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U.S. Job Flows and the China Shock*

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Abstract

International trade exposure affects job flows along the intensive margin (from expansions and contractions of firms' employment) as well as along the extensive margin (from births and deaths of firms). This paper uses 1992-2011 employment data from U.S. establishments to construct job flows at both the industry and commuting-zone levels, and then estimates the impact of the 'China shock' on each job-flow type. Using the two most influential measures of Chinese exposure, we find that the China shock affects U.S. employment mainly through deaths of establishments. At the commuting-zone level, we find evidence of large job reallocation from the Chinese-competition exposed sector to the nonexposed sector. Moreover, we demonstrate that the job-flow effects of the China shock are fundamentally different from those of a more general adverse shock affecting the U.S. demand for domestic labor.

JEL Classification: F14, F16

Keywords: China shock, import penetration, PNTR status, job flows, local labor markets

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> But for too many of our citizens, a different reality exists... rusted-out factories scattered like tombstones across the landscape of our nation...
>
> President Donald Trump, Inaugural Address, January 20, 2017

1 Introduction

Net employment changes conceal large changes in gross job flows (Davis, Haltiwanger, and Schuh, 1996). Hence, to properly assess the costs and benefits of a shock that affects U.S. labor markets, it is crucial to understand not only the shock's net employment effects but also its impact on gross job creation and destruction.[1] This paper performs an analysis of U.S. gross job flows in response to a shock that has reshaped the international economic order: the fast rise of China as the world's largest trader.

For the U.S. and other countries, the 'China shock' has been found responsible for good and (mostly) bad outcomes such as net job losses (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016), higher innovation (Bloom, Draca, and Van Reenen, 2016), higher rates of drug overdoses and suicides (Pierce and Schott, forthcoming), poor marriage prospects for young men (Autor, Dorn, and Hanson, forthcoming), and political polarization (Autor, Dorn, Hanson, and Majlesi, 2016). The economic, social, and political consequences of the China shock in the U.S. have their roots not only in its net effect on the labor market, but also on the characteristics of its associated job churning process. This paper's epigraph, for example, shows President Trump appealing to his base by reminding them of a particular form of job destruction: plant deaths, which he has repeatedly attributed to trade during his campaign and presidency. Despite their policymaking importance, little attention has been devoted to study the dynamics of gross job flows due to the China shock.[2]

This paper closes this gap by estimating the impact of the China shock on each of the components of U.S. job flows at both the industry and commuting zone levels. We separate gross job creation into its births and expansions components, and gross job destruction into its deaths and contractions components. Moreover, to assess the generality of our results, we perform our analysis using the two most influential measures of the China shock in the recent literature: the increase in Chinese import penetration in the U.S. (from Autor, Dorn, and Hanson, 2013), and the U.S. trade policy change that granted Permanent Normal Trade Relations (PNTR) status to China (from Pierce and Schott, 2016—PS hereafter). To guide our empirical exercise we build on the com-

[1] A shock may have near zero net employment effects but cause at the same time large increases in job creation and destruction (which end up cancelling each other out). More job creation and destruction potentially increase costs of adjustment for firms and workers, but this would be missed by an analysis based on net employment changes.

[2] To our knowledge, the only exception is an earlier version of the paper by Pierce and Schott (2016), whose results are described below.

prehensive work of Acemoglu, Autor, Dorn, Hanson, and Price (2016)—AADHP hereafter—who perform both an industry-level analysis and a local labor markets analysis of the China shock on net employment changes.

Our analysis makes three important and novel contributions. First, we show that Chinese-induced net job destruction in the U.S. is mainly driven by an increase in the rate of job destruction due to deaths of establishments. The implications of the deaths result can range from longer-lasting negative effects in regional and local markets to political candidates effectively exploiting the result for political gain. Second, at the commuting zone level we find evidence of job reallocation from the Chinese-competition-exposed sector to the nonexposed sector. And third, we establish the distinctiveness of the China shock by showing that its effects on gross job flows are fundamentally different from those of a general adverse shock to the U.S. demand for domestic labor.

These results arise from the estimation of specifications with two stacked periods (1992-1999 and either 1999-2007 or 1999-2011), where the dependent variable is a measure of net or gross employment change, and the main regressor is one of the two measures of the China shock (either import exposure or PNTR exposure). For the industry-level analysis, the net dependent variable is the log change in industry employment, while for the local labor markets analysis we instead use sectoral employment-to-population ratios at the commuting zone level. Net employment responses are the result of linear combinations of the four gross job-flow components so that, by construction, linear combinations of the China shock coefficients from the gross job-flow regressions add up to the coefficient from the net change regression; hence, this framework provides a clear-cut estimation of the contribution of each gross job flow on net and total Chinese-induced job reallocation.

The deaths result is robust for both measures of the China shock. It appears at the industry level for the direct effect of the China shock on manufacturing employment, and it appears at the commuting-zone level for the effects of local Chinese exposure on the Chinese-competition-exposed sector. Across specifications, the estimated share of deaths in total Chinese-induced gross job reallocation ranges between 55 and 95 percent. To shed light on the characteristics of dying establishments, we sort them within industries into low, middle, and high productivity terciles based on labor productivity. In line with previous industry-level studies, we find that the lowest tercile is disproportionately more affected by the China shock (its share in death-driven job losses is higher than its share in manufacturing employment); however, in absolute terms the highest tercile accounts for about 40 percent of job destruction by deaths.

In contrast to AADHP, the commuting zone level analysis in this paper finds evidence of Chinese-induced job reallocation from the exposed sector to the nonexposed sector. The nonexposed sector is indirectly affected by the China shock through job reallocation effects and aggregate demand effects. These indirect channels have opposite effects on employment in the nonexposed sector (they cancel each other out), and therefore it is not surprising that previous studies have not found evidence of their existence when looking at net employment changes. This paper is not only able to find statistically significant evidence of *net* job reallocation effects, but by focusing on all the job flow components, it is also able to capture evidence of these counteracting indirect effects.

Highlighting the benefits of looking at gross job flows, we also find evidence of job reallocation *within* the exposed sector; this result is impossible to detect when looking only at net employment responses. Moreover, the large and positive net job reallocation from the exposed sector to the nonexposed nontradable sector happens in spite of a large increase in the latter sector's rate of job destruction by deaths (evidence of aggregate demand effects), which is dominated by an even larger increase in the rate of job creation by births (evidence of job reallocation effects). When using import exposure as the measure of the China shock, the net job creation in the nonexposed sector is as large as the net job destruction in the exposed sector, resulting in an almost neutral net effect of the China shock.

Finally, our local labor markets analysis demonstrates the uniqueness of the gross employment effects of the China shock. Although previous contributions have noted the negative net employments effects of Chinese exposure in the U.S., they cannot establish whether the effects of the China shock on jobs are similar to the effects of a generic adverse shock affecting the U.S. demand for labor. Using a Bartik shock variable at the commuting zone level, which accounts for national changes in labor demand while taking into account regional specialization patterns, we show that the effects of the China shock on gross job flows are fundamentally different from the effects of a generic adverse labor demand shock. While an adverse Bartik shock causes net job destruction mainly through a reduction in the rates of job creation by births and expansions, the net job destruction caused by the China shock is driven by the increase in deaths.

This paper uses the National Establishment Time Series (NETS) database to calculate gross and net job flows. NETS has strengths as well as limitations. Its main advantage is that its license does not impose any confidentiality restrictions and can be used in any computer or location, as opposed to the comparable Census Bureau's Longitudinal Business Database (LBD), which can only be accessed—after a multi-step approval process—in secure Federal Statistical Research Data Center (FSRDC) locations subject to strong confidentiality restrictions and frequent disclosure reviews. The main limitation of NETS is its large degree of stickiness in yearly employment changes, which is a consequence of extensive use of rounding and imputation, especially for small establishments and early years in the survey. By calculating job flows over seven-, eight-, and twelve-year periods, we are confident that our empirical analysis largely avoids the NETS stickiness problem (Neumark, Zhang, and Wall, 2007 verify that using three-year differences avoids most of the problem).

Nevertheless, our comparison between the County Business Patterns (CBP) data of AADHP—which has the same source as the LBD—and NETS shows industry-level correlations for stacked differences in employment and establishment counts that are relatively low (0.695 and 0.331).[3] Moreover, our assessment shows large employment differences between CBP and NETS across different sectors, suggesting important industry-classification discrepancies between them. In light of these data issues, which are likely to reflect the lower quality of NETS when compared to Census's data, the results of this paper should be taken as the first attempt to fully disentangle the effects of the China shock on U.S. job flows and should be validated using the LBD.

In the following, section 2 provides the background for our paper, and section 3 describes our data and provides an overview of the evolution of U.S. job flows. Sections 4 and 5 present our empirical analysis of the impact of Chinese exposure on job flows, starting with the industry-level analysis and then moving to the local labor markets approach. Section 6 concludes.

2 Theoretical and Empirical Background

From an empirical perspective, an analysis based on gross job flows—rather than on net employment changes—provides a more complete picture of the impact of the China shock on U.S. labor markets. Looking only at net employment changes ignores a substantial part of labor market activity, as net changes represent a very small fraction of total gross job reallocation. To illustrate this with the U.S. establishment-level data used in this paper, Figure 1 shows the ratio of three-year net employment changes (gross job creation – gross job destruction) to total gross job reallocation (gross job creation + gross job destruction) for manufacturing, non-manufacturing, and all industries from 1992-1995 to 2009-2012. In absolute value, the averages of these ratios are only 0.16 for manufacturing, 0.17 for non-manufacturing, and 0.15 for all industries, showing a stark contrast between net employment changes and actual job turnover in the U.S. economy.

From a theoretical perspective, our focus on gross job flows is inspired by the mechanisms identified in the seminal models of trade with heterogeneous firms of Bernard, Eaton, Jensen, and Kortum (2003) and Melitz (2003). Behind these models' powerful implications for the effects of trade liberalization on market-share reallocations and aggregate productivity, there are clear-cut predictions for gross job creation and destruction. Bernard, Eaton, Jensen, and Kortum (2003)

[3] For the commuting-zone analysis the CBP-NETS correlations are above 0.82.

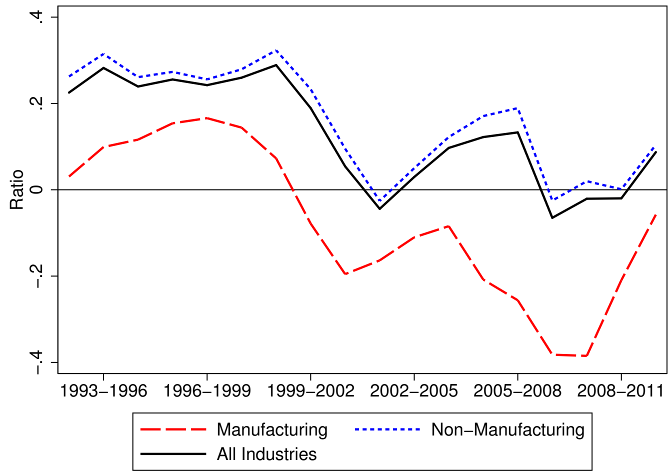


Figure 1: Ratio of U.S. net employment changes to total gross job reallocation (three-year changes)

explicitly address these predictions in a simulation of their Ricardian model: for a 5 percent decline in trade barriers, they obtain an increase of 1.5 percent in the rate of gross job creation (from plants that expand) and an increase of 2.8 percent in the rate of job destruction (from plants that contract or die), for a net employment decline of 1.3 percent. Bernard, Redding, and Schott (2007) tackle the job turnover implications of a Heckscher-Ohlin augmented version of the Melitz model. After trade liberalization, the standard Melitz model predicts gross job creation from expanding exporting firms and new entrants, and gross job destruction from the death and contraction of less productive firms. In their model, Bernard, Redding, and Schott (2007) obtain that the net employment effect is positive in industries in which a country has comparative advantage, and is negative otherwise.

