THE UNIVERSITY OF CHICAGO

ESSAYS ON INTERNATIONAL ECONOMICS

A DISSERTATION SUBMITTED TO

THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES

IN CANDIDACY FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

KENNETH C. GRIFFIN DEPARTMENT OF ECONOMICS

BY

ZIHO PARK

CHICAGO, ILLINOIS

JUNE 2021

To my parents, who taught me the value of education.

Contents

List of Figures

List of Tables

Acknowledgements

I would like to thank my advisors Steven Davis, Rodrigo Adao, and Felix Tintelnot for their guidance. They gave me invaluable advice on my research. More broadly, I also learned about how to navigate my career. I have no doubt that their advice will be a very important source of inspiration in my whole career.

Although he is not on my committee, Jonathan Dingel also provided numerous feedback on my work. His advice challenged the way I approach my research. At the International Trade Working Group, he always types all the important questions that were asked in the seminar, and shares it with the presenter. This helped all presenters at this seminar including me.

I thank participants of the internal seminars at the University of Chicago. Namely, the International Trade Working Group, Applied Macroeconomic Theory Working Group, and Capital Theory Workshop at the University of Chicago.

I thank Allen Sanderson for allowing me to serve as a TA for his undergraduate classes. They were invaluable experiences.

I also thank the participants of the European Economic Association conference, Urban Economics Association conference, Western Economic Association International, INFER, Royal Dutch Economic Association conference, and Academy of Economics and Finance. Among them, I especially thank Ufuk Akcigit, Fernando Alvarez, Robert Gulotty, Kilian Huber, Jay Hyun, Eelke de Jong, Greg Kaplan, Hanbaek Lee, Simon Mongey, Esteban Rossi-Hansberg, Thomas Sampson, Robert Shimer, and Harald Uhlig. I also thank valuable comments from Erik Hurst, Robert Lucas, and Thomas Winberry.

I was lucky to have many job market preparations with Mauricio Chikitani, Gustavo de Souza, Harry Li, and Bradley Setzler. I thank them for incisive questions and comments, and also for making the job market process more fun.

I also thank my coauthors Jay Hyun and Vladimir Smirnyagin, who worked together on my second paper on the propagation of trade shock through within-firm networks.

I dedicate this thesis to my parents. My parents showed me the importance of hard work through their actions throughout their lifetime, not just through words. They instilled in me the value of education as well. Their life wisdom has been the fundamental source of my journey. I am greatly indebted.

Part I
Trade Adjustment: Establishment-Level Evidence

Abstract

Using data on a near-universe of US establishments from 1991 to 2007, I show that US businesses adapt to rising trade exposure from China along several margins. First, manufacturers of "directly exposed" products experiencing high import growth from China tend to become importers and retail-wholesalers by 2007, consistent with offshoring of products that are similar to those that they produced on their own. Manufacturers in "downstream" industries that buy from directly exposed industries tend to become retail-wholesalers and servicers, consistent with sourcing from directly exposed industries, leading to a loss of manufacturing employment. However, manufacturers in "upstream" industries that sell to directly exposed industries are less likely to become importers or retail-wholesalers, likely because they lose US domestic demands. Second, direct and downstream exposure is associated with becoming exporters, consistent with theories that offshoring makes firms efficient enough to export. Third, all three types of exposure are associated with switching industries within manufacturing, typically toward less-exposed industries. Lastly, the prediction of Holmes and Stevens (2014) that large establishments are more negatively affected is supported.

JEL Codes: E23, F40, F14, G34, D22, R23
Keywords: Trade, Multinationals, Offshoring, China Shock, Import Competition, Firm Dynamics, Micro Data, Trade Adjustment

1 Introduction

The growth of China and its integration into global trade marks one of the most important changes in the world economy in the last three decades. The literature documents the significant impact that imports from China have had on employment, earnings, investment, political and social events in the U.S. and beyond.[1]

To understand the mechanisms behind this fundamental change in the world economy, we should know how firms responded to imports from China. According to modern trade theory, firms provide a key channel through which trade shocks affect aggregate employment, wages, and welfare. Moreover, the firm-level adjustments are intrinsically important from the perspective of corporate finance, firm dynamics, and management.

