our specification of local China shock exposure, implying potentially interesting lessons for changes in commuting patterns.

5.1 Local China Shock Exposure

Before investigating the importance of differences in measuring local China shock exposure, we point out two drawbacks with using local-industry employment shares from the CBP instead of constructing them from the LBD establishment-level data. First, due to data confidentiality rules, some of the local-industry employment counts in the CBP are only available as an interval. The resulting imputation of actual values may result in substantial measurement error. Second, CBP industry aggregates are only available in NAICS after 1997.[28] For the 2000-2007 interval, Autor et al. (2013) therefore need to concord NAICS industry-CZ employment counts to SIC employment counts. As described and illustrated in Appendix B, building this concordance is not obvious because many of the NAICS industries do not uniquely map into SIC industries.[29]

To assess the quantitative importance of these measurement and concordance issues, we replicate Autor et al. (2013)'s construction of local China shock exposure with actual industry-CZ job counts from the LBD, all translated from NAICS to SIC at the establishment level based on Fort and Klimek (2018)'s codes. Perhaps surprisingly, the resulting estimates are very similar to the ones obtained by Autor et al. (2013). As shown in row (2) of Table 8, the estimate for the negative effect of local exposure to Chinese import penetration on manufacturing employment is slightly more negative while the effects on service employment and total CZ employment remain negative and insignificant. This implies that the difference between Autor et al. (2013)'s results and ours is indeed due to some combination of (i) how industries are classified and therefore how industry import penetration is apportioned to local labor markets, (ii) the definition of import penetration at the industry level, and (iii) the time interval over which import penetration is computed. We

[28]Even though NAICS-based industry codes were collected in the 1997 Economic Census, the public-use CBP data for 1997 reports employment on a SIC-basis because the production release was scheduled before the updated codes were available.

[29]See https://www.ddorn.net/data.htm for details of Autor et al. (2013)'s concordance.

now systematically investigate each of these differences.

Row (3) of Table 8 shows the consequence of changing the SIC industry classification that Autor et al. (2013) use to our NAICS 1997 classification. Relative to row (2), the negative estimate for local manufacturing employment is attenuated by about one fourth, although the estimate remains highly significant, and the negative coefficient for local service employment attenuates to nearly zero. This difference in estimates occurs for two reasons. First, some manufacturing industries are recoded into the service sector by the 1997 introduction of NAICS and vice versa. Since import penetration and therefore the apportioning of these shocks to local labor markets is defined for manufacturing only, this affects the scope of the China shock. However, the effect of this change is minor as only a small amount of employment and imports from China are recoded. Second and more importantly, while many NAICS codes map one-to-one into SIC codes, others combine old SIC sub-sectors or split codes into multiple new NAICS codes. To illustrate this issue, Appendix B provides descriptive statistics on SIC versus NAICS-based trade flows and the result of using NAICS-based employment shares to apportion industry import penetration to local labor markets. We show that in some key sectors, for instance in electronic equipment and circuits where technology advanced rapidly, the mapping between SIC and NAICS is many-to-many in Chinese import data. As a result, the allocation of import flows to industries is different on a NAICS basis compared to a SIC basis. Subsequently, this affects how the industry import penetration is apportioned to CZs.

Row (4) changes the definition of industry import penetration from imports per worker that Autor et al. (2013) use to imports over domestic absorption that has been adopted widely in more recent studies, including Autor et al. (2014), Acemoglu et al. (2016) and Autor et al. (2021).[30] This change results in a more negative estimate for local manufacturing employment while the estimate for local service employment turns positive and the estimate on total CZ employment remains negative. Note, however, that these latter estimates are not significantly different from zero and that the larger magnitude of the different estimates is due to the smaller variation in the import penetration measure based on domestic absorption and in fact implies a somewhat smaller total CZ effect.

Row (5) keeps the regression specification of row (4), but changes the time intervals 1990-2000

[30] Specifically, Autor et al. (2013) define industry import penetration as $\Delta IPW_{i\tau} = \frac{\Delta M^{cu}_{i\tau}}{L_{it}}$, whereas we follow most of the literature and define industry definition as $\Delta IP_{i\tau} = \frac{\Delta M^{cu}_{i\tau}}{Y_{it}+M_{it}-EX_{it}}$ where i denotes industry, t the base year, and τ the subsequent years over which industry penetration is computed.

and 2000-2007 used by Autor et al. (2013) to the three five-year differences 1992-1997, 1997-2002 and 2002-2007 that are aligned with the Economic Census years when data in the LBD and the CBP are of the highest quality. This change cuts the negative effect on manufacturing employment down somewhat while the positive effect on services employment remains about the same. As a result, the total CZ effect turns positive although this estimate is surrounded by a lot of uncertainty.

Row (6) changes to our baseline long-difference 1997-2007, which covers the main time period of the China shock while staying aligned with Economic Census years. This change results in a further drop of the estimated effect on manufacturing employment whereas the estimated effect on services employment more than triples and becomes significant, resulting in large positive total CZ effect that is significant as well.

Row (7), finally, shows our baseline estimates from Table 2 that include employment growth pre-trends. As discussed above, adding these pre-trends is important to address potential concerns about local differences in job trends that are unrelated yet correlated with local exposure to the China shock. Indeed, adding these pre-trends generally renders the effect on manufacturing jobs somewhat more negative and reduces the positive effect on services employment and total CZ employment by about one quarter. The estimate on services employment remains highly significant while the estimate on total CZ employment becomes insignificant at the usual confidence levels.

The results in rows (3) through (6) illustrate that how and over what time interval the local China shock is measured matters importantly. In Appendix B, we discuss this further by showing the relation between Autor et al. (2013)'s local shock measures and our shock measures across several time periods. Moving away from year 2000 as the starting year of the main China shock has a major impact, while our estimates remain robust and in some instances even become stronger when using shorter time intervals from 97-02 and 02-07 or longer 15-year time intervals from 1997-2012.

A priori, neither of the measurement choices that Autor et al. (2013) or we make is necessarily right or wrong. In the current context, however, our choices appear more natural. As we describe above, industry classifications of economic activity in the U.S. and elsewhere have been based on NAICS from 1997 onward, and NAICS represents a conceptual improvement over SIC (Walker and Murphy, 2001). Dividing Chinese imports by domestic absorption scales the shock relative to the size of the domestic market rather than number of workers. As such it measures the change in the market share of imports from China relative to domestic expenditure, which may not be proportional to the number of workers across sub-sectors. Finally, moving away from year 2000 as the start year towards 1997 is preferable both because 1997 aligns with an Economic Census year when data quality is highest and because it helps capture potential anticipatory effects of China's WTO accession, especially with respect to trade-related services. Of course, researchers with different questions and different underlying public-use or administrative data could justify different choices, and some of the differences we highlight in Table 9 may be inconsequential for other types of shocks (e.g. different countries with different industry compositions of trade). Appendix B provides several examples of diagnostics researchers could check before performing significant data construction exercises or when comparing results across methods of measurement and apportionment to labor markets.

5.2 Job Location versus Worker Residence Location

As mentioned above, another difference to Autor et al. (2013) is that we measure CZ employment outcomes from the LBD, which is based on the location of the job whereas Autor et al. (2013) measure CZ employment outcomes from Census household survey data, which is based on the residence of the worker. As seen by our replication of Autor et al. (2013)'s estimates with SIC-based LBD data in row(2) of Table 8, this difference does not affect their results. Likewise, Autor et al. (2014), Acemoglu et al. (2016) and Autor et al. (2021), which all use Autor et al. (2013)'s local China shock but adopt a jobs-based concept of employment outcomes, find similar results as Autor et al. (2013).

As a final exercise, we investigate whether our baseline estimates are equally robust to using a residential concept of employment instead of a jobs-based concept. To do so we construct CZ employment outcomes from the Local Area Unemployment Statistics (LAUS), which are derived primarily from household survey data from the Current Population Survey (CPS) and the American Community Survey (ACS) that associates the labor market status of respondents to their place of residence.[31] One advantage of using LAUS is that it provides us not only with information on employment but also with information on unemployment and not-in-the-labor-force (NILF). For each of these three variables, we compute the change in the rate relative to CZ civilian working age population and regress these changes on our baseline 1997-2007 local China shock measure, using

[31] Details of how these survey data are combined to estimate state and county level employment measures can be found at the BLS webpage for LAUS at https://www.bls.gov/opub/hom/lau/home.htm (accessed July 19, 2024).

the same instrumental variable strategy and controls as above.

Table 9 reports the results and adds as a comparison the estimate for the change in the employment-population ratio computed with the jobs-based employment measure from the LBD. As shown by columns (1) through (3), we find consistent with the results in Autor et al. (2013) that local exposure to Chinese import penetration is associated with an increase in both the rate of unemployment and the rate of non-participation but a decrease in the rate of employment of residents.[32] As shown by column (4), in contrast, local China shock exposure is associated with an increase in the ratio of jobs to population as measured from the LBD (although as for jobs growth in Table 2, this estimate is small and surrounded by considerable uncertainty). As shown by column (5), finally, when we subtract this LBD-based employment estimate from the LAUS-based employment estimate in column (3), we find a large and significant difference.

Aside from the residence versus job location difference, there are two other reasons why the LAUS-based employment estimate may differ from the LBD-based estimate. First, the LBD captures the *number of jobs* in a location, which may react more to the China shock than the *number of employed workers* because of an increase in multiple part-time job holdings. While interesting, this is unlikely to be the major source of the discrepancy in estimates since average earnings per job react positively to the China shock (see Table A.2 in the Appendix).