The predictions of the previous heterogeneous-firm models have strong empirical support from several studies using manufacturing plant-level data. For example, Pavcnik (2002) for Chile, Bernard, Jensen, and Schott (2006a) for the U.S., and Eslava, Haltiwanger, Kugler, and Kugler (2013) for Colombia show that trade liberalization induces aggregate productivity gains and an increase in death likelihood, especially for low-productivity plants. Trefler (2004) shows that the U.S.–Canada Free Trade Agreement is associated with productivity gains in import-competing industries, which he attributes to plant exit and market-share reallocation toward high-productivity plants, and calculates a 12 percent decline in employment in those industries. Closer to our paper, Bernard, Jensen, and Schott (2006b) show that exposure to imports from low-wage countries is associated with a fall in employment and lower firm survival, especially for small and low-productivity plants. Relatedly, Groizard, Ranjan, and Rodriguez-Lopez (2015) find that reductions in final-good or input trade costs cause job destruction and a higher death probability for low-productivity establishments.

All of these studies identify plant exit as a prominent consequence of direct import exposure. Similarly, the first part of our empirical analysis looks at the impact of direct Chinese exposure on manufacturing employment and finds that deaths play a major role; our advantage is that we are able to pin down the precise contribution of deaths in total gross job reallocation. Moreover, and in line with the previous studies and the predictions of heterogeneous-firm models, our analysis of job destruction by deaths shows that manufacturing establishments in the low- and mid-productivity terciles are relatively more affected by direct Chinese exposure than establishments in the high-productivity tercile. Nevertheless, in absolute terms the high-productivity tercile—which accounts for 60 percent of employment—is responsible for about 40 percent of job destruction by deaths. The last result can be explained by relocation decisions of multinational firms (as in Bernard and Jensen, 2007), or by large high-productivity plants producing goods that are closer substitutes to Chinese imported goods (as in Holmes and Stevens, 2014).

Our finding that the China shock is mostly felt through plant closings can improve our understanding of the costs associated with this trade. A net employment decline due to an increase in job destruction by deaths of establishments is likely to be more costly than a decline due to a reduction in the rate of expansions or births, or by job loss from contractions. Klein, Schuh, and Triest (2003), for example, refer to the destruction of human capital, and search and relocation costs associated with higher rates of job destruction, as opposed to less pervasive effects of a reduction in the rate of job creation. From a local labor markets point of view, regional economies are likely to suffer more from deaths than from contractions (which tend to be one-off events or cyclical) because closed establishments can more permanently reduce local employment. Herzog and Schlottmann (1995) find, for example, that displaced workers have the lowest reemployment rates in areas that have suffered higher plant closing rates.

At the worker level, the long-run outcome may be better after a death than after a contraction (Stevens, 1997), in part because mass layoffs may reflect firms getting rid of lower-productivity workers first and thus giving a negative signal about the fired workers' quality (Gibbons and Katz, 1991). However, the better prospects after a plant closing than after a contraction are weaker if the closing plants hire more lower-productivity workers in the first place. Along these lines, Abowd, McKinney, and Vilhuber (2009) find that closings are more likely for firms that disproportionately hire workers from the bottom quartile of the human capital distribution.

Browning and Heinesen (2012) find that plant closures are associated with higher mortality and hospitalizations in Denmark, highlighting a possible channel through which the China shock drives an increase in the U.S. mortality rate, as found by Pierce and Schott (forthcoming). Moreover, there is evidence of more adverse effects of plant closings on minorities and women. Black men experience larger earning losses than white men after plant closings (Hu and Taber, 2011), and more women report depression after plant closings than men (Brand, Levy, and Gallo, 2008). Hence, policy makers concerned with less-advantaged workers may worry more about establishment deaths than contractions.

3 The NETS Data and U.S. Job Flows

The NETS database is constructed by Walls and Associates from January snapshots of the Duns Marketing Information file of Dun & Bradstreet (D&B). D&B attempts to cover the universe of U.S. establishments and collects information such as detailed location, employment, sales, industry, first year, and headquarter links. The data collection process is a massive yearly effort involving phone calls, media and news reports, company filings, and Yellow Pages, among other methods. For each establishment (defined in a precise physical location), D&B issues a nine-digit DUNS number, which is unique and never reused.[4] D&B has strong incentives for maintaining high data quality, as its products (such as D&B ratings and Paydex scores) are based on that information. In agreement with D&B, Walls and Associates creates the NETS longitudinal file and verifies the consistency of the entire dataset.

Section A in the Appendix presents a comprehensive discussion about the reliability of NETS.[5] As discussed in the Introduction, the most important limitation of NETS is its extensive use of rounding and imputation. This problem, however, is considerably reduced when calculating job flows over three-year periods rather than shorter periods (Neumark, Zhang, and Wall, 2007), and thus, it should be negligible for the seven-, eight-, and twelve-year periods used in this paper. Moreover, although older versions of D&B data have been criticized regarding their ability to track new establishments, the Appendix discusses several exercises that show that NETS does a very good job in tracking establishment births.

As mentioned before, AADHP use employment data from the County Business Patterns (CBP) of the Census Bureau. The CBP is constructed from the Census Bureau's Business Register (BR)

[4] Every year, D&B contacts an establishment in the last year's location. If not found, it goes to an "out of business" file. Before issuing any new DUNS number, the "out of business" file is checked to make sure the establishment did not exist before. If a new establishment is found by D&B, it is contacted to verify the start date and is assigned a DUNS number. Businesses have a self-interest in obtaining a DUNS Number because it is used in credit reporting, and is required to bid on federal government contracts (see https://www.sba.gov/contracting/getting-started-contractor/get-d-u-n-s-number).

[5] The Appendix is available at http://www.socsci.uci.edu/~jantonio/Papers/jobflows_chinashock_app.pdf.

data, which is the same source used to construct the LBD. Every year NETS reports more employment and higher establishment counts than CBP and LBD as a result of NETS including nonemployer businesses and counting proprietors (and independent contractors) in employment—CBP and LBD only count payroll employees. The Census Bureau also publishes the Nonemployer Statistics (NES) database, which is constructed exclusively from nonemployer businesses. Haltiwanger, Jarmin, and Miranda (2013) mention that the sum of establishments from CBP/LBD data and from NES data yields a larger establishment count than NETS, so that NETS does not comprise the entire universe of U.S. establishments. Barnatchez, Crane, and Decker (2017) show that after excluding establishments with fewer than 10 employees (which almost certainly covers all nonemployer businesses captured by NETS, which typically report only one "employee"), NETS continues to report between 1.33 percent and 4.61 percent more establishments than CBP. Thus, even if NETS does not comprise the universe of establishments, it very likely contains all employer businesses.

To avoid nonemployer businesses as much as possible so that our data is closer in scope to CBP and LBD, we restrict our NETS data to establishments with two or more employees in at least one year from 1992 to 2012.[6] After carefully following AADHP's industry codes, we create a version of the NETS database that matches their industry classification. There are 392 manufacturing industries at the four-digit Standard Industry Classification (SIC) level, and 87 non-manufacturing industries. Across years, our restricted NETS data reports on average about 24 percent more employment than CBP for all industries, and 21 percent more employment for manufacturing industries.[7] For the employment data used in our benchmark specifications, the Appendix shows that the correlation between employment levels in the NETS and CBP is 0.931 at the industry level, and 0.997 at the commuting zone level. For stacked differences in employment (for periods 1992-1999 and 1999-2007), the NETS-CBP correlations are 0.695 at the industry level, and between 0.894 and 0.914 at the commuting zone level. For establishment counts, the NETS-CBP correlations in levels are 0.845 at the industry level and 0.958 at the commuting zone level, while for stacked differences the correlations are 0.331 at the industry level and between 0.821 and 0.852 at the

[6]Similarly, Barnatchez, Crane, and Decker (2017) suggest making NETS more comparable to CBP by excluding one-person establishments and subtracting one employee from every headquarter establishment (to avoid counting proprietors)—a similar rule was proposed by Neumark, Zhang, and Wall (2007). We do not subtract one employee from all headquarter establishments, as this modification does not affect the calculation of job flows. We do exclude the relatively small number of establishments for which county was not conclusively determined.

[7]With the further restriction of subtracting one employee from headquarter establishments, Barnatchez, Crane, and Decker (2017) report between 13 and 19 percent more employment in NETS than in CBP. They also show that most of this difference is accounted for by establishments with fewer than 10 employees or more than 1000 employees. If these are excluded, the difference in employment between NETS and CBP is only between 2.2 percent and 5.0 percent.

commuting zone level.

Although the stacked-differences correlation coefficients between NETS and CBP are high at the commuting zone level, they are relatively low at the industry level. The Appendix shows large differences in employment between NETS and CBP across different sectors, which suggests discrepancies in the classification of industries between the two datasets. Given that NETS data is likely to be of lower quality than Census's data, an important matter for future research is to verify if the results obtained in this paper are confirmed with the LBD.

We calculate job flows from our restricted NETS dataset as follows. Let L_{ijt} denote total employment in commuting zone i, in industry j, at year t. Hence, for any period τ starting in year $t_{\tau,\text{start}}$ and ending in year $t_{\tau,\text{end}}$, it always holds that

$$L_{ijt_{\tau,\text{end}}} - L_{ijt_{\tau,\text{start}}} \equiv \underbrace{(B_{ij\tau} - D_{ij\tau})}_{\text{Extensive margin}} + \underbrace{(E_{ij\tau} - C_{ij\tau})}_{\text{Intensive margin}},$$

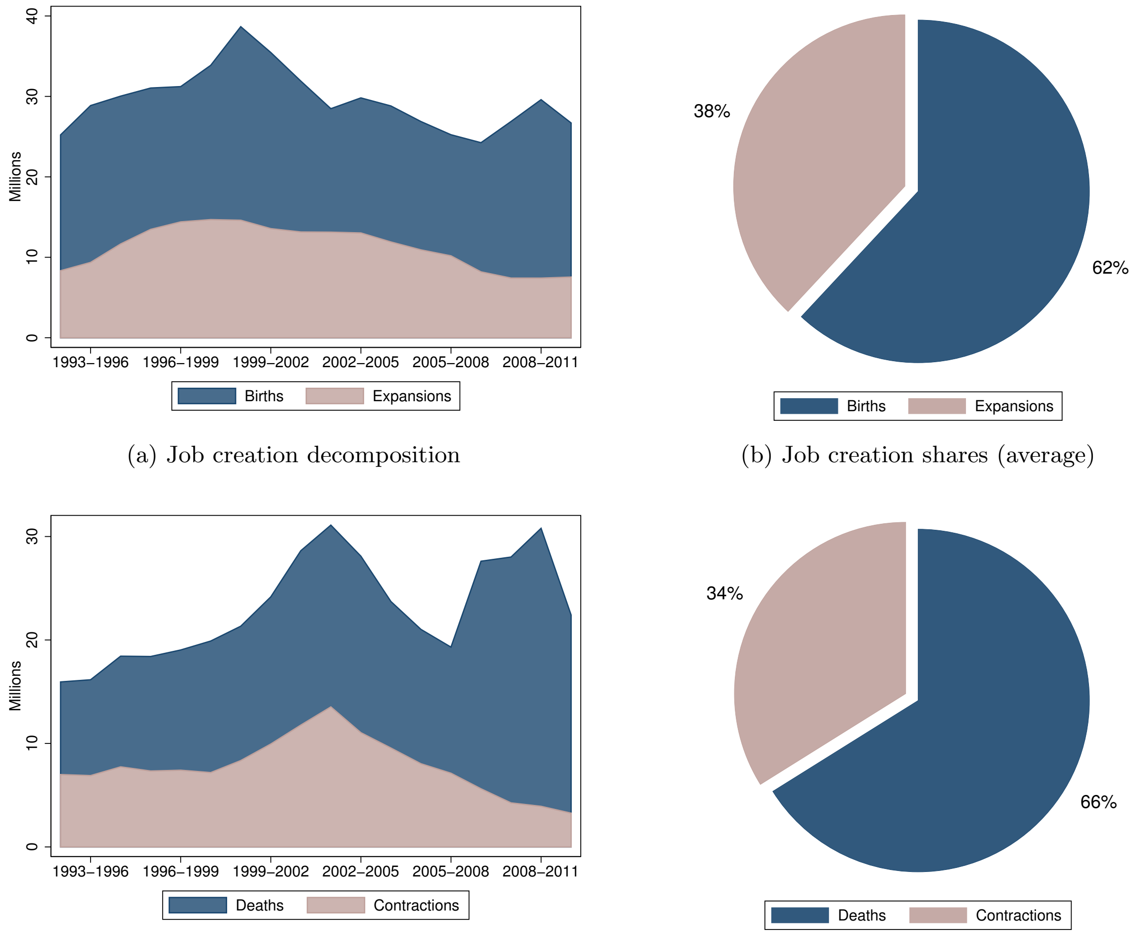
where $L_{ijt_{\tau,\text{end}}} - L_{ijt_{\tau,\text{start}}}$ is the net employment change during period τ, $B_{ij\tau}$ is the employment change due to births of establishments, $D_{ij\tau}$ is the employment change due to deaths of establishments, $E_{ij\tau}$ is the employment change due to expansions of establishments, and $C_{ij\tau}$ is the employment change due to contractions of establishments.[8] The previous identity ignores the *relocation margin* of employment, *i.e.*, move-ins and move-outs of establishments across commuting zones. However, as shown by Neumark, Zhang, and Wall (2006, 2007) using NETS data, the relocation margin is largely insignificant, so we exclude it from the computations to sharpen the focus on the four job-flow drivers described above.[9]