The main purpose of this paper is to advance understanding of how US businesses have responded to the growth and opening of China ("China shock"). A feature of my paper is that I take multiple margins of adjustments from the recent theoretical literature where firms' multiple decisions are *inter*dependent (Antras, Fort, and Tintelnot 2017; Bernard, Jensen, Redding, and Schott 2018). In these models, businesses choose what to produce, whether and what to import and export, and whether to exit. Their empirical counterparts in this paper are industry switching, importing and exporting, building affiliates in China, and exits, respectively. These are not merely disconnected margins of adjustments. Motivated by the aforementioned theoretical models, I explain how one type of adjustment rationalizes another. I will support such joint interpretations by comparing residuals from different regressions of different outcome variables.

The sectoral exposures are constructed as in Autor, Dorn, Hanson, and Song (2014) and Acemoglu et al. (2016b). The direct exposure is constructed as the growth of import penetration from China to the US from 1991 to 2007 at the SIC 4-digit level for all manufacturing industries.[2] Then this industry-level measure is assigned to each manufacturing establishment according to its affiliated industry in 1991. Next, as in Acemoglu et al. (2016b), I construct upstream and downstream exposures using the weights obtained from the BEA input-output table, in which "upstream exposure" means the propagation of direct exposure to suppliers, and "downstream exposure" means the propagation of direct exposure to buyers. The direct, upstream, and downstream exposures are included in the regression simultaneously.

As in Autor, Dorn, and Hanson (2013) and in the subsequent large literature, the exogeneity of Chinese economic reform contributes to identification. The triumph of Deng Xiaoping and reformists in the Communist Party of China led to rapid improvements in infrastructure, productivity, and urban migration

[1] The literature finds a significant negative impact on manufacturing employment and investment in the US (Bernard, Jensen, and Schott 2006a; Autor, Dorn, and Hanson 2013; Acemoglu et al. 2016b; Pierce and Schott 2016b; Autor et al. 2019b; Asquith et al. 2019) and beyond the US (Dauth et al. 2014; Balsvik et al. 2015; Dix-Carneiro et al. 2017; De Lyon et al. 2020). It has also influenced social and political events that are reshaping the world, such as Trump's election and Brexit (Autor et al. 2020; Colantone et al. 2018; Che et al. 2016; Dippel et al. 2017).

[2] 1991-2007 is the period during which Chinese imports into the U.S. surged prior to the Great Recession.

(Naughton 2006, Hsieh and Ossa 2016). Nonetheless, to further eliminate the demand-driven component of China-to-US import growth, as in Autor et al. (2014), China-to-US growth in import penetration is instrumented for by growth in import penetration from China to other high-income countries. I also control for a variety of industry-level measures and establishment-level characteristics.

I take this methodology to the National Establishment Time Series (NETS) data, which covers a near-universe of US establishments from 1991 to 2007.[3] Here, an establishment is a physical location having a unique, separate, and distinct operation. A firm is a legal entity that has one or multiple establishments that are either branches or subsidiaries.

Using the empirical strategy and detailed microdata, I uncover a rich set of patterns that suggest that US businesses restructured to fit into the new global supply chain involving China.

Offshoring of own product: Take electronic computers as an example. When a product (e.g., electronic computer) experiences a large increase in import penetration from 1991 to 2007, the initial 1991 manufacturers of electronic computers are more likely to become importers, retailers, and wholesalers by 2007, consistent with *offshoring of products that they used to make on their own.* This correlation would not arise if establishments that were non-manufacturers in 1991 (e.g., electronic products wholesalers) were the only importers of electronic computers.[4] It would also not arise if manufacturers of other products (e.g., printed circuit boards) were primary importers of electronic computers. Instead, it is consistent with US businesses offshoring the goods that they used to produce on their own.[5]

Indirect sourcing by downstream manufacturers: If a product is directly exposed to China shock, the "downstream" manufacturers[6] tend to become retailers, wholesalers, and commercial servicers by 2007, although I do not find strong evidence that they become importers. This is consistent with *indirect sourcing,* wherein manufacturers purchase the imported goods from the directly exposed US businesses, rather than directly from China. Such indirect sourcing is prevalent in the Belgian context, as shown by Dhyne, Kikkawa, Mogstad, and Tintelnot (2020).