Second, the LBD excludes self-employment as well as government and agricultural employment whereas they are included in LAUS. However, the local employment growth differences from this inclusion in LAUS are too small to be of first order importance.

This leaves the resident-based employment concept in LAUS versus the job-based employment concept in the LBD as the most likely explanation for the difference in estimates. This is suggestive of disproportionate increase in commuting from areas outside of CZs that are relatively heavily exposed to Chinese import competition; e.g., West Coast CZs such as San Jose or Los Angeles, which receive a relatively large weight in the regressions (see Table B.2 in the Appendix for a ranking of large CZs with the heaviest exposure to the China shock). Indeed, when we estimate the regression in Table 9 separately for HHC and LHC-HMS areas, we find that the difference in estimated employment effect from LAUS versus LBD is accounted entirely by HHC areas, which

[32] Since the civilian population (Pop) can be decomposed into employed (E), unemployment (U) and not-in-the labor force (N), we have by definition that $E/Pop + U/Pop + N/Pop = 1$. Hence, the regression coefficients for the change in these three ratios sum to zero.

are disproportionally coastal cities with large changes in commuting patterns.

We believe that this difference in results is interesting and worthy of further investigation. More generally, the results suggest that researchers should proceed with caution when using survey data measures on employment to estimate differences by demographic categories such as age, sex, and race at the local level. This may be especially important when choosing data sources to quantify the effects of policies for specific demographic groups or locations.

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. We use disaggregated, establishment-level microdata from the U.S. Census to analyze job creation and destruction margins of local labor markets. We find that the impact of Chinese import competition on U.S. manufacturing had a striking variation in the contribution of job growth margins. Much of the apparent job losses in manufacturing are at continuing firms and establishments that switch from primarily manufacturing activity to services that are related to manufacturing. The effects of the shock differ across firm characteristics such as size, activity across sectors, and average wages. They also vary by initial human capital endowments.

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 firms we find these Chinese trade manufacturing job losses came mainly from large firms 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 globalization suggested in the theoretical literature (Acemoglu, 2003; Thoenig and Verdier, 2003).

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 reallocation was driven in large part by within-firm reorganization and was much more pronounced in local labor markets with relatively high human capital, resulting in a net positive effect on total jobs. In local labor markets with relatively low human capital and large manufacturing dependence, by contrast, job gains in services did not outweigh manufacturing job losses. The China shock therefore created winners and losers, not just across workers within local labor markets as documented for instance by Autor et al. (2014) and Pierce et al. (2024) but also across regions by reallocating jobs from the U.S. industrial heartland to the coasts and large cities, thereby contributing to the rise in regional inequality (Moretti, 2012).

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A Appendix Data Construction and Robustness

This Appendix describes how we construct time-consistent local-industry employment aggregates, and industry imports and domestic absorption. As explained in Section 3, these measures are then used to construct employment growth and the different decomposition terms at the CZ-industry levels (equations 1 and 2), the local import penetration shock (equation 3) and its instrument (equation 5). We then include several additional sets of results, robustness checks, and figures referenced in the main text.

A.1 Local-Industry Employment Aggregates

We build employment counts at the CZ-industry level from the ground up, using establishment-level information from the LBD. Each establishment record in the LBD has a unique time-invariant identifier (LBDNUM) and provides for each year among other information an employment count, a location code, and an industry code (see Jarmin and Miranda, 2002 for a description of the LBD). The U.S. Census Bureau determines industry codes from multiple sources. When 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 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. 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.

An important challenge with constructing time-consistent local-industry aggregates from data provided by U.S. statistical agencies is that industry classification systems change over time, most importantly from SIC 1987 to NAICS 1997 but also across different vintages of SIC and NAICS. Furthermore, establishments in the LBD may change industry classification independent of system changes for a variety of reasons: incomplete codes, errors, or legitimate changes due to change in primary activity of the establishment.

In an impressive data effort, Fort and Klimek (2018) use longitudinal information from the Economic Censuses (when the quality of reporting is higher) to correct for incomplete or erroneous industry classification in the LBD and then construct concordances between the various SIC and NAICS vintages, exploiting various sources of information including that for several Economic Censuses, each establishment record contains different industry codes (for instance, the 1997 Economic Census contains SIC 1987 codes as well as NAICS 1997 codes). See Fort and Klimek (2018) for further details.

The result is a time-consistent 6-digit NAICS code for each establishment that is supposed to change only when the establishment experiences a legitimate change in primary activity. We use these "FK codes" in our construction of local-industry employment aggregates as well the different decomposition terms, including industry switching.

While using NAICS instead of SIC represents a departure from the China shock literature based on Autor et al. (2013), we believe this change is warranted because of the availability of time-consistent FK codes and, perhaps more importantly, because NAICS provides a consistent classification methodology across industries that is based on the productive activity of an establishment and that reflects changes in the industry characteristics of the U.S. economy. SIC, in contrast, classifies establishment based on a mix of concepts, including both production and demand-based definitions. In addition, SIC focuses disproportionally on the manufacturing sector and was last revised in 1987. It therefore does not adequately classify various industries that have emerged over time and have grown in importance.[33] Since our analysis is about how Chinese import competition from the late 1990s onward impacted U.S. labor markets and job reallocation, using NAICS instead of SIC therefore seems the natural choice.

A.2 Industry Import Flows

All trade flows are sourced from the UN Comtrade database, which provides imports and exports by country pairs at the 6-digit level of the Harmonized System (HS). To allocate these flows to 6-digit NAICS industry codes (which map many-to-many at the HS6 level) we follow the same procedure as Autor et al. (2013) for their HS6-to-SIC4 concordance. First, we take the crosswalk from Pierce and Schott (2012), as updated in 2017 on Peter Schott's webpage, which uniquely maps 10-digit HS codes to 6-digit NAICS codes. We then us data on U.S. imports from all countries, which are

[33] See Office of Management and Budget (2022, 1997), Office of Management and Budget (2022)and Walker and Murphy (2001) for more details on the development of NAICS relative to SIC and its main classification principles.

available from the USITC at the 10-digit HS code level, average these imports over 1995-2005 to reduce the influence of shocks to any particular product or country, and aggregate them to the HS6 level. This provides us with a trade-weighted HS6-to-NAICS6 concordance.

Second, we use the Comtrade HS6-level imports by the U.S. from China together with this HS6-to-NAICS6 concordance to construct Chinese imports at the NAICS6 level. We proceed similarly to construct Chinese imports at by the other countries used in the instrument (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland).

Alternatively, for the U.S., we could have used directly the HS10-to-NAICS6 concordance from Pierce and Schott (2012). We could also have created the HS6-to-NAICS6 concordance by only keeping the largest trade-weighted HS10 code within a HS6 group for each NAICS6 code; or we could have used only Chinese imports to construct the weights. None of these alternative choices would have made a big difference.

A.3 Domestic Absorption and Deflator

For domestic absorption at the NAICS6 level (the denominator in our definition of import penetration), we use output from the NBER-CES Manufacturing Industry database (version 5818v1_n1997), and imports and exports from the Comtrade data using the trade-weighted HS6-to-NAICS6 concordance described above.

To deflate the different trade flows and outputs, we use the PCE deflator and index everything to 2007 US$.

A.4 Robustness of Baseline Estimation Results to Different Specifications

Table A.1 reports instrumental variable estimates of the long difference regression in (4) for different time periods, with employment growth pre-trends (Panel A) and without pre-trends (Panel B). When several time periods are included, the different cross-sections are stacked and estimated with a separate time intercept for each time period, as in Autor et al. (2013) and Acemoglu et al. (2016).

For the stacked 5-year periods 1992-1997 / 1997-2002 / 2002-2007 (row 1) and 1997-2002 / 2002-2007 (row 2), we find a very similar estimate for manufacturing employment and a somewhat smaller estimate for services employment as for our baseline specification (row 3). For the 15-year period 1997-2012 (row 4), we find a larger negative estimate for manufacturing employment and again a somewhat smaller estimate for services employment. Nonetheless, the estimate for services employment is significant at the 5% level and the estimate on total employment remains positive for all specifications.[34]

As discussed in the main text, we prefer the 1997-2007 period as our baseline because we want to focus on the main period of the China shock (2000 to 2010) while starting and ending the estimation in Census years (1997, 2007) when industry affiliation of establishments in the LBD is most accurate. Starting in 1997 has the additional advantage that we include potential anticipatory effects of China's accession to the WTO, while ending in 2007 reduces the risk that we confound the effects of the China shock with the effects of the Great Recession (e.g., areas where exposure to Chinese import penetration was stronger may have been systematically hit harder by the bursting of the housing bubble that led to the Great Recession and disproportionally affected employment, especially services employment).

Also note that adding employment growth pre-trends generally increases the estimates for manufacturing employment and reduces the estimates for services employment, but overall these differences are small and well within standard confidence intervals. To remain conservative about the reallocative effects of the China shock, all estimates reported in the main text include pre-trends.

A.5 Estimation Results for Payroll and Average Earnings Growth

Table A.2 reports instrumental variable estimates of the long difference regression in (4) with either the growth rate of worker payroll or average earnings per worker as the left-hand side variable. Both variables are constructed by summing over all establishments in the sector (manufacturing or services) and CZ, and computing growth rates as the annualized log difference between 1997 and 2007. The regressions include the same CZ controls and pre-trends as for the employment regressions in the main text. Hence, the coefficient estimates of log payroll growth can be decomposed into the sum of the coefficients of average earnings growth and (log) employment growth.[35]

For manufacturing, we find a negative effect of the China shock on total payroll growth (column

[34] In earlier versions of the paper, we also estimated specifications over all 5-year periods from 1991-2014 (i.e., 19 sets of 5-year stacked differences spanning 24 years of data). Our results, especially with regards to the positive effect on services employment, remained robust. Results are available upon request.