Figure 2 shows four metrics for three-year gross job flows across all industries from 1992 to 2012. The first metric shows job creation due to births and expansions (Figure 2a), the second shows the average share of job creation due each to births and expansions (Figure 2b), the third shows job destruction due to deaths and contractions (Figure 2c), and the fourth and last shows the average share of job destruction due each to deaths and contractions (Figure 2d). Unsurprisingly, given the business cycle, Figure 2a shows a peak for births toward the end of the 1990s, and Figure 2c shows two peaks for deaths around 2001-2004 and 2008-2011. Figures 2b and 2d show that births and deaths dominate the job creation and destruction processes, respectively.

Reinforcing the previous point, Figure 3 shows the evolutions of the net extensive margin of employment (Births − Deaths), the intensive margin of employment (Expansions − Contractions),

[8]After processing the NETS database to obtain employment levels and job flows at the industry-commuting zone level, we can further aggregate job flows at the industry level, or at the commuting zone level.

[9]The NETS dataset reports the first and last year an establishment was in business, irrespective of whether it relocated. We use these variables to report when a firm was born and died, so that a business relocation cannot be confused with a birth or death.



(a) Job creation decomposition

(b) Job creation shares (average)

(c) Job destruction decomposition

(d) Job destruction shares (average)

Figure 2: Employment creation and destruction in all industries (three-year windows)

and overall net job creation. Note that the intensive margin is a source of job creation for the U.S. economy during the entire period (except over 2001-2004), but the extensive margin is the main driver of overall net effects. Section B in the Appendix provides a deeper overview of the evolution of U.S. job flows, looking separately at manufacturing and non-manufacturing industries, and reviewing the relative importance of the extensive margin processes through time.

4 Manufacturing Employment and the China Shock

This section studies the impact of the China shock on job flows in the U.S. manufacturing sector. We start by describing the measures of the China shock used in this paper, then we present our estimation results, discuss their economic significance, and conclude by sorting all manufacturing establishments into labor-productivity terciles (low, middle, and high productivity) to analyze the

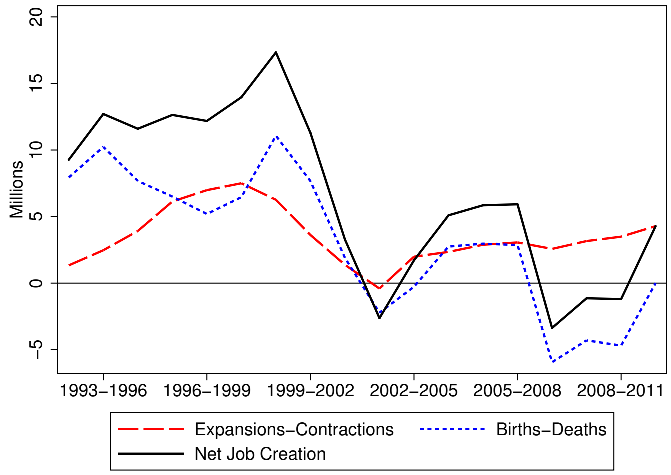


Figure 3: Net employment changes in all industries (three-year windows)

importance of each tercile in the responses of job flows.

4.1 Measures of the China Shock

To assess the generality of our results, we use the two most influential measures that attempt to capture the China shock in the United States: *(i)* the measure of Autor, Dorn, and Hanson (2013) and AADHP, which captures the change in Chinese import penetration, and *(ii)* the measure of Pierce and Schott (2016), which captures the U.S. trade policy change of granting PNTR status to China. Here we describe the construction of the two measures for the 392 manufacturing industries in our dataset.

4.1.1 Chinese Import Exposure

Closely following AADHP, our empirical analysis focuses on three subperiods: 1992-1999, 1999-2007, and 1999-2011. Our specifications below stack either the first two subperiods, or the first and third subperiods. As in AADHP, we use the operator "Δ" to denote the annualized change of a variable times 100. Hence, for any variable X we define its annual change during subperiod τ, ΔX_τ, as

$$\Delta X_\tau = \lambda_\tau \left(X_{t_{\tau,\text{end}}} - X_{t_{\tau,\text{start}}} \right),$$

where $\lambda_\tau = \frac{100}{t_{\tau,\text{end}} - t_{\tau,\text{start}}}$ is the annualizing factor, $t_{\tau,\text{end}}$ is the end-year of subperiod τ, and $t_{\tau,\text{start}}$ is the start-year of subperiod τ. It is always the case that $\tau \in \{1, 2\}$, where subperiod 1 corresponds to 1992-1999, and subperiod 2 corresponds to either 1999-2007 or 1999-2011.

To construct AADHP's measure of *direct* Chinese import exposure for the 392 manufacturing industries, we begin by defining Chinese import penetration in industry j at year t as

$$IP_{jt} = \frac{\mathbb{M}^{C}_{jt}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}},$$

where $\mathbb{M}^{C}_{jt}$ represents real U.S. imports from China of goods from industry j at year t, and $\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}$ is real domestic absorption of U.S. industry j (the industry's real output, plus real imports, less real exports) in 1991.[10] An increase in IP_{jt} over time indicates tougher competition from China, and thus, larger changes in IP_{jt} are related to higher Chinese import exposure. The measure of Chinese import exposure in industry j during subperiod τ—our first measure of the China shock—is then given by the annual change in import penetration, $\Delta IP_{j\tau}$; that is,

$$\Delta IP_{j\tau} = \frac{\Delta\mathbb{M}^{C}_{j\tau}}{\mathbb{Y}_{j91} + \mathbb{M}_{j91} - \mathbb{X}_{j91}}. \tag{1}$$

As in Autor, Dorn, and Hanson (2013), AADHP refer to the China shock as a *Chinese supply shock* to the rest of the world, and thus construct an instrument that attempts to isolate the Chinese supply effects captured by $\Delta IP_{j\tau}$. To get rid of potential U.S. domestic shocks that increase U.S. demand for Chinese imports, AADHP use as an instrumental variable for $\Delta IP_{j\tau}$ the sum of Chinese exports to other high-income countries. In particular, the instrument is defined as $\Delta IP^{*}_{j\tau}$, with

$$IP^{*}_{jt} = \frac{\mathbb{M}^{C*}_{jt}}{\mathbb{Y}_{j88} + \mathbb{M}_{j88} - \mathbb{X}_{j88}},$$

where $\mathbb{M}^{C*}_{jt}$ is the sum of eight high-income countries' real imports from China of goods from industry j at year t, and the denominator is real domestic absorption of U.S. industry j in 1988.

4.1.2 China's PNTR Status

As noted by PS, although U.S. tariffs imposed on Chinese goods were low—at most-preferred-nation levels—since the 1980s, they had to be renewed every year by the U.S. Congress, which created a latent threat for U.S.–China trade. Facing uncertainty of renewal every year, firms in both countries were not willing to engage in long-lasting trade relationships as they would be facing very high tariff rates in case of non-renewal. This year-to-year uncertainty was removed in October 2000, when the U.S. Congress granted PNTR status to China to begin with its accession to the World Trade Organization (WTO) in December 2001.

PS argue that the elimination of the uncertainty would affect U.S.–China trade along several channels, from giving U.S. firms incentives to relocate and invest in China, to encouraging Chinese

[10] Nominal imports and exports data is gathered from the United Nations COMTRADE database, and nominal output is given by the value of shipments from the NBER productivity database. To calculate real values, we follow AADHP and use as deflator the Personal Consumption Expenditure Price Index (PCEPI) of the Bureau of Economic Analysis (BEA).

firms to expand more aggressively in the U.S. market. The key insight of PS was that the latent threat of non-renewal was more serious in industries that were facing a larger potential tariff increase. Hence, the granting of PNTR status to China is likely to have a larger impact on those industries that had a larger *NTR gap*, calculated as the difference between the non-renewal tariff and the Normal Trade Relations (NTR) tariff. Following this insight, PS exploit cross-industry variation in NTR gaps in the manufacturing sector, and show that granting PNTR status to China caused a 15 percent decline in U.S. manufacturing employment by 2007.

In the construction of the NTR gaps for our 392 manufacturing industries, we begin with the NTR gaps provided by PS for Harmonized System (HS) 'families.' PS create these families using an algorithm developed in Pierce and Schott (2012a) which yields time-consistent industry codes that account for the transition from SIC to NAICS in 1997, and the subsequent NAICS revisions in 2002 and 2007.[11] From the HS time-consistent families, we use the concordances provided by PS to map families into SIC codes, taking the average across the (HS) NTR gaps that match each SIC code. Finally, we use the concordance table of Autor, Dorn, and Hanson (2013) that maps four-digit SIC codes to the final AADHP 392 manufacturing industries.

Letting GAP_j denote the NTR gap of industry j, we define the PNTR-status variable in subperiod τ as

$$PNTR_{j\tau} = GAP_j \times \lambda_\tau \times \mathbb{1}\{\tau = 2\}, \tag{2}$$

where $\mathbb{1}\{\tau = 2\}$ is a dummy variable taking the value of 1 for the second period, and is zero otherwise. Hence, $PNTR_{j\tau}$ is zero for every industry during the 1992-1999 period, and equals an annualized version of GAP_j for either 1999-2007 or 1999-2011.[12] The variable $PNTR_{j\tau}$ serves as our second measure of the China shock.

4.2 Specifications and Estimation

The empirical analysis in this section is at the industry level, and thus we aggregate employment and job flows across all commuting zones for each of the 392 manufacturing industries. The specification to study the impact of the China shock on net employment changes in U.S. manufacturing is

$$\Delta \ln L_{j\tau} = \alpha_\tau + \beta S_{j\tau} + \eta Z_j + \varepsilon_{j\tau}, \tag{3}$$

[11] To construct their NTR gaps, PS use non-NTR and NTR tariff rates in 1999, which are obtained at the HS eight-digit level from the tariff database of Feenstra, Romalis, and Schott (2002). They then use their algorithm from Pierce and Schott (2012a) to map HS eight-digit NTR gaps to their time-consistent HS families, and lastly they map these families to their NAICS classification using concordances from the BEA.