Lost offshoring opportunity by upstream manufacturers: If a product (e.g., wallets) is directly exposed to China shock, the "upstream" manufacturers (e.g., leather makers) are less likely to become importers and retail-wholesalers by 2007. Recall that directly exposed sectors such as garments offshore and

[3]The source of NETS is Dun & Bradstreet data, which has been used in seminal papers on FDI and global supply chain (Fajgelbaum, Grossman, and Helpman 2015; Alfaro, Chor, Antras, and Conconi 2019).

[4]Recall that trade exposure is defined only for establishments that were classified as manufacturing in 1991.

[5]An impediment to tightly connecting these findings with a unifying economic story is that the establishment-level export and import status variable is binary. Thus, it does not have information about the destination country of export, origin country of import, or the product being exported or imported. However, I show that a coherent economic rationalization can be made based on two incentives that US firms will have: Partial offshoring and avoiding import competition. The rationalization is also consistent with several anecdotes I have found.

[6]"Downstream" industries are those that buy a large share of their inputs from the directly exposed sectors. "Downstream" manufacturers are the businesses that operate in such industries.

switch out of manufacturing. That will shrink US domestic demands for upstream manufacturers such as fabrics producers. Therefore, they will have a less reason to import to or sell in the US.

Export: US manufacturers of directly exposed industries and their downstream industries respond by exporting. Recall that these industries display importing patterns consistent with foreign sourcing–an outcome consistent with theories in which global sourcing makes firms efficient enough to export (Antras, Fort, and Tintelnot 2017; Bernard, Jensen, Redding, and Schott 2018).

Within-manufacturing industry switching: Direct, upstream, and downstream exposures make it more likely that manufacturers switch industries within manufacturing. This switching occurred toward the industries that were less exposed to Chinese imports. This is consistent with anecdotal evidence from Burlington Coat Factory, which switched to product lines less exposed to import competition.[7] The response of upstream manufacturers is consistent with anecdotal evidence from the US fabrics manufacturer Cone Mills, which switched toward types of fabrics (upstream) that are used in garments (downstream) less exposed to import competition.[8]

Manufacturing employment: Consistent with the pattern of industry switching, direct and downstream exposures lead to a decline of manufacturing employment shares, whereas upstream exposures lead to its increase. This implies that incorporating input-output linkages matters for the important literature on manufacturing employment declines.

Exit and entry: Direct exposure is associated with suppressed entries and increased exits. Downstream exposure is associated with a heightened level of both entries and exits, which supports the hypothesis put forth by Acemoglu et al. (2016b) that downstream manufacturers might gain from cheap inputs but also might lose due to the loss of relationship-specific production.

Greater selection into exporting and importing in China-shock-exposed industries: In addition to the fact that old and large establishments are more likely to *be* exporters and importers than young and small ones, I find that the gap between old and young establishments in becoming exporters and importers is even greater in industries exposed to trade shocks. That is, China shock exacerbates selection into exporting and importing.

Support for Holmes and Stevens (2014)'s **theory of the plant size distribution**: The impact of direct exposure on employment declines and exiting is greater for businesses that have large employment. This provides granular-level support for Holmes and Stevens (2014)'s theory of plant size distribution. They postulate that large plants produce standardized goods, small plants produce specialty goods, and because

[7] Their 10-K document states that "China has recently gained admission to the WTO and access to the more liberal trade regime currently being phased in. (...) Over the years, the Company has attempted to offset the negative impact of increased imports by focusing on product lines and markets that are less vulnerable to import penetration."

[8] 10K document of Cone Mills states that "The Company has focused its operations on the manufacture of fabrics for use in garments that are less vulnerable to import penetration."

imports from China are mostly standardized goods, large plants are hit harder by China shock.

Section 2 describes the empirical model and data. NETS data are introduced in detail. Section 3 studies establishment-level responses. Section 4 documents the industry-level employment response, and decomposes it into eight elements. Section 5 presents results for heterogeneous responses. Section 6 introduces firm-level analog of establishment-level results. Section 7 extends the baseline results. Section 8 concludes.

Related Literature

Bernard, Jensen, and Schott (2006a) study the industry switching response to trade shock from all low-wage countries, rather than specifically from China. Their methodology differs from mine.[9] They do not study the industry switching response to upstream and downstream shocks, nor do they document the direction of switching. Because I also study multiple adjustment margins in one paper, I put each margin into context more effectively.

Bernard, Jensen, and Schott (2006a) and Kamal and Lovely (2017) study the impact of direct exposure (but not upstream and downstream exposures) to all low-income countries (not just to China) on establishment-level or firm-level employment and production employment. The study of upstream and downstream exposures is the key distinction in the current paper compared to theirs.