[35] Log employment growth rates are highly correlated across CZs with with the employment growth rates computed as in (1) that we use for the regressions in the main text. Hence, the estimates for log employment growth are very similar although not exactly the same as the estimates reported in Table 1.

1) and a positive, marginally significant effect on average earnings growth (column 2). These opposite effects reflect that employment declined faster than payrolls in response to the China shock, which suggests that the job losses were on average higher for low wage manufacturing workers.

For services, the estimate on payroll growth is positive and significant (column 3), and the estimate on average earnings grow is also positive but not significant (column 4). Thus, in the services sector, earnings increase marginally in response to the shock because payrolls increase faster than employment. This suggests that the service jobs created as a consequence of the China shock were on average higher paying. As noted in the main text, our data does not allow us to know whether these newly created jobs went to workers who lost manufacturing jobs and if so, whether these new service jobs are paid better than the previous manufacturing jobs. See Pierce et al. (2024) for results on this point.

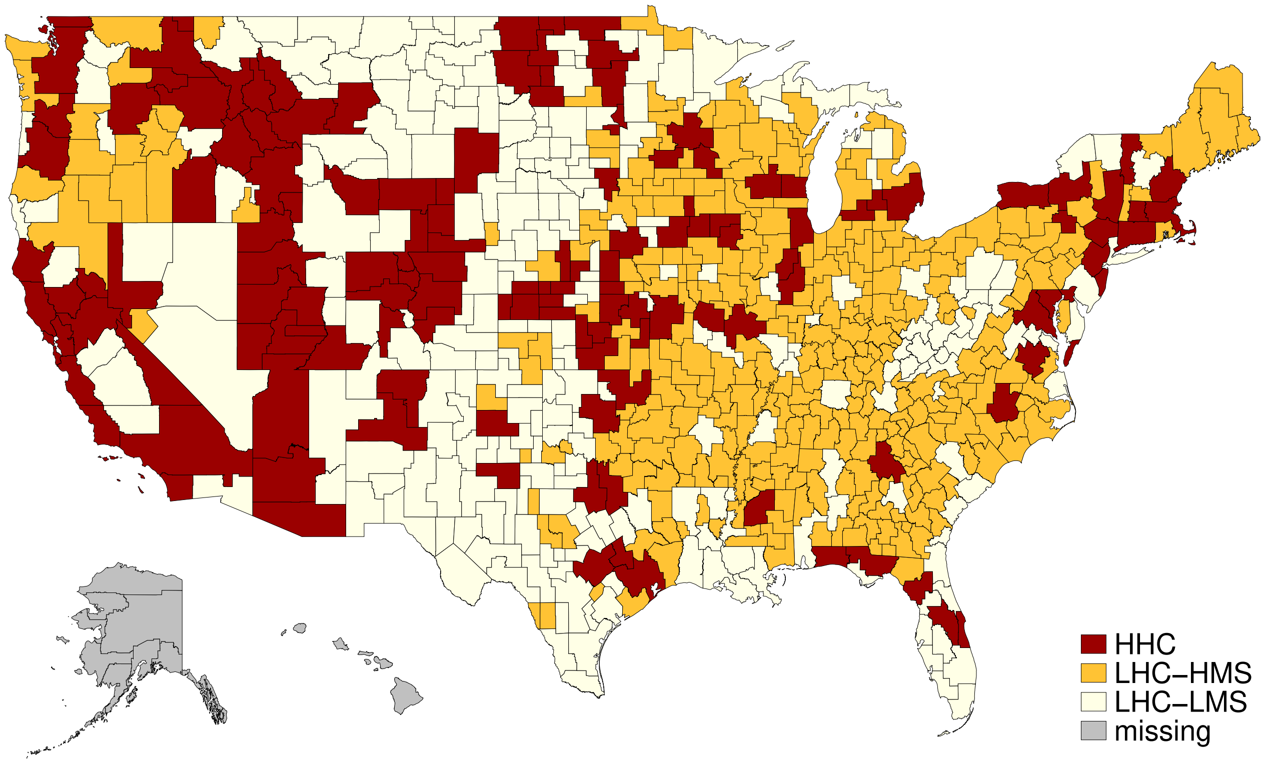
Columns 5 and 6, finally, show that payrolls and average earnings both increase at the aggregate CZ level as well. This is because the service sector is, on average, several times larger than the manufacturing sector.

A.6 High versus Low Human Capital Labor Markets

Figure 3 shows a map of CZs by initial human capital and initial manufacturing share. As described in the main text, we approximate human capital by college education and sort CZs according to whether their share of population with a college degree in 1990 is above or below the (population-weighted) median. We then further split the CZs with below median share of college-educated population into whether their 1990 share of manufacturing employment is above or below the (population-weighted) median. This yields a three way split: high-human capital, low-human capital and high-manufacturing and low-human capital and low manufacturing CZs.[36]

[36] We refrain from dividing the CZs with above-median human capital into low and high manufacturing share subgroups because this would present disclosure and sample size issues.

Figure 3: Commuting Zones by Human Capital and Manufacturing Share



Notes: This map shows Commuting Zones (CZs) by initial Human Capital endowment and Manufacturing share. HHC denotes the CZs with 1990 share of college-educated population above the population-weighted median. LHC-HMS denotes the CZs with 1990 share of college-educated population above the population-weighted median that have a 1990 share of manufacturing employment above the population-weighted median. LHC-LMS denotes the CZs with 1990 share of college-educated population above the population-weighted median that have a 1990 share of manufacturing employment below the population-weighted median. Data on share of college-educated population and share of manufacturing employment are taken from the replication files of Autor et al. (2013). See their paper for details on the data.

The HHC CZs areas are located primarily on the coasts and around major cities. In contrast, the LHC-LMS CZs are located primarily in the Mountain and West Central states while the LHC-HMS CZs are concentrated in the Midwest and South as well as the parts of the Pacific West. In HHC and LHC-LMS CZs, the average

Table A.3 shows summary statistics for the three groups of CZs. Exposure to Chinese import penetration in LHC-HMS areas is on average about twice as large as in LHC-LMS and HHC areas (0.134 versus 0.055, respectively 0.079), reflecting that the average manufacturing share over 1997-2007 is about 22% in LHC-HMS CZs versus 10% in LHC-LMS CZs and 13% in HHC CZs. In other words, LHC-LMS and HHC labor markets are simply not as exposed to the China shock as LHC-LMS labor markets. In contrast, total employment growth is much weaker in LHC-HMS areas than in LHC-LMS and HHC areas. This is primarily because of weaker growth services employment and to a lesser extent because of larger declines in manufacturing employment (which account for a relative small share of total employment).

Table A.4 repeats the regression estimates for LHC-HMS CZs (Panel A) and HHC CZs (Panel C) from Table 7 of the main text and, for completeness, shows the estimates for LHC-LMS CZs (Panel B). For manufacturing employment, the estimated effect of China shock exposure for LHC-LMS CZs resembles the estimated effect for HHC CZs whereas for services employment, the estimated effect for LHC-LMS CZs resembles the estimated effect of LHC-HMS CZs. As a result the estimated effect on total employment for LHC-LMS CZs remains small. All of these estimates are surrounded by considerable uncertainty.

Table A.5, finally, reports the regression estimates for the manufacturing and services employment growth decomposition terms of LHC-HMS CZs and HHC CZs. As shown in part (a) of the table and discussed in the main text, the effect of local exposure to the China shock on manufacturing employment is larger in HHC CZs than in LHC-HMS. In terms of implied job losses relative to total jobs, however, this negative effect is on average about the same across the two groups because in LHC-HMS CZs, the average local China shock is much larger and manufacturing employment accounts for a larger share of total jobs.

The two CZs also differ strikingly in terms of the extent of firm reorganization induced by the China shock. Essentially all of the industry switching of establishments from manufacturing to services occurs in HHC CZs, accounting for half of the difference in negative manufacturing employment effect between HHC CZs and LHC-HMS CZs. The other half of the larger negative manufacturing employment effect in HHC CZs is due to continuing firms opening fewer new establishments and closing more existing establishments. This implies that the negative manufacturing effect in HHC CZs is almost entirely due to within-firm reorganization as opposed to firm death. In LHC-HMS, by contrast, the negative manufacturing employment effect is in large part driven by downsizing of continuing establishments and firm death.

As shown in part (b) of Table A.5, there are also large differences in the positive effects of services employment across the two groups. More than half of the much larger positive employment effect of local exposure to the China shock in HHC CZs is due to firms creating more jobs in continuing establishments, firms opening new establishments, and establishments switching from manufacturing to services. In addition, almost once third of the larger positive employment effect comes from fewer services firms dying. In LHC-HMS CZs, by contrast, the positive effects on service employment from firm reorganization are much smaller. Again, this shows that within-firm reorganization is an important driver of the disparate local labor market effects of the China shock.

B Appendix on Understanding Differences in Data Choices For Import Shock Measures

As discussed in Section 5, Autor et al. (2013) use SIC codes to allocate import flows to industries, define import penetration at the industry level as the change in Chinese imports per worker, and focus on the periods 1990-2000 and 2000-2007. In contrast, we use NAICS codes to allocate import flows to industries, define import penetration at the industry level as the change in imports from China divided by domestic absorption, and focus on the period 1997-2007.