[12] We multiply GAP_j times λ_τ for convenience in the scaling of the estimated coefficients in our empirical analysis below. Suppressing λ_τ does not have any impact in the interpretation of the results.

where for industry j during subperiod τ, $\Delta \ln L_{j\tau}$ is the annual change in log employment, and $S_{j\tau}$ is the China shock variable, measured as either $\Delta IP_{j\tau}$ in (1) or $PNTR_{j\tau}$ in (2). The term α_τ denotes a subperiod fixed effect, Z_j is a vector of time-invariant industry-level controls, and $\varepsilon_{j\tau}$ is the error term.

The annual change in industry j's log employment can be split into its job-flow components. In particular, given that the employment change in industry j during subperiod τ is due to establishments' expansions, contractions, births and deaths, we can write $\Delta \ln L_{j\tau}$ as

$$\Delta \ln L_{j\tau} \equiv b_{j\tau} - d_{j\tau} + e_{j\tau} - c_{j\tau},$$

where $b_{j\tau}$ denotes the contribution of births to the industry's log employment change, and the same for deaths ($d_{j\tau}$), expansions ($e_{j\tau}$), and contractions ($c_{j\tau}$). We calculate $b_{j\tau}$ as

$$b_{j\tau} \equiv \lambda_\tau \left(\frac{B_{j\tau}}{\Delta L_{j\tau}}\right) \Delta \ln L_{j\tau},$$

with analogous expressions for $d_{j\tau}$, $e_{j\tau}$, and $c_{j\tau}$.

Thus, for each job flow we estimate

$$F_{j\tau} = \alpha_\tau^F + \beta^F S_{j\tau} + \eta^F Z_j + \varepsilon_{j\tau}^F, \tag{4}$$

where $F_{j\tau} \in \{b_{j\tau}, d_{j\tau}, e_{j\tau}, c_{j\tau}, b_{j\tau} - d_{j\tau}, e_{j\tau} - c_{j\tau}, b_{j\tau} + e_{j\tau}, d_{j\tau} + c_{j\tau}\}$. Note that we also estimate the impact of the China shock on the net extensive margin of employment, $b_{j\tau} - d_{j\tau}$, the net intensive margin of employment, $e_{j\tau} - c_{j\tau}$, gross job creation, $b_{j\tau} + e_{j\tau}$, and gross job destruction, $d_{j\tau} + c_{j\tau}$. By construction, linear combinations of the China-shock coefficients from (4) must be equivalent to the China-shock coefficient from the regression of the log-employment annual change in (3). That is, it must always be the case that

$$\beta \equiv \beta^b - \beta^d + \beta^e - \beta^c \equiv \beta^{b-d} + \beta^{e-c} \equiv \beta^{b+e} - \beta^{d+c}.$$

Table 1 presents our industry-level results for the manufacturing sector. All regressions include 392 manufacturing industries, subperiod fixed effects, and are weighted by 1992 employment, but differ in their China-shock regressor, period coverage, and estimation method. Each estimated coefficient represents the China-shock outcome of a regression, with standard errors clustered at the three-digit SIC level. The first row shows $\hat{\beta}$ from the estimation of (3), while the following rows show $\hat{\beta}^F$ from the estimation of (4), for $F \in \{b, d, e, c, b-d, e-c, b+e, d+c\}$. To provide a comparison with the NETS's net employment results presented in the first row, the last row of coefficients shows the estimation of equation (3) using AADHP's CBP data.

Table 1: Effects of the China Shock on Manufacturing Employment

	Chinese Import Exposure					**PNTR Status**	
	1992-2007	*1992-2007*	*1992-1999*	*1999-2007*	*1992-2011*	*1992-2007*	*1992-2011*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Net employment growth	-0.27**	-0.45***	-0.90*	-0.41**	-0.46***	-0.29***	-0.36***
	(0.11)	(0.16)	(0.51)	(0.16)	(0.17)	(0.09)	(0.13)
Job Flows							
Births	0.01	0.01	0.14	-0.00	-0.01	-0.02	-0.00
	(0.03)	(0.03)	(0.14)	(0.03)	(0.06)	(0.03)	(0.06)
Deaths	0.22***	0.35***	0.89***	0.29***	0.38***	0.22***	0.35***
	(0.07)	(0.11)	(0.32)	(0.10)	(0.11)	(0.05)	(0.09)
Expansions	0.03*	0.01	0.03	0.00	0.02	-0.03	-0.01
	(0.01)	(0.02)	(0.13)	(0.02)	(0.02)	(0.02)	(0.02)
Contractions	0.09	0.12*	0.19*	0.12*	0.09*	0.02	-0.01
	(0.05)	(0.07)	(0.11)	(0.07)	(0.05)	(0.04)	(0.04)
Net extensive margin	-0.21***	-0.34***	-0.74**	-0.29***	-0.39***	-0.24***	-0.35***
	(0.06)	(0.11)	(0.36)	(0.10)	(0.14)	(0.06)	(0.11)
Net intensive margin	-0.06	-0.12	-0.16	-0.11	-0.07	-0.05	-0.01
	(0.06)	(0.08)	(0.21)	(0.08)	(0.06)	(0.05)	(0.06)
Job creation	0.03	0.02	0.18	0.00	0.01	-0.05	-0.02
	(0.03)	(0.04)	(0.21)	(0.04)	(0.07)	(0.04)	(0.06)
Job destruction	0.31***	0.47***	1.08***	0.41***	0.47***	0.24***	0.34***
	(0.11)	(0.15)	(0.37)	(0.14)	(0.13)	(0.08)	(0.10)
CBP data:							
Net employment growth	-0.68***	-1.26***	-2.37*	-1.15***	-1.33***	-0.94***	-1.26***
	(0.18)	(0.40)	(1.37)	(0.35)	(0.44)	(0.20)	(0.27)
Estimation method	OLS	IV	IV	IV	IV	OLS	OLS
Observations	784	784	392	392	784	784	784

Notes: This table reports $\hat{\beta}$ and $\hat{\beta}^F$ from the estimation of equations (3) and (4) for the manufacturing sector (392 industries). Regressions in columns 1, 2, and 5-7 include two subperiods, 1992-1999 and either 1999-2007 or 1999-2011, and regressions in columns 3 and 4 include only the subperiod indicated at the top of the column. All regressions include subperiod fixed effects (not reported) and are weighted by 1992 employment. The net growth regression with CBP data is weighted by 1992 CBP employment and is reported for the purpose of comparison with the net growth regression with NETS data. Standard errors (in parentheses) are clustered at the three-digit industry level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

In Table 1 and throughout the paper, we treat 1992-2007 as our benchmark period because this makes the lengths of our subperiods, 1992-1999 and 1999-2007, more similar (the first subperiod is a seven-year difference and the second is an eight-year difference). This is important when doing a job-flows analysis because longer time periods will generally increase the importance of the extensive margin of employment (births and deaths). This implies that when splitting the 1992-2011 period into a seven-year difference and a twelve-year difference (for the 1999-2011 subperiod), we likely exaggerate the importance of the extensive margin in the second subperiod.[13] Nevertheless, in the estimation of all the specifications in this paper, the main results of the 1992-2007 regressions are always qualitatively similar to those of the 1992-2011 regressions.

Columns 1-5 use Chinese import exposure as the China shock regressor. Columns 1 and 2 use the 1992-2007 period but differ in their estimation method, with column 1 presenting the OLS estimation and column 2 presenting the instrumental variables (IV) estimation. Comparing columns 1 and 2, note that OLS and IV results are very similar in sign and statistical significance, but the IV net growth coefficients using either NETS or CBP data are more than 1.6 times larger than the OLS coefficients. For the rest of the paper, we focus exclusively on IV estimation results when using Chinese import exposure as the China shock regressor. As in AADHP, an increase in Chinese import penetration is associated with net job destruction. The most important result in column 2, however, comes from the analysis of the job-flow coefficients. Note that increases in job destruction by deaths and contractions significantly matter for explaining the effects on net employment growth, but deaths are far more important. On the other hand, the coefficients on births and expansions are very close to zero. Column 5 shows that the results barely change if we expand the second subperiod to include the Great Recession years.

To quantify the importance of establishment deaths due to the China shock, we calculate the estimated share of deaths in total Chinese-induced job reallocation. Denoting the estimated death share with $\hat{\delta}$, we calculate it as

$$\hat{\delta} \equiv \frac{|\hat{\beta}^d|}{|\hat{\beta}^b| + |\hat{\beta}^d| + |\hat{\beta}^e| + |\hat{\beta}^c|}. \tag{5}$$

As shown in the last column of Table 2, which presents predicted job reallocation along each job-flow type for the main specifications in this paper as well as their estimated death shares, the values

[13]Longer time periods may also miss substantial shorter-term job creation and destruction on both the intensive and extensive margins. For example, for the twelve-year difference from 1999 to 2011, expansions and contractions of employment would be calculated only for those establishments that are active in both periods, job flows from deaths would be calculated as the sum of 1999 employment of all the firms that were active in that year but no longer alive in 2011, and job flows due to births would be the sum of 2011 employment of all the firms that are active in that year but that did not exist in 1999. Hence, we would be missing the employment action of the survivors in the middle of the period, but we would also be missing all those firms that were born after 1999 but did not survive to 2011.

Table 2: Predicted U.S. Employment Changes due to the China Shock and the Estimated Death Share

Specification	*Exposure type—Sector*	*Net change*	*Births*	*Deaths*	*Expan.*	*Contr.*	$\hat{\delta}$
A. Chinese import exposure (in thousands of jobs)							
1992-2007:							
Table 1, col. 2	Direct—*Manufacturing*	**-477**	11	**-371**	11	**-127**	0.71
Table 4, col. 1	Local—*Exposed*	**-2,128**	**580**	**-2,167**	329	**-871**	0.55
Table 4, col. 2	*Nonexposed tradable*	198	**-258**	198	**-218**	**476**	0.17
Table 4, col. 3	*Nonexposed nontrad.*	**2,225**	**3,772**	**-2,476**	967	-39	0.34
1992-2011:							
Table 1, col. 5	Direct—*Manufacturing*	**-491**	-11	**-406**	21	**-96**	0.76
Table C.8, col. 1	Local—*Exposed*	**-2,515**	427	**-2,358**	0	**-584**	0.70
Table C.8, col. 2	*Nonexposed tradable*	114	**-297**	**388**	**-320**	**343**	0.29
Table C.8, col. 3	*Nonexposed nontrad.*	**2,222**	**4,285**	**-2,630**	**1,043**	-476	0.31
B. PNTR status (relative change for interquartile shift in the NTR gap)							
1992-2007:							
Table 1, col. 6	Direct—*Manufacturing*	**-0.049**	-0.004	**-0.037**	-0.005	-0.004	0.76
Table 5, col. 1	Local—*Exposed*	**-0.017**	-0.001	**-0.012**	0.001	**-0.004**	0.67
Table 5, col. 2	*Nonexposed tradable*	**-0.003**	0.000	**-0.002**	0.000	-0.001	0.75
Table 5, col. 3	*Nonexposed nontrad.*	**0.012**	**0.018**	**-0.010**	**0.005**	-0.001	0.30
1992-2011:							
Table 1, col. 7	Direct—*Manufacturing*	**-0.061**	-0.001	**-0.059**	-0.002	0.001	0.95
Table C.9, col. 1	Local—*Exposed*	**-0.028**	**-0.005**	**-0.018**	**-0.005**	0.000	0.64
Table C.9, col. 2	*Nonexposed tradable*	**-0.005**	0.000	**-0.004**	-0.001	-0.001	0.67
Table C.9, col. 3	*Nonexposed nontrad.*	**0.020**	**0.024**	**-0.015**	**0.015**	**-0.004**	0.27

Notes: Panel A reports the change in employment attributed to changes in Chinese import exposure for the specifications described in the first column. Negative values indicate that import exposure reduces employment. Equation (6) shows a general formula to calculate predicted employment changes from import-exposure specifications in Table 1, and equation (14) shows the general formula to calculate predicted employment changes from Tables 4 and C.8. For the PNTR-status specifications described in the first column, Panel B reports the relative log change in employment (for Table 1) or the change in the employment-to-population ratio (for Tables 5 and C.9) for an interquartile shift in the NTR gap. The numbers in bold denote predicted changes corresponding to statistically significant coefficients in the corresponding tables. For each specification, the last column shows the estimated share of deaths in total Chinese-induced job reallocation, $\hat{\delta}$, as defined in equation (5).

of $\hat{\delta}$ from columns 2 and 5 of Table 1 are 0.71 and 0.76, respectively. Thus, in the manufacturing sector, deaths of establishments account for more than 70 percent of total job reallocation induced by Chinese import exposure.