A concurrently developed paper by Bloom, Handley, Kurman, and Luck (2019) studies the impact of commuting-zone-level shock on employment. My finding is distinct from theirs in several respects. First, in contrast to my study, they do not study upstream and downstream exposures, which better contextualize findings on direct exposure. Second, I use an industry-level measurse of trade exposure rather than region-level measures. As discussed in Acemoglu et al. (2016b), region-level measures capture reallocation and demand effects, while industry-level measures isolate the direct impact on exposed industries. Third, I include within-manufacturing industry switching (in and out), which is missing in their work. Fourth, I decompose the destination non-manufacturing industries into retail, wholesale, and commercial service.[10] I show that the patterns differ across these destination industries. Fifth, commuting-zone level analysis performed by Bloom et al. (2019) holds even if only large establishments switch to non-manufacturing, whereas I show that small establishments also switch to non-manufacturing, especially to retailing.[11]

[9] They used different instrument than the one popularized since Autor, Dorn, and Hanson (2013). Moreover, although they were the first to pioneer the product switching response to trade shock, their finding was statistically insignificant when their instrument was used. Their concept of trade exposure was also different from that of Autor, Dorn, Hanson, and Song (2014)'s in several ways: They regressed their outcome variables on *past* 5 years of *average* import penetration from *all low-wage countries*, rather than *concurrent* period's *growth* of import penetration from *China alone*.

[10] The non-manufacturing sector includes various industries that manufacturers are unlikely to switch to. Non-manufacturing industries also include agriculture, forestry, fishing, mining, construction, transportation, communications, electric, gas, sanitary services, finance, insurance, real estate, and non-commercial personal services such as laundry.

[11] Breinlich, Soderbery, and Wright (2018) find that UK tariff reduction led firms to switch to the service industry. The first, second, and fifth distinctions from Bloom et al. (2019) broadly apply to distinguish my contribution from that of Breinlich,

Similarly, in an independently developed paper, Ding, Fort, Redding, and Schott (2019) find that a shock similar to direct exposure in my paper induces a decrease in the share of a firm's manufacturing employment, and that a shock similar to downstream exposure induces both a decrease in the share of manufacturing employment and an increase in the share of a firm's professional services employment.

There are important differences. First, I study many margins of adjustments that they do not study. They do not specifically study industry switching toward retail and wholesale, industry switching within manufacturing, and importing. Second, they do not study how businesses respond to upstream exposures. Third, and do not study heterogeneous response by age and size. Fourth, they conduct their analyses only at the firm-level, but do not include establishment-level analyses. Since trade shocks are defined at manufacturing industries, and each establishment is assigned a distinct industry, having an establishment-level analyses is important. Fifth, their firm-level analyses rely on a much smaller sample: Their sample contains only 72,500 firms whereas my sample contains 254,390 firms.

Sixth, I obtain a seemingly opposite result on the margin of exporting. They find that their measure of import penetration is associated with firms lowering exports, the number of exporting countries, and the number of exporting products. However, again, their sample contains a much fewer number of firms. Although my result is not necessarily contradictory to theirs, I will have to understand where the difference comes up in the next version of my paper.

Using NETS data, Asquith, Goswami, Neumark, and Rodriguez-Lopez (2019) find that establishment exits account for the largest fraction of China-shock-induced manufacturing employment declines. They do not study industry switching, trade participation, and building affiliates in China. Moreover, their commuting-zone-level regressions cannot study the interaction between trade shocks and establishment characteristics, which, as explained in Introduction, has implications for trade theories.

More broadly, this paper is related to several key strands in the literature. First, I contribute to the literature on establishment- and firm-level responses to trade exposure. Second, this paper is relevant to the literature on manufacturing employment declines in developed economies (reviewed in Fort, Pierce, and Schott 2018b and Abraham and Kearney 2018). Section 3.1 further discusses my findings in relation to this literature. Third, this paper is directly related to the vast applied literature on China shock. Fourth, I contribute to the literature on economic shock propagation through networks, in particular input-output linkages (Acemoglu et al. 2016b; Acemoglu et al. 2016a; Wang et al. 2018). All these strands in the literature are too broad to exhaustively cite in one place. I will discuss the literature further in next sections below.