In this part of the Appendix, we study the consequences of these data choices for measuring local exposure to Chinese import penetration (henceforth called local IP shocks). We start by illustrating differences in SIC versus NAICS affects how Chinese imports at the individual goods level are allocated to industries and ultimately apportioned to CZ. Then we discuss how the definition of industry IP and the time interval over which IP is constructed can lead, conceptually, to similar differences. Finally, we provide quantitative evidence on how these choices result in different rankings and magnitudes of local IP shocks across CZs and connect these differences to the estimation results in the main text.

B.1 Allocation of Import Flows to SIC versus NAICS Industry Codes

As described in Appendix A, trade flows for the U.S. are reported at 10-digit HS code level. To build local IP shocks for CZs c, as defined in equation (3) and repeated here for convenience

$$\Delta IP_{c\tau} = \sum_{i \in M} \frac{L_{ict}}{L_{ct}} \Delta IP_{i\tau}, \tag{7}$$

these flows are allocated to industries i, using either a HS6-to-NAICS6 or a HS6-to-SIC4 concordance. The issue is that trade flows, specifically imports from China to the U.S., do not generally map one-to-one from SIC to NAICS.

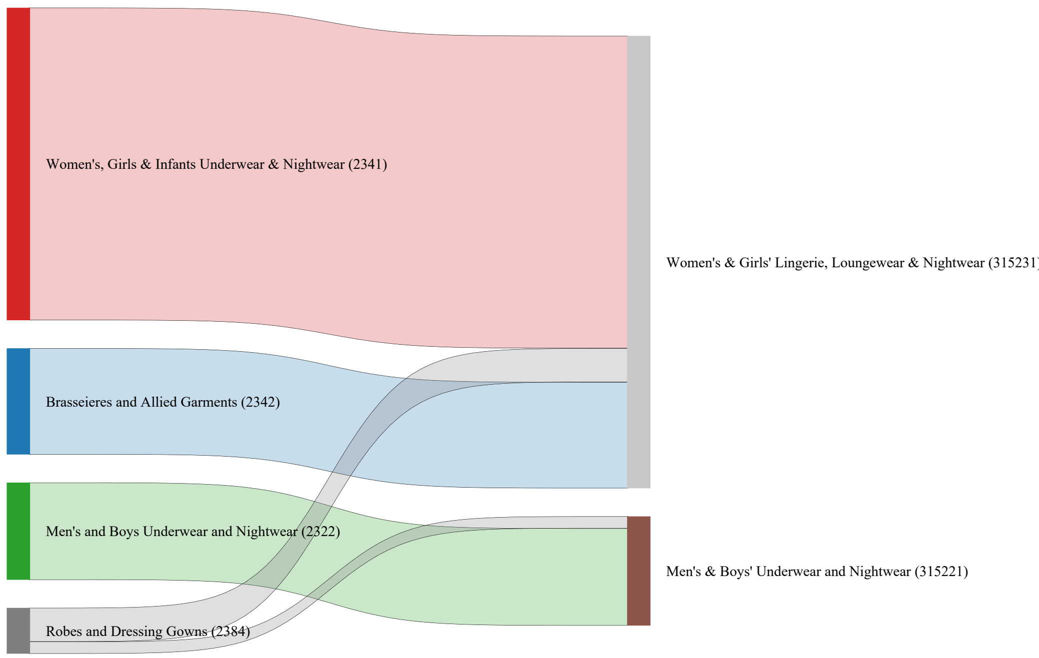
To show this, we exploit the fact that for 1997, the USITC provides unique 4-digit SIC 1987 and 6-digit NAICS 1997 codes for each of the 10-digit commodity codes. There are 9,047 10-digit commodity codes, 418 NAICS codes, and 413 SIC codes with positive imports from China in 1997. Note that for different country trade flows and different time periods these statistics and the analysis that follows would be different.

One can consistently aggregate the Chinese imports up to SIC or NAICS, but we instead aggregate them up by SIC-NAICS *pairs* to obtain a trade flow based link between SIC and NAICS codes. There are 505 unique SIC-NAICS pairs with positive imports from China in 1997, which is almost 20% more than the number of unique SIC or NAICS codes. 222 of these pairs are one-to-one-matches, 20 pairs are many-to-one, and 21 pairs are one-to-many. These matches account for 48% of trade by value in 1997 and do not present a serious problem translating back and forth between SIC and NAICS. But the other 242 SIC-NAICS pairs, accounting for 52% of trade by value, are all many-to-many. For those cases, the allocation of trade flows to industries and therefore the apportioning of the resulting industry IP measures to CZs may differ substantially depending on whether industries are classified by SIC or NAICS.

As a simple example, consider two CZs $c \in [x, z]$ and three manufacturing goods $m \in [1, 2, 3]$. Suppose that according to SIC, the three goods are allocated to two industries $i \in [a, b]$ as follows: $1 \rightarrow a$, $2 \rightarrow b$ and $3 \rightarrow b$; and according to NAICS, the three goods are instead allocated to two industries $i \in [A, B]$ as follows: $1 \rightarrow A$, $2 \rightarrow A$ and $3 \rightarrow B$. In other words, SIC a and b map many-to-many to NAICS A and B. Suppose further that CZ x only produces good 1 whereas CZ z only produces good 3, and that the China shock leads to a disproportionate increase in imports of good 2 (the one that neither CZ produces). Hence, $\Delta IP_{a\tau} < \Delta IP_{b\tau}$ according to SIC and $\Delta IP_{A\tau} > \Delta IP_{B\tau}$ according to NAICS. But then, since good 2 is allocated to SIC b together with good 3 (which CZ z produces) and to NAICS A together with good 1 (that CZ x produces), it will be the case that CZ x will be less exposed to the China shock than CZ z according SIC (i.e., $\Delta IP_{x\tau} < \Delta IP_{z\tau}$) but more exposed according to NAICS (i.e., $\Delta IP_{x\tau} > \Delta IP_{z\tau}$).

The extent to which such changes in ordering (and magnitude) of CZ exposure occur is a quantitative question that is difficult to analyze systematically. Instead, we consider here two cases of industries that were heavily affected by Chinese import competition and for which the relationship between SIC and NAICS is many-to-many.

Figure B1: Women's and Men's Undergarments—SIC to NAICS transition for 1997 import values

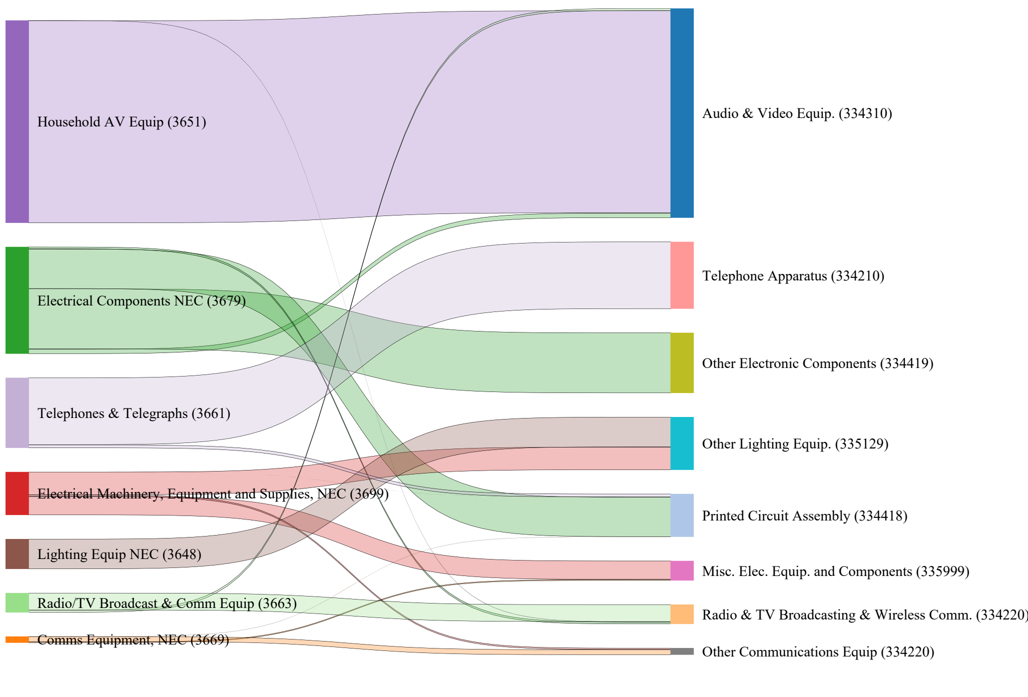


Notes: Left axis codes are on a SIC 1987 basis. Right axis codes are on a NAICS 1997 basis. Flows between codes aggregate the value U.S. of imports on a 10 digit basis to SIC or NAICS industry codes. Bars scaled relative to total value of $418 million in imports. Import data downloaded from USITC at 10 digit level and concorded to SIC and NAICS using USITC Commodity Translation Wizard for Imports.

In Figure B1 we show a collection of imports for women's and men's undergarments, robes, brassieres and nightwear that are consolidated from 4 SIC codes to 2 NAICS codes. The codes account for $418 million in total imports in 1997 and the bars for each code are scaled in relative dollars of imports. Many of these items were subject to quotas that were gradually removed in the 2000s and were the subject of a major trade dispute between China and Europe. Import flows for the last two industry codes are partially crossed between SIC and NAICS. This is likely to result in differences in local IP shocks, although in this particular case, the differences are likely to be modest since the value of imports that are crossing between SIC and NAICS is relatively small.