Returning to Table 1, columns 3 and 4 separately estimate the impact of Chinese import exposure in each of the subperiods. The same story holds but the magnitudes of the net and death coefficients are more than twice as large when using the 1992-1999 subperiod. This, however, does not imply that there was more Chinese-induced job destruction in the first period, as changes in Chinese import penetration during the 1990s were small compared to changes in the 2000s.

Columns 6 and 7 use PNTR status as the China shock regressor. PS make a strong case for the exogeneity of the PNTR-status regressor; thus, all the PNTR specifications in this paper are estimated by OLS.[14] Notably, the results from columns 6 and 7 are very similar to those obtained using Chinese import exposure. The only difference is that the coefficient on contractions is no longer significant in the PNTR regressions. But the main message remains: deaths of establishments are by far the main driver of Chinese-induced job reallocation in the manufacturing sector, with estimated death shares of 0.76 from column 6 and 0.95 from column 7; see the last column of Table 2, which shows the values of $\hat{\delta}$ for our main PNTR specifications, as well as their implied relative employment changes for interquartile shifts in the NTR gap.

Our PNTR net-employment-growth results are qualitatively similar to those obtained by PS with the Longitudinal Business Database. Moreover, their working paper version includes a brief job flows analysis that splits employment changes into their job creation and job destruction components. For the 2001-2007 period, they find that job destruction accounts for 83 percent of total job reallocation induced by China's PNTR status (see Figure 4 in Pierce and Schott, 2012b). With remarkable similarity, in our case (from column 6 in Table 1) the estimated share of job destruction in total job reallocation is also 83 percent.

As robustness checks, Table C.1 in the Appendix builds on columns 2, 5, 6, and 7 from Table 1 by adding industry-level time-invariant controls proposed by AADHP. These are: *(i)* ten one-digit manufacturing sector dummies (*manufacturing sector controls*), *(ii)* 1991 levels of the share of production workers in total industry employment, the log average wage, and the ratio of capital to value-added, as well as 1990 levels of the share of computer investment in total investment, and the share of high-tech equipment in total investment (*production controls*), *(iii)* 1976-91 changes in the log average wage and in the share of the industry's employment in total U.S. employment (*pretrend controls*), and *(iv)* industry fixed effects. We find that our deaths result is robust to the inclusion of manufacturing sector, production, and pretrend controls, but loses its statistical significance when adding industry fixed effects.

Given that the specifications are already in differences, the results from the industry fixed-effects robustness check suggest important industry-level trends in the NETS data that can be hard to disentangle from the effects of import competition. Given that our main results hold when we include the pretrend controls, we do not think that these latter results undermine our conclusions. Moreover, we believe there are a few reasons the specifications with industry-specific trends may be less informative about the China shock. First, as AADHP suggest, effects within industry

[14] In their robustness checks, PS perform an IV estimation using the non-NTR tariff rates from 1930 as an instrument for the NTR gap, as well as an OLS estimation using 1990 tariffs (instead of the 1999 tariffs). In both cases, their results for the impact of PNTR-status on employment become stronger.

can be weakened by the exacerbation of measurement error within narrow industry cells. Second, weaker within-industry results can reflect other firms in the same industry responding to prior and anticipated import competition, so that it can be particularly hard to identify the timing of the effect of import competition from the within-industry data. Finally, recent work in the minimum wage literature has emphasized that it can be very hard to distinguish between a treatment effect and unit-specific time trends when much of the effect of the treatment is on changes or growth rates, rather than levels (Meer and West, 2016).

Following PS, AAHDP argue that upstream and downstream linkages across industries can increase or decrease the impact of the China shock on U.S. employment.[15] Accordingly, section C.2 in the Appendix extends our industry-level analysis to account for input-output linkages (for which measurement error in NETS may be more problematic). We find that both upstream and downstream exposures to Chinese imports or PNTR status are associated with net job destruction for U.S. establishments. Moreover, job destruction by deaths continues to be the main source of total Chinese-induced job reallocation, with $\hat{\delta}$ ranging between 63 and 98 percent.

4.3 Economic Significance of the Results

Following AADHP and PS, we assess the economic significance of the results by calculating predicted employment changes when using Chinese import exposure as the China shock variable, and relative employment changes for interquartile shifts in the NTR gap when using the PNTR-status measure.[16]

Using the counterfactual formula of Autor, Dorn, and Hanson (2013) and AADHP, we calculate predicted employment changes from the Chinese-import-exposure specifications during the 1992-2007 period as

$$\textit{Predicted employment change}(IP) = \sum_j \left[1 - e^{-\hat{\beta}\rho(IP_{j07} - IP_{j92})}\right] L_{j07}, \tag{6}$$

where $\hat{\beta}$ is the coefficient from the net growth regression in columns 2 or 5 of Table 1, L_{j07} is the

[15] Upstream linkages refer to effects flowing upward from a purchasing industry to a selling industry: if an industry is negatively affected by the China shock, it will decrease its purchases and hence negatively affect providing industries. Hence, it is expected that an increase in upstream Chinese exposure drives down an industry's employment. Downstream linkages, on the other hand, refer to effects flowing downward from a selling industry to a purchasing industry: if an industry contracts due to higher Chinese exposure, purchasing industries have less access to domestic inputs, which may cause them to contract too; however, these displaced domestic inputs may be replaced by cheaper Chinese inputs, which has a countervailing impact on purchasing industries. Thus, an increase in downstream Chinese exposure may decrease or increase an industry's employment.

[16] As pointed out to us by Peter Schott and an anonymous referee, the differences-in-differences approach in the PNTR specifications only allows for the calculation of relative employment changes—and not total predicted employment changes—because all industries are "treated" (all of them have a positive NTR gap and also the PNTR policy might have had an effect on all of them that is not captured by the approach), so that there are no "untreated" industries that serve as point of comparison.

employment in industry j in 2007, and ρ is the partial R–squared from the first-stage regression of $\Delta IP_{j\tau}$ on $\Delta IP^{*}_{j\tau}$.[17] With an analogous formula for the 1992-2011 period, panel A in Table 2 shows predicted net employment changes—as well as the implied contributions from births, deaths, expansions, and contractions—from the specifications in columns 2 and 5 of Table 1. The Chinese-import-exposure specifications predict losses in the U.S. manufacturing sector of 0.48 million jobs during 1992-2007 and 0.49 million jobs during 1992-2011, with deaths accounting for losses of 0.37 million jobs and 0.41 million jobs, respectively.

For the PNTR specifications in Table 1, we calculate the relative log change in employment for an industry-level interquartile shift in the NTR gap as

$$\textit{Predicted interquartile log change in employment} \ = \hat{\beta}(GAP_{75th} - GAP_{25th}), \tag{7}$$

where $\hat{\beta}$ is the coefficient from the net growth regressions in columns 6 or 7 of Table 1, and $GAP_{25th} \equiv 0.23$ and $GAP_{75th} \equiv 0.40$ are the NTR gaps for the industries at the 25th and 75th percentiles of the NTR-gap distribution. Hence, for an interquartile shift in the NTR gap, panel B in Table 2 shows that the policy of granting PNTR status to China is associated with further net employment losses of -0.049 log points up to 2007, and -0.061 log points up to 2011. Deaths of establishments are the main driver of these further losses, accounting for a 0.037 log-point relative decline in employment up to 2007, and for a 0.059 log-point decline up to 2011.

Comparing the net employment growth results from the NETS data in the first row of Table 1 to the net growth results from the CBP data of AADHP in the last row, we see that they are similar in sign and statistical significance but they differ in magnitude. In the Chinese-import-exposure columns, the $\hat{\beta}$'s from CBP are between 2.5 and 2.9 times larger in magnitude than the $\hat{\beta}$'s from NETS. With NETS reporting more employment than CBP, Table C.7 in the Appendix shows that predicted net employment losses from the CBP import-exposure specifications in columns 2 and 5 of Table 1 are between 1.6 and 1.8 times larger than the NETS net losses. This discrepancy may be due to idiosyncratic characteristics of each dataset, or differences in the classification of establishments by industry.

For the PNTR specifications in columns 6 and 7 of Table 1, the CBP net coefficients are between 3.2 and 3.5 times larger than the NETS net coefficients, implying that CBP relative predicted losses for an interquartile shift in the NTR gap are also between 3.2 and 3.5 times larger. For example, up to 2007 the increase in relative job losses for an industry that moves from the 25th to the 75th percentile in the NTR-gap distribution is 0.16 log points when using the CBP data, while it is 0.049

[17] The value of ρ is 0.66 when using NETS data and 0.60 when using CBP data.

log points when using the NETS data. The prediction with NETS data is closer to PS, who use LBD data and find an increase in job losses of 0.08 log points.

4.4 Establishment-Level Productivity and the China Shock

With deaths playing the key role in Chinese-induced employment dynamics in the manufacturing sector, it is important to learn more about the dying establishments' characteristics. Are they low-productivity or high-productivity establishments? To shed light on this matter, we sort establishments within an industry into labor-productivity terciles (low, middle, and high productivity) and then we aggregate job flows for each tercile.

Our labor-productivity measure is based on sales per worker, which can be calculated for an establishment in each year it appears in the NETS data.[18] Given that an establishment takes time to realize its productivity—so that it is not appropriate to rank an establishment based on the first year it appears in the data—our within-industry labor-productivity ranking uses the average real sales per worker from all years an establishment appears in the data (we use the PCEPI as deflator). After ranking all establishments within each of the 392 manufacturing industries from the lowest to the highest real sales per worker, we sort them into low-, middle-, and high-productivity terciles (that is, each tercile contains one third of each industry's establishments). The last step simply aggregates industry-level job flows for each tercile.

For the 1992-2007 period, Table 3 shows the contributions of each productivity tercile on the net and gross employment effects of the China shock in the manufacturing sector. By construction, for each China shock measure the sum of the three tercile coefficients is identical to the overall effect, which corresponds to either column 2 or column 6 of Table 1.[19] Note that high-productivity establishments lead in net job destruction, accounting for about 46 percent ($-0.21/-0.45$) of net job losses under the import-exposure measure, and for about 42 percent ($-0.12/-0.29$) of net job losses under the PNTR-status measure. This, however, does not imply that high-productivity establishments are relatively more affected than less productive establishments, as high-productivity establishments account for a large share of total employment. Indeed, the average manufacturing employment shares during the 1992-2007 period are about 12 percent for the lowest tercile, about 29 percent for the middle tercile, and about 60 percent for the highest tercile. Thus, high-productivity establishments are relatively less affected by the China shock (the employment shares of both the lowest and middle terciles are smaller than their shares in net job losses).