Soderbery, and Wright (2018). Also, the topic of my study, the US-China trade relation, features the trade liberalization episode that arguably has had the greatest global economic impact.

2 Empirical Approach

2.1 Measures and Empirical Model

Establishment-Level Direct China Shock

To each establishment i, I assign the SIC 4-digit level trade shock constructed by Autor et al. (2014) for manufacturing industries. Let $j(i)$ denote the SIC 4-digit industry of establishment i in 1991. Direct China shock is defined as the change in import penetration from China into the US, i.e.,

$$\Delta IP_{j(i)} = \frac{\Delta M^{UC}_{j(i)}}{Y_{j(i),91} + M_{j(i),91} - E_{j(i),91}}, \tag{1}$$

where $\Delta M^{UC}_{j(i)}$ represents the change in real imports from China to the U.S. from 1991 to 2007 in industry $j(i)$ and $Y_{j(i),91} + M_{j(i),91} - E_{j(i),91}$ is 1991 real domestic absorption of industry $j(i)$, which is industry total shipments $Y_{j(i),91}$ plus industry imports $M_{j(i),91}$ minus industry exports $E_{j(i),91}$.[12] To ease interpretation, this measure 1 and all the other measures of various exposures 2 to 5 will be standardized so as to have mean 0 and standard deviation 1.

Establishment-Level Upstream and Downstream Shocks

I also use two measures of China shock propagation to look at the indirect effect through input-output linkage. Upstream shock is defined so that if China starts to export garments to the US, US fabrics (garments' upstream) establishments are exposed to upstream shock. Downstream shock is defined so that if China starts to export a certain machine part to the US, US final machine producers are exposed to downstream shock.

To each establishment i, I assign the SIC 4-digit level upstream and downstream trade shock constructed by Acemoglu et al. (2016b). Upstream shock $\Delta IP^{U}_{j(i)}$ is defined so that it is higher when Chinese imports are higher in industries that use more of industry j's output. More precisely, upstream China shock for establishment i is defined as the weighted average of import penetration (1) for the industries b that buy from industry $j(i)$:

[12] In the China shock literature, the early 1990s is the most common starting year of this time period. This is the period in which the HS-level bilateral trade data for many country pairs became available. The selection of this time period is also justified by the observation that the presence of Chinese manufacturing in the global economy surged mostly during the 1990s. For example, Naughton (2006) documents that Chinese policy shifts signaled by Deng Xiaoping's Southern Tour in 1992 unleashed a flood of FDI into China.

$$\Delta IP^U_{j(i)} = \sum_{b \neq j(i)} w^U_{b,j(i)} \Delta IP_b \tag{2}$$

where the weight $w^U_{b,j(i)}$ is the sales ($) of the industry $j(i)$ to the buying industry b divided by the total sales of industry $j(i)$:

$$w^U_{b,j(i)} = \frac{\mu_{b,j(i)}}{\sum\limits_{b'} \mu_{b',j(i)}}$$

where $\mu_{b,j(i)}$ is the value of industry $j(i)$'s output purchased by buying industry b, which was obtained from the 1992 BEA input-output table.[13]

Similarly, downstream shock $\Delta IP^D_{j(i)}$ is defined so that it is higher when Chinese imports are higher in industries from which industry j buys. More precisely, downstream China shock $\Delta IP^D_{j(i)}$ is defined as:

$$\Delta IP^D_{j(i)} = \sum_{s \neq j(i)} w^D_{j(i),s} \Delta IP_s \tag{3}$$

where the weight $w^D_{j(i),s}$ is the amount that industry $j(i)$ buys from the selling industry s divided by the total purchases of industry $j(i)$:

$$w^D_{j(i),s} = \frac{\mu_{j(i),s}}{\sum\limits_{s'} \mu_{j(i),s'}}.$$

Again, all measures 1, 2, and 5 are standardized for the ease of interpretation.