In Figure B2 we show a collection of industry codes for electronics, audiovisual equipment, and communications equipment that sum to over $8 billion in imports in 1997. Here the visualization looks like a tangle of fettuccine noodles even though we omitted graphing SIC sectors with less than $100 million in imports. This figure highlights an important issue with SIC codes last revised in 1987. Certain catch-all codes like Electrical Components, Not Elsewhere Classified (NEC), or

Figure B2: Electronic, AV and Communications Equipment—SIC to NAICS transition for 1997 import values



Notes: Left axis codes are on a SIC 1987 basis. Right axis codes are on a NAICS 1997 basis. Flows between codes aggregate the value U.S. of imports on a 10 digit basis to SIC or NAICS industry codes. Bars scaled relative to total value of $8 billion in imports. Flows of less than $100 million omitted from graph. Import data downloaded from USITC at 10 digit level and concorded to SIC and NAICS using USITC Commodity Translation Wizard for Imports.

SIC 3679, capture a large share of new technologies and products by 1997, and thus get split out and merged in the more modern NAICS sectors in 1997. For example, about half of SIC 3679 goes to Printed Circuit Assembly (NAICS 334418), which has its own code as part part of the broader semiconductor sector (NAICS 3344). Only half of the trade flows continue into Other Electronic Component Manufacturing (NAICS 334419), which is close *in name only* to the 1987 SIC source industry. The larger point remains that even if the respective shocks on a SIC or NAICS basis are internally consistent, one cannot be reverse engineered from the other after aggregation. And since the crossing of industries in this example is much more important than in the previous example, the differences in resulting local IP shocks are also likely to be more important.

B.2 Definition of Import Penetration and Time Interval of Shock

Not unlike the allocation of trade flows to SIC versus NAICS industries, the definition of industry import penetration matters for the distribution of industry import penetration. In their original paper, Autor et al. (2013) construct industry import penetration as the change in imports from China to the U.S. over time interval τ divided by initial employment, $\Delta IP_{i\tau}^{ADH2013} = \frac{\Delta M_{i\tau}^{cu}}{L_{it}}$. We instead follow Autor et al. (2014), Acemoglu et al. (2016), Autor et al. (2021) as well as many others and construct industry import penetration as the change in imports from China to the U.S. divided by initial domestic absorption, $\Delta IP_{i\tau}^{BHKL} = \frac{\Delta M_{i\tau}^{cu}}{Y_{it}+M_{it}-EX_{it}}$. For a given industry definition, Autor et al. (2013)'s industry import penetration therefore amounts to reweighing our measure by domestic absorption per worker

$$\Delta IP_{i\tau}^{ADH2013} = \Delta IP_{i\tau}^{BHKL} \times \frac{Y_{it} + M_{it} - EX_{it}}{L_{it}}. \tag{8}$$

Since both domestic absorption per worker and CZ employment shares vary substantially by industry, this results in potentially large differences in ordering and relative magnitude of local IP shocks.

A similar change in the distribution of industry import penetration can occur with different starting and end points of the time interval for which import penetration is computed. Again, this then affects the ordering and relative magnitude of local IP shocks.

B.3 Resulting Differences in Local China Shock Exposure

To quantify the consequences of the different choices, we regress Autor et al. (2013)'s local IP shock measure, denoted $\Delta IP_{c\tau}^{ADH2013}$, on our NAICS-based measure that constructs import penetration as change in imports relative to domestic absorption, denoted $\Delta IP_{c\tau}^{BHKL}$. We do this both for the original 1990-2000 and 2000-2007 time intervals used by Autor et al. (2013) and the 1997-2007 time interval used in our baseline specification.

Table B.1 reports the results. Panel A shows a very close relationship between Autor et al. (2013)'s measure and a SIC-based replication of their measure constructed from our LBD establishment-level data, with R^2s around 0.8. As reported in Table 8, row (2) of the main text, using this measure results in estimates that are very close to the ones obtained by Autor et al. (2013).

Panel B shows the relationship between Autor et al. (2013)'s $\Delta IP_{c\tau}^{ADH2013}$ and our $\Delta IP_{c\tau}^{BHKL}$. While there is still a positive and highly significant relationship between the two measures, the R^2 is substantially lower, around 0.6, independent of the time interval considered. Thus, the local IP shock measures are similar, but there is residual variation between the two that is not just noise and may therefore be systematically related to local labor market outcomes. Also note that the estimated slope coefficients in Panel B are substantially larger than 1, reflecting that for a given industry definition, Autor et al. (2013)'s definition of import penetration equals our definition times domestic absorption per worker (see equation 8 above). The regression coefficients in Panel B therefore equal a weighted mean of domestic absorption per worker across industries and CZs.

To delve deeper into these differences, we compare the geographic distribution of local IP shocks. Due to disclosure restrictions, we are not able to disclose our local IP shocks built from the confidential LBD establishment-level data. We instead rebuild these local IP shocks from the publicly available CBP data using the same methods as Autor et al. (2013) but for NAICS industries instead of SIC industries. Those shocks are thus necessarily an approximation of the LBD-based shocks.

Figure B3 shows a map of Autor et al. (2013)'s local IP shocks for 2000-2007, a map of our local IP shocks based on NAICS industries and domestic absorption for 2000-2007, and a map of the same local IP shocks for 1997-2007. Because the shocks are constructed from different definitions of import penetration, the map shows the bottom 4 quintiles and top 2 deciles of the the respective shock rankings instead of the shock values.

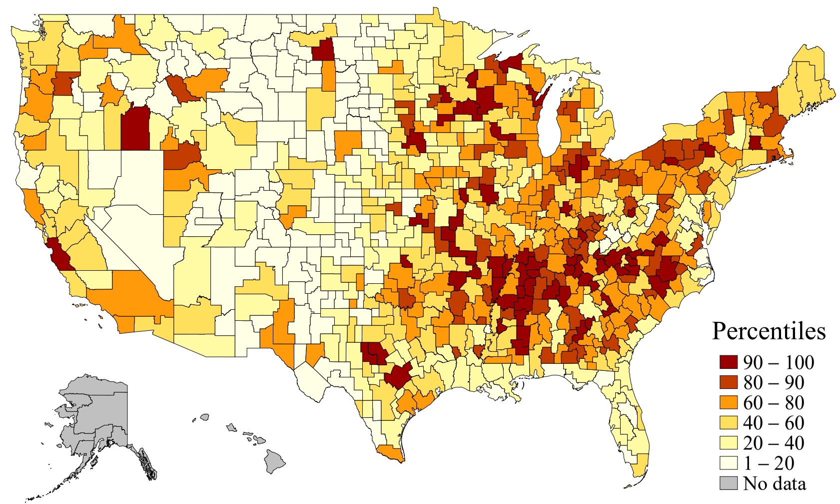
The shocks are not geographically distributed in a dramatically different way, but they are not the same either. To analyze these differences further, Table B.2 ranks the top 10 CZs by local IP shock among the 40 largest CZs by population across the different shock measures and time periods. While somewhat similar, the ranking and relative magnitudes differ in meaningful ways. More generally, for the full set of 722 CZs, the Spearman rank correlation is 0.93 between Autor et al. (2013)'s 2000-2007 measure and our 1997-2007 measure, and the weighted correlation is 0.81.

B.4 Consequences for Local China Shock Estimates

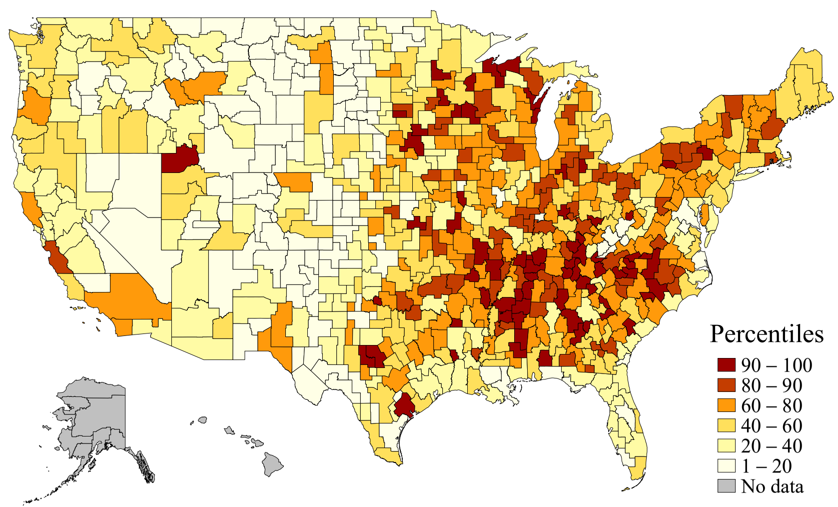
The last question is how these differences in ranking and magnitude of the local IP shocks across CZs affect estimated local labor market effects of the China shock. In essence, we estimate a positive effect on local services employment because our local IP shock measure is on average larger in more

Figure B3: Geography of the China Shock for Different Measurement Units and Industry Coding, 2000-2007

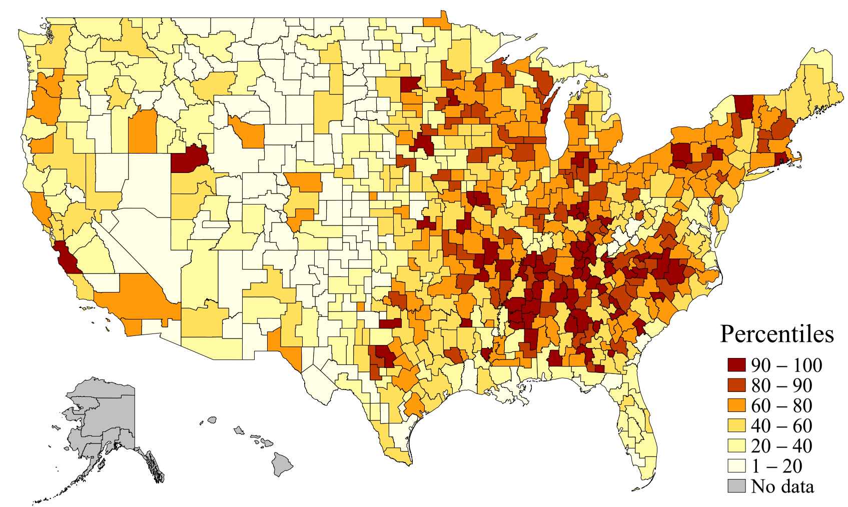
ADH Imports per Worker Shock, SIC Basis (2000-2007)