[18] Due to limitations of the NETS data, we cannot calculate any measure of establishment-level total factor productivity, nor of a labor-productivity measure based on value added per worker.

[19] Small discrepancies in the sum are due to two-decimal rounding.

Table 3: Effects of the China Shock on Manufacturing Employment by Labor-Productivity Tercile, 1992-2007

	Chinese Import Exposure				**PNTR Status**			
	Overall	*Lowest tercile*	*Middle tercile*	*Highest tercile*	*Overall*	*Lowest tercile*	*Middle tercile*	*Highest tercile*
Net employment growth	-0.45***	-0.10*	-0.15*	-0.21*	-0.29***	-0.05*	-0.11*	-0.12*
	(0.16)	(0.06)	(0.08)	(0.12)	(0.09)	(0.03)	(0.06)	(0.07)
Job Flows								
Births	0.01	0.00	0.02	-0.01	-0.02	-0.01	-0.01	-0.01
	(0.03)	(0.01)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.04)
Deaths	0.35***	0.08*	0.13*	0.14	0.22***	0.03**	0.10**	0.08
	(0.11)	(0.05)	(0.07)	(0.09)	(0.05)	(0.02)	(0.04)	(0.05)
Expansions	0.01	0.01	0.02	-0.02	-0.03	0.00	0.01	-0.04*
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
Contractions	0.12*	0.03*	0.06*	0.04	0.02	0.01	0.02	-0.01
	(0.07)	(0.02)	(0.03)	(0.05)	(0.04)	(0.01)	(0.03)	(0.04)
Net extensive margin	-0.34***	-0.08*	-0.11	-0.15*	-0.24***	-0.04**	-0.11**	-0.09*
	(0.11)	(0.05)	(0.07)	(0.08)	(0.06)	(0.02)	(0.05)	(0.05)
Net intensive margin	-0.12	-0.02	-0.04	-0.06	-0.05	-0.01	-0.01	-0.04
	(0.08)	(0.01)	(0.03)	(0.06)	(0.05)	(0.01)	(0.02)	(0.04)
Job creation	0.02	0.01	0.04	-0.03	-0.05	-0.01	0.01	-0.05
	(0.04)	(0.02)	(0.04)	(0.06)	(0.04)	(0.02)	(0.04)	(0.05)
Job destruction	0.47***	0.11*	0.19*	0.18	0.24***	0.04*	0.12**	0.07
	(0.15)	(0.06)	(0.10)	(0.12)	(0.08)	(0.02)	(0.06)	(0.08)
Observations	784	784	784	784	784	784	784	784

Notes: This table reports $\hat{\beta}$ and $\hat{\beta}^F$ from the estimation of equations (3) and (4) for the manufacturing sector (392 industries) including the contributions of each of the three productivity terciles. The sum of the three tercile coefficients is identical to the overall effect. The columns for the overall effects are columns 2 and 6 from Table 1. Regressions include two subperiods, 1992-1999 and 1999-2007. All regressions include subperiod fixed effects (not reported) and are weighted by 1992 employment. Standard errors (in parentheses) are clustered at the three-digit industry level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

The coefficients on deaths tell a similar story. For the import-exposure measure, the lowest tercile accounts for 23 percent of job destruction by deaths, the middle tercile accounts for 37 percent, and the top tercile accounts for 40 percent. For the PNTR-status measure, the shares in job destruction by deaths are respectively 14 percent, 48 percent, and 38 percent. Note that for both China shock measures the lowest and middle terciles account for about 60 percent of the job destruction by deaths, which is much larger than their share in total employment (about 40 percent). The only difference is that the lowest tercile is relatively more affected under the import-exposure measure, while the middle tercile is relatively more affected under the PNTR measure.

These results show that the China shock affects all types of manufacturing establishments—though to different degrees—and indicate different potential mechanisms of transmission. On one hand, by causing deaths of the least-productive establishments, the China shock may simply be accelerating the process of creative destruction, which may lead to Melitz-type aggregate productivity gains and be a source of benefits (see, for example, Davis, Haltiwanger, and Schuh, 1996). On the other hand, the result that the China shock is also associated with deaths of middle- and high-productivity establishments highlights that *(i)* higher-productivity establishments are not immune to Chinese competition, and *(ii)* the shock may be a powerful driver of plant relocation by multi-plant, multinational firms. Along these lines, previous research by Bernard and Jensen (2002) shows that the kinds of plants most likely to die after exposure to import competition from low-income countries are low-wage, labor-intensive plants within exposed industries, and those owned by multi-plant, multinational firms (Bernard and Jensen, 2007). Relatedly, Magyari (2017) indicates that plant closures from the China shock are mostly among multinational firms that are redistributing jobs between their factories.

Holmes and Stevens (2014) also provide a mechanism that can help explain why establishments in the highest-productivity tercile are also negatively affected by the China shock. They describe an Eaton-Kortum model in which each industry is split into two subsectors: a primary segment that produces standardized goods and a specialty segment that produces custom goods. The primary segment is composed of large plants, which are highly productive and take advantage of mass production methods to produce standardized goods, while the specialty segment is composed of small plants that cannot use the mass production techniques of large plants and thus end up producing niche or custom goods. After estimating their model, they show that the surge in imports from China reduces the share of plants in the primary subsector, which they attribute to Chinese imported goods being closer substitutes to standardized goods than to custom goods; that is, the primary segment within each industry is more exposed to Chinese competition.

5 Local Labor Markets Analysis

The influential work of Autor, Dorn, and Hanson (2013) showed that, due to aggregate demand effects, import competition from China has employment effects in local labor markets that go far deeper than the impact in directly-exposed sectors. For example, displaced workers from an exposed industry in Pittsburgh will have less income, which then drives these fired workers to spend less on other goods and services such as haircuts, which then depresses the incomes of barbershops and hair salons, and so forth. AADHP extend this framework to try to capture job reallocation from exposed sectors to nonexposed sectors.

Here we expand AADHP's local labor markets analysis along three dimensions. First, by looking at each of the components of job flows rather than only at net employment changes, we are in a better position to capture evidence of job reallocation across exposed and nonexposed sectors. Second, we also look at the local labor market employment effects of U.S. exposure to China's PNTR status, which helps to establish the generality of our results. And third, we add a Bartik shock (Bartik, 1991) as a regressor in our specifications, which allows us to study whether the employment responses we observe due to the China shock are distinctive, or if they are similar to responses to a generic negative shock that affects the demand for U.S. labor.

5.1 Measures of the China Shock at the Commuting-Zone Level and the Bartik Shock

The analysis is based on the 722 U.S. commuting zones of Autor, Dorn, and Hanson (2013) and AADHP. The first step is to obtain the measure of Chinese import exposure at the commuting zone level. This variable is defined as a weighted average of the annual changes in industry-level import penetration, with the weights—the initial employment share of each industry in total commuting-zone employment—accounting for regional specialization patterns. Hence, the annual change in import penetration in commuting zone i during subperiod τ, $\Delta IP^{CZ}_{i\tau}$, is given by

$$\Delta IP^{CZ}_{i\tau} = \sum_j \left(\frac{L_{ijt_{\tau,\text{start}}}}{L_{it_{\tau,\text{start}}}} \right) \Delta IP_{j\tau}, \tag{8}$$

where $L_{ijt_{\tau,\text{start}}}$ denotes industry j's employment in commuting zone i at $t_{\tau,\text{start}}$ (the initial year of subperiod τ), $L_{it_{\tau,\text{start}}} = \sum_{j'} L_{ij't_{\tau,\text{start}}}$ is total employment in commuting zone i at $t_{\tau,\text{start}}$, and $\Delta IP_{j\tau}$ is the annual change in import penetration in industry j during subperiod τ as defined in (1).

Analogously, the measure of exposure to China's PNTR status for commuting zone i during subperiod τ, $PNTR_{i\tau}^{CZ}$, is given by

$$PNTR_{i\tau}^{CZ} = \sum_{j} \left(\frac{L_{ijt_{\tau,\text{start}}}}{L_{it_{\tau,\text{start}}}} \right) PNTR_{j\tau}, \tag{9}$$

where $PNTR_{j\tau}$ is defined as in (2), taking the value of zero if $\tau = 1$ and being equal to the annualized NTR gap in industry j if $\tau = 2$. As before, $\tau \in \{1, 2\}$, with period 1 corresponding to 1992-1999, and period 2 corresponding to either 1999-2007 or 1999-2011.

The industry-level analysis in Section 4 shows that the Chinese-induced net job destruction in the U.S. is mainly driven by deaths of establishments. An important concern is whether this result is particular to the China shock, or if it is the typical way the U.S. labor market responds to a more general adverse shock affecting the U.S. demand for labor. A key advantage of the local labor markets approach is that we can explore the particularity of the China shock by introducing a Bartik shock at the commuting zone level.[20]

Following Autor, Dorn, Hanson, and Majlesi (2016), the Bartik measure for commuting zone i during subperiod τ, $\mathbb{B}_{i\tau}$, is defined as

$$\mathbb{B}_{i\tau} \equiv \sum_{j} \left(\frac{L_{ijt_{\tau,\text{start}}}}{L_{it_{\tau,\text{start}}}} \right) \frac{\Delta L_{j\tau}^{-i}}{L_{jt_{\tau,\text{start}}}^{-i}}, \tag{10}$$

where $L_{jt_{\tau,\text{start}}}^{-i}$ is industry j's employment across all U.S. commuting zones with the exception of commuting zone i in the initial year of subperiod τ, $t_{\tau,\text{start}}$, with $\Delta L_{j\tau}^{-i}$ denoting its annual change during subperiod τ. The Bartik shock indicates the predicted change in employment in commuting zone i as a result of national industry-level employment changes, using as weights the initial share of each industry in the commuting zone's employment to account for regional specialization patterns.[21]

5.2 Specifications

Following AADHP's approach, each of the 479 industries (no longer restricted to manufacturing) is classified into one of three sectors: exposed, nonexposed tradable, and nonexposed nontradable.[22]

[20] We thank Gordon Hanson for raising this point and suggesting the construction of the Bartik measure.

[21] The Bartik measure captures all factors that affect the U.S. demand for domestic labor, including the China shock. Fortunately, the correlations between the Bartik variable and our measures of Chinese exposure are low, which allows us to keep a high degree of precision in our estimates when we include both types of shocks.

[22] AADHP classify an industry as exposed if predicted import exposure from the first-stage regression increased by more than 2 percentage points between 1991 and 2011, or if the predicted higher-order upstream exposure measure increased by more than 4 percentage points during the same period. From 1992 to 2011 and using our NETS data, the employment share of the exposed sector declined from 19 percent to 13 percent, the share of the nonexposed tradable sector declined from 6 percent to 4 percent, and the share of the nonexposed nontradable sector increased from 75 to 83 percent. With the CBP data, the shares respectively changed from 20 to 13 percent, 7 to 4 percent, and 73 to 83 percent.

We use $k \in \{1, 2, 3\}$ to indicate sector type, so that 1 identifies the exposed sector, 2 identifies the nonexposed tradable sector, and 3 identifies the nonexposed nontradable sector. After classifying each industry, we aggregate the NETS job flows data across industries of the same sector for each commuting zone. This creates a panel with 4,332 observations: 722 commuting zones, three sectors, and two subperiods.