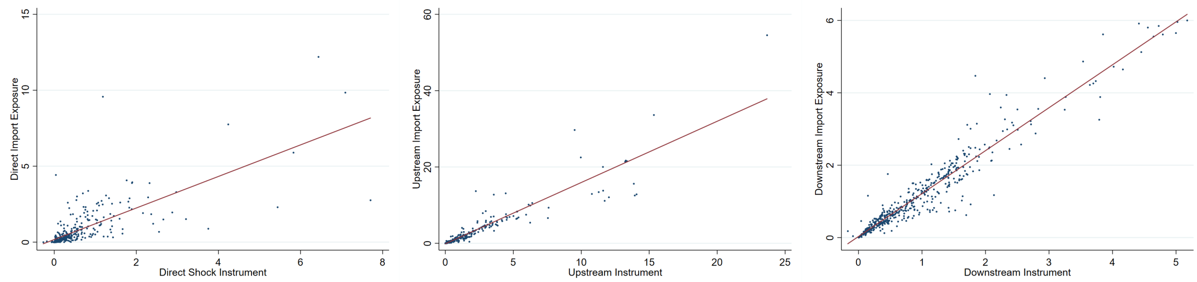
Establishment-Level Instruments

The common purpose in the literature using the measure 1 is to capture the *supply-shock-driven component of the import growth from China*. That is, I want it to capture the aspect of import growth that can be attributed to the supply shock that hit Chinese productivity rather than US domestic demand shocks. Even without the instrument that I will shortly introduce, history indicates that the measure 1 would serve my purpose quite well. That is, the Chinese productivity surge and subsequent increase in trade came about as a result of internal Chinese economic and political reforms and a power struggle within Communist Party of China, that was exogenous to the US.

Nonetheless, the increase in the import penetration ratio may partly come from domestic US demand shocks. To tackle this concern (as in Autor et al. (2014)), I instrument $\Delta IP_{j(i)}$ by the import penetration

[13] Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) are among the prominent works that have used the BEA input-output table to incorporate the shock propagation.

Figure 1: Association between Regressors and Instruments



Notes: Each dot represents a SIC 4-digit industry. The first graph relates the direct China shock 1 with its instrument 4. The second one relates the upstream shock 2 with its instrument (the first one in 5). The third one relates the downstream shock 3 with its instrument (the second one in 5).

from China to eight non-US high-income countries[14] defined by

$$\Delta IPO_{j(i)} = \frac{\Delta M^{OC}_{j(i)}}{Y_{j(i),88} + M_{j(i),88} - X_{j(i),88}} \tag{4}$$

where $\Delta M^{OC}_{j(i)}$ is the change in real imports from China to the eight non-US high-income countries from 1991 to 2007 in industry $j(i)$, and $Y_{j(i),88}+M_{j(i),88}-X_{j(i),88}$ is 1988 real domestic absorption. The use of 1988 rather than 1991 absorption in (4) is standard in the literature and is meant to account for firms switching industries in anticipation of the future growth of imports from China. Now the identifying assumption is that the industry import demand shocks of the US and that of the other high-income countries are not correlated.

Analogously, the instruments for the upstream and downstream shocks (2) and (3) are constructed as

$$\Delta IPO^U_j = \sum_{b \neq j} w^U_{bj} \Delta IPO_b \text{ and} \tag{5}$$
$$\Delta IPO^D_j = \sum_{s \neq j} w^D_{js} \Delta IPO_s,$$

respectively. As shown in Figure 1, all three instruments are closely associated with the regressors. I will also report the first-stage F statistics for my results. Again, all the measures from 1 to 5 will be standardized so as to have mean 0 and standard deviation 1.

Establishment-Level Empirical Model

I run the following empirical model

[14] The other advanced economies are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. In this set of high-income countries, bilateral trade data is available at the level of Harmonized System since 1991.

$$
\begin{aligned}
Y_{it} = &\beta_0 + \beta_1 \underbrace{\Delta IP_{j(i)}}_{\text{Direct shock}} + \beta_2 \underbrace{\Delta IP^U_{j(i)}}_{\text{Upstream shock}} + \beta_3 \underbrace{\Delta IP^D_{j(i)}}_{\text{Downstream shock}} \\
&+ \beta_4 1\{\text{Importer}_{i,1991}\} + \beta_5 1\{\text{Exporter}_{i,1991}\} + \beta_6 \mathbf{X}^{'}_{i,0} + \beta_7 \mathbf{Z}^{'}_{j(i),0} + e_i
\end{aligned}
\tag{6}
$$

where Y_i is some measure of establishment i's adjustment between 1991 and 2007, which will be introduced below in Table 1 and elsewhere in later sections.

The regressors are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ as defined in (4) and (5). Again, upstream shock is defined so that if China starts to export garments to the US, US fabrics establishments are exposed to upstream shock. Downstream shock is defined analogously.