Import Penetration Shock, NAICS Basis (2000-2007)

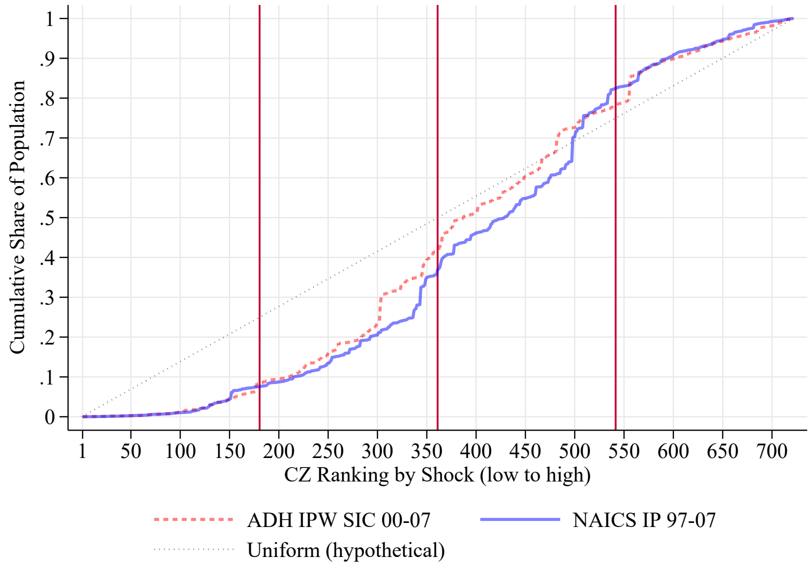


Import Penetration Shock, NAICS Basis (1997-2007)



Notes: The top figure shows Autor et al. (2013)'s local IP shock measure across CZs. The bottom two figures shows our NAICS-based local IP shock measure for 2000-2007 and 1997-20007. Magnitudes of these shocks are difficult to compare because the units differ. The first four quintiles of each shock distribution are the the bottom 4 categories in the map. The top 2 categories are the 9th and 10th deciles of the shock distribution. Data for Autor et al. (2013)'s local IP shock measure are from their replication files. Data for our NAICS-based local IP shock measure are reconstructed from public-use CBP data. Confidential micro-data based measures cannot be disclosed at this level of detail.

Figure B4: Empirical Distribution of Population Regression Weights Across Shock Measures



Notes: Each local IP shock measure is sorted from least exposed CZ (1) to most exposed CZ (722). The 1991 CZ population weights are then cumulated across the ranked CZs. Verticals are at the 25th, 50th, and 75th percentile of the distribution. Population is shifted toward the higher end of the distribution in both measures relative to a uniform distribution (gray dotted line). Data for Autor et al. (2013)'s local IP shock measure are from their replication files. Data for our baseline NAICS local IP shock measure are reconstructed from public-use CBP data. Confidential micro-data based measures cannot be disclosed at this level of detail.

populous CZs that experience stronger services employment growth. To demonstrate this point visually, we rank the local IP shocks from lowest to highest across the 722 CZs using Autor et al. (2013)'s measure from 2000-2007 and our own measure from 1997-2007. In the regressions, each CZ is weighted by its 1991 population. So we cumulate the population weights across the CZs from lowest to highest to generate an empirical distribution of the population weights by local IP shock. Figure B4 shows the result. The distribution of population using our local IP shock measure for 1997-2007 is shifted toward higher shock CZs compared to Autor et al. (2013)'s measure from 2000-2007. We avoid cluttering the figure with multiple lines, but a large part of this shift of the population weights to the right is due to starting in 1997 instead of 2000. The rest is due to NAICS instead of SIC and defining import penetration as change in imports per domestic absorption instead of change in imports per worker, as described above.

Table 1: Summary statistics for baseline sample, 1997-2007

	Mean	Standard deviation	25th percentile	50th percentile	75th percentile
Panel A: *Change in import penetration (annualized, in percent)*					
From China to the U.S.	0.087	0.055	0.055	0.074	0.112
From China to other high-income countries (instrument)	0.101	0.067	0.060	0.084	0.119
Panel B: *Employment growth (annualized, in percent)*					
Manufacturing	-2.153	1.741	-3.144	-2.201	-1.235
Services	1.814	1.022	1.310	1.692	2.488
Total	1.275	1.100	0.630	1.124	1.960

Notes: This table shows the change in import penetration and employment growth across Commuting Zones (CZ) for 1997-2007. Import penetration is computed as 100 x CZ employment-share weighted change in industry imports divided by domestic industry absorption. See text for details. Employment growth is measured as the change in employment divided by average employment over the period. All statistics are weighted by CZ working-age population and annualized. Percentiles represent averages over 11 observations across true percentiles, in accordance with Census disclosure avoidance rules.

Table 2: Manufacturing and Non-Manufacturing Employment Growth Regressions, 1997-2007

IMPORT PENETRATION FROM CHINA AND SECTORAL EMPLOYMENT GROWTH
2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variable: annualized growth rate (in percent)

	Manufacturing Employment	Services Employment	As a share of CZ employment		
			Manufacturing	Services	Total
	(1)	(2)	(3)	(4)	(5)
Annual Δ in local Chinese IP	-6.324**	4.667***	-1.739***	3.914***	2.174
	(3.079)	*(1.630)*	*(0.519)*	*(1.389)*	*(1.560)*
Observations (rounded)	700	700	700	700	700

Notes: The local import penetration (IP) measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 3: Employment Growth Rate Decomposition

	Manufacturing		Services	
	Rate	Share	Rate	Share
Total Net Job Growth	-2.15	100%	1.81	100%
Net JC at continuing establishements	-0.34	16%	0.66	37%
Net Entry	-1.80	84%	1.15	63%
Net Switching	0.01	1%	0.00	0%
Gross Job Creation	3.46		6.64	
Continuing establishments	1.42	41%	1.82	27%
Firm openings of new establishments	0.84	24%	2.16	33%
Firm birth	1.20	35%	2.66	40%
Gross Job Destruction	5.60		4.83	
Continuing establishments	1.76	31%	1.16	24%
Firm closings of establishments	1.24	22%	1.01	21%
Firm death	2.60	46%	2.66	55%
Gross Switching				
Total Switch In	0.27		0.03	
Total Switch Out	0.28		0.03	

Notes: Means are for the 10 year 1997-2007 growth rate decomposition for baseline regression sample and weighted by 1991 CZ population. Shares are relative to total net job creation or gross job creation/destruction. Component of Total Net Job Creation sum to total. Components of Gross measures sum to total. Net JC is Gross JC-Gross JD + Net Switching.

Table 4: Employment Growth Decomposition of the Impact of Chinese Trade

IMPORT PENETRATION FROM CHINA AND SECTORAL EMPLOYMENT GROWTH COMPONENTS

2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variables: annual growth contribution to average sectoral employment

	Net Employment Growth	Continuing Establishments		Establishments Entry		Establishments Exit		Industry switching	
		Job Creation	Job Destruction	Continuing Firms	Firm Birth	Continuing Firms	Firm Death	Switch In from Other Sector	Switch Out to Other Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: *Manufacturing Sector*									
Annual Δ in local Chinese IP	-6.324**	1.128	-0.514	-0.477	0.791	-2.365	-2.336	-0.087	-2.464***
	(3.079)	*(0.943)*	*(1.236)*	*(1.116)*	*(0.786)*	*(1.755)*	*(1.550)*	*(0.302)*	*(0.852)*
Panel B: *Services Sector*									
Annual Δ in local Chinese IP	4.667***	0.946**	1.091***	0.861	0.619	0.284	0.595	0.280***	0.004
	(1.630)	*(0.475)*	*(0.383)*	*(0.704)*	*(0.667)*	*(0.459)*	*(0.601)*	*(0.096)*	*(0.029)*

Notes: The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reorted in parenthesis.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 5: Impact of Chinese Imports on Industry Switching out of Manufacturing

IMPORT PENETRATION FROM CHINA AND CHANGE IN INDUSTRY SWITCHING COMPONENT

2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variables: growth contribution of switching component relative to average CZ manufacturing employment

			Switching into non-manufacturing			
			NAICS 42 (Wholesale)	NAICS 54 (Prof and Tech Services) & 55 (Management)	Other Non-manufacturing	Total Non-manufacturing
			(1)	(2)	(3)	(4)
Switching out of manufacturing	NAICS 31 (Food & Beverage, Textile mills, Apparel, Leather)	(1)	-0.019 *(0.113)*	0.011 *(0.024)*	0.026 *(0.103)*	0.018 *(0.168)*
	NAICS 32 (Wood, Paper, Petro & Coal, Chemicals, Plastics & Rubber, Nonmetallic)	(2)	0.088 *(0.066)*	-0.292 *(0.221)*	-0.042 *(0.108)*	-0.246 *(0.259)*
	NAICS 33 (Metal, Machinery, Computer & Electronics, Electrical, Transportation equm, Furniture)	(3)	0.830*** *(0.211)*	1.742** *(0.724)*	0.119 *(0.115)*	2.691*** *(0.764)*
	Total Manufacturing	(4)	0.900*** *(0.247)*	1.461* *(0.749)*	0.103 *(0.185)*	2.464*** *(0.852)*