The dependent variable in the local labor market analysis is based on the employment-to-population ratio. Here we define the annual change in the employment-to-population ratio in sector k in commuting zone i in subperiod τ as

$$\ell_{ik\tau} = \frac{\Delta L_{ik\tau}}{\bar{P}_{i\tau}}, \tag{11}$$

where for each commuting zone i during subperiod τ, $\Delta L_{ik\tau}$ is the annual employment change in sector k, and $\bar{P}_{i\tau}$ is the mid-point working-age population (*i.e.*, $\bar{P}_{i\tau} = (P_{it_{\tau,\text{end}}} + P_{it_{\tau,\text{start}}})/2$). We obtain the working-age population for each commuting zone i and each year t, P_{it}, from AADHP, who construct it from Census population estimates.[23]

The specification to estimate the net impact of local exposure to the China shock on employment-to-population ratios for different sectors is

$$\ell_{ik\tau} = \alpha_{k\tau} + \sum_K \beta_K \left[S_{i\tau}^{CZ} \times \mathbb{1}_k(K)\right] + \sum_K \gamma_K \left[\mathbb{B}_{i\tau} \times \mathbb{1}_k(K)\right] + \eta Z_{ik\tau} + \varepsilon_{ik\tau}, \tag{12}$$

where for commuting zone i and sector $k \in \{1, 2, 3\}$ during subperiod τ, $S_{i\tau}^{CZ}$ is the China shock variable, measured as either $\Delta IP_{i\tau}^{CZ}$ in (8) or $PNTR_{i\tau}^{CZ}$ in (9), and $\mathbb{B}_{i\tau}$ is the Bartik shock from (10). In addition, $\mathbb{1}_k(K)$ is a sectoral dummy variable taking the value of 1 if $k \equiv K$, for $K \in \{1, 2, 3\}$, $Z_{ik\tau}$ is a vector of commuting zone i–sector k controls, $\alpha_{k\tau}$ indicates a sector-time fixed effect, and $\varepsilon_{ik\tau}$ is the error term. Note that the specification not only allows for different sectoral net responses to the China shock (accounted for by β_1, β_2, and β_3), but also allows for different sectoral responses to the Bartik shock (accounted for by γ_1, γ_2, and γ_3).

With a slight notational abuse, we can now split the annual change in the employment-to-population ratio into its job-flow components as

$$\ell_{ik\tau} \equiv b_{ik\tau} - d_{ik\tau} + e_{ik\tau} - c_{ik\tau},$$

where $b_{ik\tau}$ denotes the contribution of births to the change in the employment-to-population ratio of sector k in commuting zone i, and the same for deaths ($d_{ik\tau}$), expansions ($e_{ik\tau}$), and contractions ($c_{ik\tau}$). We calculate $b_{ik\tau}$ as

$$b_{ik\tau} \equiv \lambda_\tau \left(\frac{B_{ik\tau}}{\bar{P}_{i\tau}}\right),$$

[23] The measure in (11) is slightly different from the measure used by AADHP, which is given by $\Delta \mathbb{E}_{ik\tau}$, where $\mathbb{E}_{ikt} = L_{ikt}/P_{it}$. We use the alternative measure to be able to separate each of the job-flow components.

where $B_{ik\tau}$ is the employment change due to births of establishments in sector k of commuting zone i during subperiod τ. Analogous expressions follow for $d_{ik\tau}$, $e_{ik\tau}$, and $c_{ik\tau}$.

Thus, our specification to estimate the impact of local exposure to the China shock on job flow $F_{ik\tau} \in \{b_{ik\tau}, d_{ik\tau}, e_{ik\tau}, c_{ik\tau}, b_{ik\tau} - d_{ik\tau}, e_{ik\tau} - c_{ik\tau}, b_{ik\tau} + e_{ik\tau}, d_{ik\tau} + c_{ik\tau}\}$ is

$$F_{ik\tau} = \alpha^F_{k\tau} + \sum_K \beta^F_K \left[S^{CZ}_{it} \times \mathbb{1}_k(K)\right] + \sum_K \gamma^F_K \left[\mathbb{B}_{i\tau} \times \mathbb{1}_k(K)\right] + \eta^F Z_{ik\tau} + \varepsilon^F_{ik\tau}. \tag{13}$$

As before, there is a perfect linear relationship between the gross coefficients from (13) and the net coefficients from (12), so it is always true that

$$\beta_k \equiv \beta^b_k - \beta^d_k + \beta^e_k - \beta^c_k \equiv \beta^{b-d}_k + \beta^{e-c}_k \equiv \beta^{b+e}_k - \beta^{d+c}_k,$$
$$\gamma_k \equiv \gamma^b_k - \gamma^d_k + \gamma^e_k - \gamma^c_k \equiv \gamma^{b-d}_k + \gamma^{e-c}_k \equiv \gamma^{b+e}_k - \gamma^{d+c}_k,$$

for $k \in \{1, 2, 3\}$.

5.3 Local Labor Market Effects of Chinese Import Exposure

Using the local measure of Chinese import exposure ($\Delta IP^{CZ}_{i\tau}$) as the China shock, Table 4 shows the IV estimation of (12) and (13) for the 1992-2007 period.[24] In contrast to Table 1, where each coefficient was the estimate of β or β^F from a single regression, in Table 4 each full row gives the estimates from a single regression. For example, the first row yields $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\gamma}_1$, $\hat{\gamma}_2$, and $\hat{\gamma}_3$ from the estimation of (12) with NETS data.

In addition to sector-time fixed effects, we follow AADHP and include as controls *(i)* the commuting zone's manufacturing share (at the beginning of each period) interacted with sector dummies, and *(ii)* regional Census division dummies interacted with sector dummies. All regressions include 4,332 observations and are weighted by total population in 1992, with standard errors clustered at the commuting-zone level.

The first coefficient in the first row of Table 4 shows a strong and highly significant negative response of the employment-to-population ratio in the exposed sector to an increase in local Chinese import exposure. As in the industry-level analysis, the job-flow coefficients in column 1 show that the main driving factor of the decline in the exposed sector's employment-to-population ratio is an increase in job destruction due to establishments' deaths. Based on our death-share measure ($\hat{\delta}$) defined in (5) and reported in the last column of Table 2, deaths account for 55 percent of total Chinese-induced job reallocation in the exposed sector during the 1992-2007 period.

[24] Following AADHP, the instrument for $\Delta IP^{CZ}_{i\tau}$ is $\Delta IP^{*CZ}_{i\tau} = \sum_j \left(\frac{L_{ij88}}{L_{i88}}\right) \Delta IP^*_{j\tau}$. They use employment weights from 1988 in the instrument to avoid covariance with the dependent variable.

Table 4: IV Estimation of the Effects of Chinese Import Exposure on U.S. Commuting Zones by Sectoral Employment (1992-2007)

	Chinese Import Exposure			**Bartik Shock**		
	Exposed	*Nonexposed tradable*	*Nonexposed nontradable*	*Exposed*	*Nonexposed tradable*	*Nonexposed nontradable*
Δ(Employment/Population)	-1.10***	0.10	1.16***	0.19***	-0.01	0.79***
	(0.21)	(0.12)	(0.44)	(0.04)	(0.02)	(0.11)
Job flows						
Births	0.30***	-0.13*	1.95***	0.23***	0.03***	1.40***
	(0.11)	(0.07)	(0.56)	(0.03)	(0.01)	(0.12)
Deaths	1.12***	-0.10	1.28**	0.19***	0.05***	0.85***
	(0.17)	(0.07)	(0.50)	(0.03)	(0.01)	(0.08)
Expansions	0.17	-0.11*	0.50	0.15***	0.03***	0.44***
	(0.11)	(0.06)	(0.31)	(0.02)	(0.01)	(0.05)
Contractions	0.45***	-0.24***	0.02	-0.00	0.02**	0.20***
	(0.10)	(0.09)	(0.23)	(0.01)	(0.01)	(0.05)
Net extensive margin	-0.82***	-0.03	0.67*	0.04*	-0.02*	0.56***
	(0.15)	(0.07)	(0.40)	(0.02)	(0.01)	(0.09)
Net intensive margin	-0.28**	0.13*	0.48***	0.15***	0.01	0.24***
	(0.12)	(0.07)	(0.16)	(0.02)	(0.01)	(0.04)
Job creation	0.47**	-0.23**	2.45***	0.37***	0.06***	1.84***
	(0.20)	(0.11)	(0.79)	(0.04)	(0.02)	(0.15)
Job destruction	1.58***	-0.34**	1.30*	0.18***	0.07***	1.05***
	(0.25)	(0.14)	(0.70)	(0.04)	(0.02)	(0.11)
CBP data:						
Δ(Employment/Population)	-1.24***	-0.10	1.39**	0.16***	0.02*	0.47***
	(0.25)	(0.10)	(0.67)	(0.02)	(0.01)	(0.08)

Notes: Using subperiods 1992-1999, 1999-2007, and import exposure as the China shock, this table reports $\hat{\beta}_k$, $\hat{\gamma}_k$, $\hat{\beta}_k^F$, and $\hat{\gamma}_k^F$, for $k \in \{1(\text{exposed}), 2(\text{nonexposed tradable}), 3(\text{nonexposed nontradable})\}$, from the estimation of equations (12) and (13). All regressions include 4,332 observations (722 commuting zones, three sectors, and two subperiods) and the following controls: sector-time fixed effects, the commuting zone's manufacturing share (at the beginning of each period) interacted with sector dummies, and regional Census division dummies interacted with sector dummies. Regressions are weighted by 1992 commuting-zone population. The net regression with CBP data is reported for the purpose of comparison with the net regression with NETS data. Standard errors (in parentheses) are clustered at the commuting-zone level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

Although job destruction by deaths is the most important gross margin of adjustment for the exposed sector, column 1 shows that an increase in job creation by births and an increase in job destruction by contractions also play a statistically significant role in the dynamics of the employment-to-population ratio. In the end, the exposed sector shows gross job reallocation that is 1.85 times larger than the observed net effect, which highlights the importance of looking at job flows rather than at net employment changes (which conceal substantial labor market activity).

Although the births coefficient for the exposed sector is only about a fourth of the size of the deaths coefficient (and about two thirds of the size of the contractions coefficient), it is still relatively large and highly significant. Given that the coefficient on births was negative or very close to zero (always non-significant) in our industry-level analysis in section 4, the positive and significant births coefficient in the first column of Table 4 points toward reallocation effects within the exposed sector and possibly from the nonexposed sectors. This indicates that even if the exposed sector is facing a mostly adverse scenario due to Chinese competition, there are still some entrepreneurs that see the shock as an opportunity to try to capture market share from dying and contracting firms.

The Bartik shock coefficients for the exposed sector in column 4 show fundamentally different effects on net and gross job flows from those observed in column 1. A positive Bartik shock increases employment in the exposed sector as a consequence of job creation driven by both births and expansions, and in spite of a statistically significant increase in job destruction due to deaths. This seems to be part of a healthy process of competition by which a positive shock stimulates entry and the expansion of some establishments, while destroying the least competitive ones. In this case, deaths only account for 33 percent of total job reallocation, while births and expansions account for 40 and 26 percent of job reallocation, respectively. Analogously, an adverse Bartik shock causes net job destruction due to declines in births and expansions, and in spite of a *decline* in deaths. Thus, in stark contrast to the local employment effects of Chinese import exposure on the U.S. exposed sector, for an adverse Bartik shock deaths are not as important for gross job reallocation, and reduce (rather than increase) the gross rate of job destruction.

Further interesting results from Table 4 arise for the nonexposed sectors. AADHP carefully discuss the China shock implications for nonexposed sectors regarding *(i)* job reallocation, and *(ii)* aggregate demand effects, but they are not able to find statistically significant evidence of any of them. This is not surprising, given that job reallocation from the exposed sector and aggregate demand effects have opposite impacts on the employment-to-population ratios in the nonexposed sectors. Both channels may be important, but if they cancel out, looking only at net changes makes it harder to find evidence of their existence. Fortunately, by being able to decompose net employment changes into their job-flow components, we are in a better position to capture and detect these separate effects. Here we discuss the implications for the nonexposed nontradable sector, which on average accounts for 78 percent of U.S. employment per year, and leave the discussion for the nonexposed tradable sector (which on average accounts for 5 percent of yearly employment) to section C.3 in the Appendix.