Notes: The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis. In each column, the estimates in the first three rows sum to the total estimate in the fourth row. In each row, the estimates in the first three columns sum to the total estimate in the fourth column.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 6: Impact of Chinese Imports by Firm and Establishment Characteristics

IMPORT PENETRATION FROM CHINA AND CHANGE IN SECTORAL EMPLOYMENT GROWTH COMPONENT

2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variables: annual growth contribution to average sectoral employment

Panel A: *Effect on CZ employment growth component in Manufacturing sector*

		Decomposition by Other-sector Activity			**Decomposition by Firm Size**		**Decomposition by Earning per Worker**	
	Manufacturing Employment Growth	Firms Expanding in Services	Firms Contracting in Services	No Presence in Services	Firms with 1000+ Employees	Less than 1000 Employees	Estabs with High Earnings per Worker	Estabs with Low Earnings per Worker
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Annual Δ in China IP	-6.324**	-5.084**	-0.331	-0.909	-3.823	-2.501*	-3.722	-2.602*
	(3.079)	(2.378)	(1.724)	(1.372)	(2.853)	(1.337)	(2.623)	(1.555)

Panel B: *Effect on CZ employment growth component in Services sector*

	Non-manuf. Employment Growth	Expanding in Manuf.	Contracting in Manuf.	No Presence in Manuf.	Firms with 1000+ Employees	Less than 1000 Employees	Estabs with High Earnings per Worker	Estabs with Low Earnings per Worker
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Annual Δ in China IP	4.667***	0.520**	1.288**	2.860**	3.424***	1.244	4.278***	0.390
	(1.630)	(0.247)	(0.502)	(1.430)	(1.014)	(0.962)	(1.070)	(1.004)

Notes: The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 7: Impact of Chinese Imports by Labor Market Characteristics—Human Capital and Initial Manufacturing Base

IMPORT PENETRATION FROM CHINA AND CHANGE IN SECTORAL EMPLOYMENT GROWTH
2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variable: annualized growth rate (in percent)

	Manufacturing Employment	Services Employment	As a share of CZ employment		
			Manufacturing	Services	Total
	(1)	(2)	(3)	(4)	(5)
Panel A: *Low Human Capital–High Manufacturing Share CZs (LHC-HMS, 350 observations rounded)*					
Annual Δ in local Chinese IP	-5.666**	2.612**	-1.548***	2.145**	0.598
	(2.347)	*(1.295)*	*(0.579)*	*(0.999)*	*(1.159)*
Panel B: *High Human Capital CZs (HHC, 150 observations rounded)*					
Annual Δ in local Chinese IP	-15.8**	11.06***	-2.691**	9.434***	6.744**
	(7.087)	*(3.561)*	*(1.130)*	*(3.097)*	*(3.233)*
Test of Equality (p-value)	0.175	0.026	0.368	0.025	0.074

Notes: Low Human Capital–High Manufacturing Share CZs in Panel A denotes the group of commuting zones with a share of college educated population in 1991 below the population-weighted median and a manufacturing employment share in 1990 above the median. High Human Capital CZs in Panel B denotes the group of commuting zones with a share of college educated population in 1991 above the population-weighted median. The estimates for the remaining group of commuting zones with below-median share of college educated and below median manufacturing employment share are reported in the Appendix. The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

** Significant at 10%; ** Significant at 5%; *** Significant at 1%.*

Table 8: Impact of Chinese Imports Across Alternative Shock Measurement, Data Sources, and Sample Frame

IMPORT PENETRATION FROM CHINA AND CHANGE IN EMPLOYMENT
2SLS ESTIMATES AT CZ LEVEL FOR VARIOUS SPECIFICATIONS
Dependent variable: annualized CZ sectoral growth rate

	Manufacturing Employment	Non-Manufacturing Employment	Total Employment
(1) ADH (2013) estimates			
Annual Δ in China Imports Per Worker	-4.231***	-0.274	-1.184[a]
	(1.047)	(0.651)	(0.764)
(2) ADH (2013) replication with LBD micro-data			
Annual Δ in China Imports Per Worker	-5.000***	-0.367	-1.015*
	(1.038)	(0.618)	(0.612)
(3) Consistent NAICS industry coding			
Annual Δ in China Imports Per Worker	-3.836***	-0.033	-0.801
	(0.755)	(0.509)	(0.495)
(4) Import penetration based on domestic absorption			
Annual Δ in China IP	-12.72***	2.073	-1.417
	(2.771)	(1.930)	(1.912)
(5) Census 5-year stacks (1992-97, 1997-2002, 2002-07)			
Annual Δ in China IP	-7.863**	2.110	0.532
	(3.505)	(1.586)	(1.560)
(6) Census 10-year stack (1997-2007)			
Annual Δ in China IP	-5.391*	6.450***	3.917**
	(3.199)	(1.974)	(1.909)
(7) Baseline: Census 10-year stack (1997-2007) and pretrends			
Annual Δ in China IP	-6.324**	4.667***	2.174
	-3.079	(1.630)	(1.560)

Notes: Each stack contains (rounded) 700 CZs. All regressions include the original ADH controls and Census division dummies. In rows (1) to (3), 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 rows (4) to (7), coefficients estimates are weighted by 1991 CZ population (as in Acemoglu et al., 2016) and robust standard errors in parenthesis are clustered at the CZ level. (a) This coefficient is the authors' estimate from ADH replication data archive and does not appear in the original paper.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 9: Impact of Chinese Imports on Alternative Measures of Employment Outcomes

2SLS ESTIMATES OF CHANGE IN CZ LABOR MARKET RATES ON CHANGE IN CZ IP

Dependent variable: Annualized difference in CZ rate relative to population

	Unemp/Pop (LAUS)	NILF/Pop (LAUS)	Emp/Pop (LAUS)	Emp/Pop (LBD)	Difference in LAUS vs LBD Emp/Pop
	(1)	(2)	(3)	(4)	(5)
Annual Δ in China IP	0.426**	1.051	-1.476*	0.195	-1.671**
	(0.195)	(0.781)	(0.846)	(0.639)	(0.767)

Notes: The import penetration measure in each regression is the change in Chinese imports / domestic absorption, apportioned to CZs using NAICS-industry employment shares. Each regression includes the original ADH controls, Census division dummies, and 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

** Significant at 10%; ** Significant at 5%; *** Significant at 1%.*

Table A.1: Robustness of Estimates to Different Time Periods and Pre-trends

IMPORT PENETRATION FROM CHINA AND CHANGE IN EMPLOYMENT

2SLS ESTIMATES AT CZ LEVEL FOR VARIOUS SPECIFICATIONS

Dependent variable: annualized CZ sectoral growth rate

	Panel A. Employment growth pre-trends			Panel B. No pre-trends		
	Manufacturing Employment	Services Employment	Total Employment	Manufacturing Employment	Services Employment	Total Employment
(1) Three 5-year periods 1992-1997, 1997-2002, 2002-2007						
Annual Δ in China IP	-6.322***	2.901**	1.226	-5.561**	3.988**	2.283
	(2.314)	*(1.324)*	*(1.296)*	*(2.353)*	*(1.595)*	*(1.571)*
(2) Two 5-year periods 1997-2002, 2002-2007						
Annual Δ in China IP	-7.164***	3.913**	2.538*	-6.567**	4.843***	3.422*
	(2.627)	*(1.523)*	*(1.446)*	*(2.634)*	*(1.838)*	*(1.754)*
(3) One 10-year period 1997-2007 (baseline)						
Annual Δ in China IP	-6.324**	4.667***	2.174	-5.391*	6.450***	3.917**
	(3.079)	*(1.630)*	*(1.560)*	*(3.199)*	*(1.974)*	*(1.909)*
(4) One 15-year period 1997-2012						
Annual Δ in China IP	-9.642***	3.163**	0.689	-9.640***	4.084**	1.580
	(3.544)	*(1.554)*	*(1.524)*	*(3.680)*	*(1.793)*	*(1.775)*

Notes: The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies. In addition, the regressions in Panel A include 1982-92 manufacturing and services employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis. For the estimations with several stacked time periods in rows (1) and (2), standard errors are clustered at the CZ level.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table A.2: Impact of Chinese Imports on Payroll and Average Earnings per Worker

2SLS ESTIMATES OF CHANGE IN PAYROLL AND AVERAGE EARNINGS OR WORKER ON CHANGE IN CZ IP

Dependent variable: Annualized log growth rate

	One 10-year period 1997-2007 (baseline)						
	Manufacturing		Non-Manufacturing		Total CZ Employment		
	Payrolls	Avg. Earnings	Payrolls	Avg. Earnings	Payrolls	Earnings	Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Annual Δ in China IP	-2.665	3.787*	6.528***	1.822	3.433*	1.247	2.186
	(3.938)	*(2.013)*	*(1.884)*	*(1.504)*	*(1.794)*	*(1.366)*	*(1.569)*

Notes: The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table A.3: Summary statistics for CZs by human capital and initial manufacturing base

	Mean	Standard Deviation	Percentiles 25th	50th	75th
Panel A: *Low Human Capital–High Manufacturing Share CZs (LHC-HMS, 350 observations rounded)*					
Change in IP from China to US	0.134	0.073	0.081	0.117	0.159
Change in IP from China to Other	0.148	0.078	0.091	0.127	0.188
Manufacturing Employment Growth	-2.458	1.708	-3.325	-2.312	-1.391
Services Employment Growth	1.404	0.961	0.848	1.361	1.964
Total Employment Growth	0.538	0.948	0.008	0.588	1.065
Panel B: *Low Human Capital–Low Manufacturing Share CZs (LHC-LMS, 250 observations rounded)*					
Change in IP from China to US	0.055	0.026	0.040	0.058	0.062
Change in IP from China to Other	0.064	0.028	0.046	0.071	0.079
Manufacturing Employment Growth	-2.045	2.180	-3.257	-2.119	-0.953
Services Employment Growth	1.871	1.093	1.308	1.632	2.468
Total Employment Growth	1.539	1.079	0.932	1.234	2.143
Panel C: *High Human Capital CZs (HHC, 150 observations rounded)*					
Change in IP from China to US	0.079	0.036	0.053	0.074	0.096
Change in IP from China to Other	0.096	0.062	0.055	0.095	0.116
Manufacturing Employment Growth	-2.048	1.452	-3.075	-2.285	-1.223
Services Employment Growth	2.001	0.954	1.375	1.904	2.495
Total Employment Growth	1.523	1.011	0.809	1.571	2.156

Notes: Summary statistics for subsamples in Table 7. Percentiles are not exact for disclosure avoidance.

Table A.5: Impact of Chinese Imports by Labor Market Characteristics—Human Capital and Initial Manufacturing Base

IMPORT PENETRATION FROM CHINA AND CHANGE IN SECTORAL EMPLOYMENT GROWTH
2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variable: annualized growth rate (in percent)

	Manufacturing Employment	Non-Manuf. Employment	As a share of CZ employment		
			Manuf.	Non-Manuf.	Total
	(1)	(2)	(3)	(4)	(5)
Panel A: *Low Human Capital–High Manufacturing Share CZs (LHC-HMS, 350 observations rounded)*					
Annual Δ in local Chinese IP	-5.666**	2.612**	-1.548***	2.145**	0.598
	(2.347)	*(1.295)*	*(0.579)*	*(0.999)*	*(1.159)*
Panel B: *Low Human Capital–Low Manufacturing Share CZs (LHC-LMS, 250 observations rounded)*					
Annual Δ in local Chinese IP	-16.7	2.575	-1.726	2.515	0.788
	(11.63)	*(6.403)*	*(1.299)*	*(5.935)*	*(6.429)*
Panel C: *High Human Capital CZs (HHC, 150 observations rounded)*					
	-15.8**	11.06***	-2.691**	9.434***	6.744**
	(7.087)	*(3.561)*	*(1.130)*	*(3.097)*	*(3.233)*

Notes: Low Human Capital–High Manufacturing Share CZs in Panel A denotes the group of commuting zones with a share of college educated population in 1991 below the population-weighted median and a manufacturing employment share in 1990 above the median. Low Human Capital–Low Manufacturing Share CZs in Panel B denotes the group of commuting zones with a share of college educated population in 1991 below the population-weighted median and a manufacturing employment share in 1990 below the median. High Human Capital CZs in Panel C denotes the group of commuting zones with a share of college educated population in 1991 above the population-weighted median. The estimates in Panel A and Panel C are the same as the estimates in Table 7. The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

** Significant at 10%; ** Significant at 5%; *** Significant at 1%.*

Table A.5: Employment Growth Decomposition of the Impact of Chinese Trade

IMPORT PENETRATION FROM CHINA AND CHANGE IN SECTORAL EMPLOYMENT GROWTH COMPONENT

2SLS ESTIMATES AT CZ LEVEL FOR 10-YEAR LONG DIFFERENCE 1997-2007

Dependent variables: annual growth contribution to average sectoral employment

Table A.5(a): Manufacturing Sector

	Net Employment Growth	Continuing Establishments		Establishments Entry		Establishments Exit		Industry switching	
		Job Creation	Job Destruction	Continuing Firms	Firm Birth	Continuing Firms	Firm Death	Switch In from Other Sector	Switch Out to Other Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. *Low Human Capital–High Manufacturing Share CZs (LHC-HMS, 350 observations rounded)*									
Annual Δ in China IP	-5.666**	0.321	-1.714*	-0.655	-0.323	-0.658	-2.142	0.113	-0.608
	(2.347)	*(0.661)*	*(0.961)*	*(1.288)*	*(0.723)*	*(1.436)*	*(1.588)*	*(0.195)*	*(0.489)*
Panel B: *High Human Capital CZs (HHC, 150 observations rounded)*									
Annual Δ in China IP	-15.80**	0.262	0.228	-3.379	-0.379	-6.813*	0.662	-0.916*	-5.468**
	(7.087)	*(2.193)*	*(2.955)*	*(2.626)*	*(1.498)*	*(4.090)*	*(3.076)*	*(0.504)*	*(2.225)*
Test of Equality (p-value)	0.175	0.979	0.532	0.352	0.973	0.156	0.418	0.057	0.033

Table A.5(b): Services Sector

	Net Employment Growth	Continuing Establishments		Establishments Entry		Establishments Exit		Industry switching	
		Job Creation	Job Destruction	Continuing Firms	Firm Birth	Continuing Firms	Firm Death	Switch In from Other Sector	Switch Out to Other Sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A . *Low Human Capital–High Manufacturing Share CZs (LHC-HMS, 350 observations rounded)*									
Annual Δ in China IP	2.612**	0.095	0.948***	0.092	1.158**	0.427	-0.177	0.084	-0.011
	(1.295)	*(0.408)*	*(0.342)*	*(0.655)*	*(0.556)*	*(0.452)*	*(0.545)*	*(0.070)*	*(0.041)*
Panel B: *High Human Capital CZs (HHC, 150 observations rounded)*									
Annual Δ in China IP	11.06***	2.023*	1.731**	3.130**	0.078	0.767	2.783**	0.497***	0.051
	(3.561)	*(1.144)*	*(0.824)*	*(1.524)*	*(1.170)*	*(0.771)*	*(1.303)*	*(0.177)*	*(0.045)*
Test of Equality (p-value)	0.026	0.112	0.380	0.067	0.404	0.704	0.036	0.030	0.313

Notes: The import penetration measure in each regression is the change in Chinese imports / absorption (AADHP), apportioned to CZs using NAICS-based employment weights. Each regression includes the original ADH controls and Census division dummies as well as 1982-92 employment growth share pretrends. Coefficients estimates are weighted by 1991 CZ population. Heteroscedasticity-robust standard errors are reported in parenthesis.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table B.1: Relation between different measures of local exposure to import penetration

RELATION BETWEEN DIFFERENT MEASURES OF LOCAL EXPOSURE TO CHINESE IMPORT PENETRATION

OLS ESTIMATES AT CZ LEVEL

Dependent variable: Autor, Dorn and Hanson's (2013) CZ ΔIP shock

	1990-2000			2000-2007		
	Intercept	Slope	R^2	Intercept	Slope	R^2
Panel A. *CZ ΔIP shock based on SIC industry change in imports per worker*						
1990-2000	-0.01	1.094***	0.827			
	(0.003)	*(0.019)*				
2000-2007				-0.021	1.075***	0.777
				(0.007)	*(0.022)*	
Panel B. *CZ DIP shock based on NAICS industry change in imports per domestic absorption*						
1990-2000	0.02	1.873***	0.596			
	(0.004)	*(0.057)*				
2000-2007				0.035	2.721***	0.607
				(0.008)	*(0.082)*	
1997-2007				0.025	2.749***	0.584
				0.009	*(0.086)*	

Notes: The import penetration measure used as the right-hand side variable in each regression is the change in Chinese imports / domestic absorption, apportioned to CZs using either SIC-based (Panel A) or NAICS-based (Panel B) employment shares constructed from the LBD establishment-level data.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table B.2: Top 10 Ranking by Shock Magnitude for the 40 Most Populous Commuting Zones

	SIC Based Import Per Worker Shock					NAICS Based Import Penetration Shock				
	ADH 1990-2000			ADH 2000-2007			2000-2007			Baseline 1997-2007	
	City	Shock		City	Shock		City	Shock		City	Shock
1	San Jose CA	0.32	1	San Jose CA	0.73	1	Providence RI	0.18	1	San Jose CA	0.26
2	Providence RI	0.26	2	Providence RI	0.50	2	San Jose CA	0.15	2	Providence RI	0.22
3	Buffalo NY	0.22	3	Los Angeles CA	0.36	3	Milwaukee WI	0.12	3	Detroit MI	0.15
4	Boston MA	0.16	4	San Diego CA	0.31	4	Los Angeles CA	0.11	4	Cleveland OH	0.14
5	Portland OR	0.15	5	Portland OR	0.30	5	San Diego CA	0.09	5	Newark NJ	0.14
6	San Diego CA	0.15	6	Pittsburgh PA	0.30	6	Chicago IL	0.09	6	Portland OR	0.14
7	Newark NJ	0.13	7	Chicago IL	0.29	7	Portland OR	0.09	7	Chicago IL	0.13
8	Los Angeles CA	0.13	8	Milwaukee WI	0.29	8	Cleveland OH	0.09	8	Milwaukee WI	0.13
9	Bridgeport CT	0.13	9	Boston MA	0.28	9	Boston MA	0.08	9	Bridgeport CT	0.13
10	Denver CO	0.12	10	Dallas TX	0.28	10	Bridgeport CT	0.08	10	Los Angeles CA	0.13

Notes: We take the 40 largest CZs by population and then rank them by shock magnitude from highest to lowest. ADH shocks are from the replication package. Baseline 1997-2007 is reproduced using public-use CBP. We are unable to disclose detailed tabluations based on the confidential LBD data.