After a local increase in Chinese import exposure, the first row in column 3 shows a large and statistically significant increase in the employment-to-population ratio of the nonexposed nontradable sector. This is strong evidence of job reallocation from the exposed sector. The job flows regressions show that the positive net effect is a consequence of a very large and statistically significant increase in the rate of job creation by births, which more than makes up for a large and significant increase in the rate of job destruction by deaths (births account for 52 percent of the sector's job reallocation, but it also helps that there is a statistically significant net expansion at the intensive margin). Therefore, as the exposed sector sheds jobs (mainly through deaths), some of the released workers find employment in new establishments in the nonexposed sector; there may even be previously exposed-sector establishments that are reborn in a different, nonexposed industry. This birth-driven reallocation mechanism is sufficiently strong to dominate the job destruction by deaths of nonexposed nontradable establishments, which is likely driven by aggregate demand effects.

Column 6 indicates that a positive Bartik shock significantly increases the rates of job creation and destruction across all margins in the nonexposed nontradable sector, but job creation (especially by births) strongly dominates, resulting in a large and highly significant positive net effect. This is very similar to the response of the exposed sector to the positive Bartik shock, and resembles a healthy process of creative destruction. On the other hand, an adverse Bartik shock reduces the rates of job destruction along its two margins, but reduces even more the rates of job creation along its two margins. This is different from what we observe in this sector after an increase in local Chinese import exposure, which is expected given that the nontradable sector is the main reallocation destination of released workers from the exposed sector due to the China shock.

Table 2 shows Chinese-induced predicted employment changes from the specifications in Table 4. Given that the dependent variable is now based on the employment-to-population ratio, we can no longer use a formula analogous to (6). Instead, the predicted net employment change in sector k from the change in local import penetration during the 1992-2007 period is given by

$$\textit{Predicted employment change in sector } k(IP) = \sum_i \hat{\beta}_k \left(IP^{CZ}_{i07} - IP^{CZ}_{i92} \right) \rho P_{i07}, \tag{14}$$

where $\hat{\beta}_k$ is the coefficient for sector k from the employment-to-population ratio regression in the first row of Table 4, $IP_{i07}^{CZ} - IP_{i92}^{CZ}$ is the change in import exposure for commuting zone i from 1992 to 2007, P_{i07} is the working-age population in commuting zone i in 2007, and $\rho = 0.66$ is the partial R–squared from the first-stage regression of the specification in column 2 of Table 1.[25]

For the 1992-2007 period, Chinese-induced net predicted losses are about 2.1 million jobs in the exposed sector, but there are also significant net predicted gains of 2.2 million jobs in the nonexposed nontradable sector. Hence, in terms of net employment changes, our local labor market results indicate an almost neutral effect of Chinese import exposure. Note that the nonexposed nontradable sector creates 3.8 million jobs from births of establishments—a sign of job reallocation from the exposed sector (gross job destruction in the exposed sector is about 3 million jobs)—but this effect is diluted by large job losses from deaths (about 2.5 million jobs).

When using the CBP data, the net coefficients for Chinese import exposure in the last row of Table 4 are remarkably close to those obtained with the NETS data in the first row, showing statistically significant net job destruction in the exposed sector, but also statistically significant net job creation in the nonexposed nontradable sector.[26] Regarding predicted employment changes, Table C.7 shows that the NETS and CBP data yield very similar net job losses in the exposed sector and very similar net job gains in the nonexposed nontradable sector. The strong similarity between the NETS and CBP local labor markets results is striking, considering that the industry-level analysis consistently predicted smaller net losses with NETS.

Finally, Table C.8 in the Appendix shows the estimation results for the 1992-2011 period. The results are very similar to those in Table 4 in terms of signs, magnitudes, and significance. Thus, our qualitative results remain strong when we include the Great Recession period. In terms of predicted employment changes, Table 2 shows more net losses in the exposed sector during 1992-2011 (2.5 million jobs in 1992-2011 vs. 2.1 million jobs in 1992-2007), but a similar amount of net job gains in the nonexposed nontradable sector (2.2 million jobs during both periods).

5.4 Local Labor Market Effects of China's PNTR Status

Table 5 mirrors Table 4, but uses instead local exposure to China's PNTR status, $PNTR_{i\tau}$, as our China shock variable. In keeping with this paper's main conclusion, column 1 shows that local exposure to China's PNTR status is associated with net job destruction in the exposed sector,

[25] We follow AADHP in using the same ρ to calculate predicted employment changes from all import-exposure specifications using the same dataset. As mentioned in section 4.3, ρ equals 0.66 when using NETS data, and 0.60 when using CBP data.

[26] AADHP did not find statistically significant evidence of net job creation in the nonexposed nontradable sector during the 1991-2007 period. Our specification differs from theirs in the time period (we start in 1992), the inclusion of the Bartik shock as control, and the definition of the dependent variable (AADHP's dependent variable cannot be split into job-flow components). Although the start year does not play any important role in the results, both of the other two factors help explain the difference between AADHP and our job reallocation results.

with deaths of establishments being the main driver of this result; according to the corresponding value of $\hat{\delta}$ from Table 2, deaths account for 67 percent of total job reallocation in that sector. Job destruction by contractions also plays an important role, but not as prominent as deaths. As with import exposure, these employment responses are fundamentally different from those of an adverse Bartik shock (in column 4), which highlights the uniqueness of the employment effects of the China shock.

As with the import-exposure measure, column 3 shows net job creation in the nonexposed nontradable sector due to local exposure to China's PNTR status. As before, this result is mostly driven by births, which account for 54 percent of job reallocation in the sector. Although there is statistically significant job destruction by deaths, there is also statistically significant job creation by expansions. In the end, these results confirm that the nonexposed nontradable sector faces negative aggregate demand effects due to local exposure to the China shock, but is also the main reallocation destination of released workers from the exposed sector.

From the results in columns 1-3 of Table 5, panel B in Table 2 shows Chinese-induced predicted changes in the employment-to-population ratio from an interquartile shift in the commuting-zone NTR gap distribution.[27] Up to 2007, moving from a commuting zone in the 25th percentile of the NTR gap distribution to a commuting zone in the 75th percentile is associated with a decline of 0.017 points in the exposed sector's employment-to-population ratio, and an increase of 0.012 points in the ratio for the nonexposed nontradable sector.

The CBP net coefficients in the last row of Table 5 are similar to the corresponding NETS coefficients in the first row, though the coefficient for the nonexposed nontradable sector is not significant. Table C.9 in the Appendix presents the PNTR estimation for the 1992-2011 period, and shows similar qualitative results to those in Table 5. The only relevant differences between them are that *(i)* in column 1 there is significant evidence of reductions in the rates of job creation by births and expansions for the exposed sector, with contractions becoming non-significant, and *(ii)* in column 3, the CBP net coefficient for the nonexposed nontradable sector is now significant, which gives confidence in the job reallocation effects found with the NETS data.

6 Concluding Remarks

The China shock is associated with net job destruction in the U.S. manufacturing industry and in sectors locally exposed to Chinese competition. Using job flows calculated from U.S. establishment-

[27] The NTR gap for commuting zone i is calculated as $GAP_i^{CZ} = \sum_j \left(\frac{L_{ij99}}{L_{i99}}\right) GAP_j$, which yields a distribution with $GAP_{25th}^{CZ} \equiv 0.019$ and $GAP_{75th}^{CZ} \equiv 0.057$.

Table 5: OLS Estimation of the Effects of China's PNTR Status on U.S. Commuting Zones by Sectoral Employment (1992-2007)

	PNTR Status			**Bartik Shock**		
	Exposed	*Nonexposed tradable*	*Nonexposed nontradable*	*Exposed*	*Nonexposed tradable*	*Nonexposed nontradable*
Δ(Employment/Population)	-0.44***	-0.07*	0.31**	0.15***	-0.02	0.82***
	(0.06)	(0.04)	(0.13)	(0.04)	(0.02)	(0.10)
Job flows						
Births	-0.02	0.00	0.47***	0.22***	0.03***	1.45***
	(0.03)	(0.01)	(0.12)	(0.03)	(0.01)	(0.12)
Deaths	0.33***	0.06***	0.27**	0.22***	0.06***	0.87***
	(0.04)	(0.02)	(0.12)	(0.03)	(0.01)	(0.08)
Expansions	0.02	0.00	0.14***	0.15***	0.03**	0.45***
	(0.03)	(0.02)	(0.05)	(0.02)	(0.01)	(0.05)
Contractions	0.12***	0.02	0.02	0.01	0.02**	0.20***
	(0.03)	(0.02)	(0.04)	(0.01)	(0.01)	(0.05)
Net extensive margin	-0.34***	-0.06***	0.20*	0.00	-0.03**	0.58***
	(0.04)	(0.02)	(0.11)	(0.02)	(0.01)	(0.09)
Net intensive margin	-0.10**	-0.02	0.11**	0.14***	0.01	0.25***
	(0.04)	(0.03)	(0.04)	(0.02)	(0.01)	(0.04)
Job creation	0.00	0.00	0.61***	0.37***	0.06***	1.90***
	(0.05)	(0.02)	(0.16)	(0.04)	(0.02)	(0.15)
Job destruction	0.44***	0.08***	0.29*	0.22***	0.08***	1.07***
	(0.06)	(0.03)	(0.15)	(0.04)	(0.02)	(0.11)
CBP data:						
Δ(Employment/Population)	-0.34***	-0.12***	0.21	0.16***	0.02	0.46***
	(0.04)	(0.02)	(0.19)	(0.02)	(0.01)	(0.08)

Notes: Using subperiods 1992-1999, 1999-2007, and PNTR status as the China shock, this table reports $\hat{\beta}_k$, $\hat{\gamma}_k$, $\hat{\beta}_k^F$, and $\hat{\gamma}_k^F$, for $k \in \{1(\text{exposed}), 2(\text{nonexposed tradable}), 3(\text{nonexposed nontradable})\}$, from the estimation of equations (12) and (13). All regressions include 4,332 observations (722 commuting zones, three sectors, and two subperiods) and the following controls: sector-time fixed effects, the commuting zone's manufacturing share (at the beginning of each period) interacted with sector dummies, and regional Census division dummies interacted with sector dummies. Regressions are weighted by 1992 commuting-zone population. The net regression with CBP data is reported for the purpose of comparison with the net regression with NETS data. Standard errors (in parentheses) are clustered at the commuting-zone level. The coefficients are statistically significant at the *10%, **5%, or ***1% level.

level data, we showed that Chinese-induced net job destruction is mainly driven by the deaths of establishments. This result holds for the two most influential measures of the China shock: the import penetration measure of Autor, Dorn, and Hanson (2013), and the PNTR-status measure of Pierce and Schott (2016). Moreover, our local labor markets analysis shows that our deaths result appears to be unique to the China shock; in particular, it does not emerge after a more general adverse shock affecting U.S. labor demand. A novelty of this paper is that it provides evidence of job reallocation in local labor markets from the exposed sector to the nonexposed sector: workers released from the exposed sector (mainly due to deaths), are reabsorbed in the nonexposed nontradable sector mainly through births of establishments.

An important caveat is that our paper does not assess the overall consequences of trade on job flows, but is restricted to the analysis of trade with one country (albeit the largest U.S. trading partner). Moreover, the finding of some positive job reallocation effects highlights the fact that trade has beneficial impacts on some sectors and establishments (if not for all workers). Also, there are likely larger net beneficial effects from trade with other countries for which exports are larger relative to imports. Thus, although our research is focused on U.S. trade with one country, policy should focus more on the overall effects of trade. Our evidence suggests that trade with China has led to some "rusted-out factories ... across the landscape of our nation." But this is not the whole story.

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