$1\{\text{Exporter}_{i,1991}\}$ and $1\{\text{Importer}_{i,1991}\}$ are indicators for establishment i being an exporter and importer in 1991, respectively.[15] $\mathbf{X}_{i,0}$ is a vector of establishment-level controls and fixed effects. It includes initial year employment, age, and state.[16] $\mathbf{Z}^{'}_{j,0}$ is a vector of industry controls. As in Autor et al. (2014) and Acemoglu et al. (2016b), I include industry-level variables drawn from NBER-CES data, which is largely derived from the Annual Survey of Manufacturers (Becker, Gray, and Marvakov 2013). That is, I include 10 industry dummies, the share of production workers, the log average production worker hourly wage, capital over value added, computers as a share of investment, and high-tech equipment as a share of investment, all in 1991. This is intended to capture the concurrent changes in patterns of U.S. manufacturing, such as computerization, automation, and the general trend away from labor-intensive industries (Doms et al. 1997; Autor, Katz, and Krueger 1998). Also included are industry-level trends before 1991, such as 1976-1991 changes in log average wages and industry share in US employment. Standard errors are clustered at the SIC 3-digit level.

Dependent variables and sample

The next section will provide results for six outcomes, which are summarized in Table 1. For the exit margin (the first dependent variable), the sample is US manufacturing establishments that exist in 1991.

From the second to the sixth margins, the sample is the continuing US manufacturing establishments from 1991 to 2007, as is usual in the literature on firm/establishment-level response to trade shock (e.g., Bernard et al. 2006a; Pierce and Schott 2018; Autor et al. 2019b). Therefore, for second to sixth margins,

[15] Inclusion of the trade status indicators is motivated by Bernard and Jensen (2007a) who find that exporters are less likely to exit, and by Timoshenko (2015) who finds that, conditional on firm size, new exporters switch products more frequently than old exporters.

[16] Inclusion of age and employment is motivated by Dunne, Roberts, and Samuelson (1988).

I caution that the interpretation of the regression estimates represents an effect conditional on not exiting. Having a continuing-business sample is especially informative when the theory that we have in mind is also in terms of continuing businesses. For example, Bernard, Redding, and Schott (2011) takes the sample of continuing firms to show that trade liberalization leads continuing firms to drop low-productivity products, which is meant to test their own theory that is also in terms of continuing firms.[17]

Moreover, I also run industry-level analogous regressions that circumvent this issue of selection,[18] where the outcome variable is the industry-level share of adjusters among continuers. The qualitative results point in the same direction.

Table 1: Dependent Variables for Baseline Regression

(1)	Exit	$100 \times 1\{\text{Establishment } i \text{ exists in 1991, but not in 2007}\}$
(2)	Importer	$100 \times 1\{\text{Importer}_{i,2007}\}$
(3)	Switch to retail/wholesale	$100 \times 1\{\text{SIC4}_{i,2007} \text{ is retail or wholesale}\}$
(4)	Switch to cml. service	$100 \times 1\{\text{SIC4}_{i,2007} \text{ is commercial service}\}$
(5)	Export	$100 \times 1\{\text{Exporter}_{i,2007}\}$
(6)	Switch in mfg	$100 \times 1\{\text{SIC4}_{i,2007} \neq \text{SIC4}_{i,1991} \& \text{SIC4}_{i,2007} \text{ is manufacturing}\}$

Notes: This table summarizes the dependent variables used in Table 3. $1\{\cdot\}$ is an indicator that takes 1 if the statement inside the bracket is true, and 0 otherwise. $1\{\text{Exporter}_{i,t}\}$ and $1\{\text{Importer}_{i,t}\}$ are indicators for establishment i being an exporter and importer in year t, respectively. $\text{SIC4}_{i,t}$ stands for the SIC 4-digit industry of establishment i in year t.

Threats to Identification

Autor, Dorn, and Hanson (2013) note that they cannot categorically reject two related threats to identification, although they are defensible. The large literature that they have created and my work share similar concerns. For example, one threat to identification is that negative or weak US productivity shocks may have led both the US and other high-income countries to import more from China. A related threat is that technology shocks that hit all high-income countries, such as automation, might have driven Chinese imports. Yet, like Autor, Dorn, and Hanson (2013), I appeal to economic and political history to argue that China's export growth is fundamentally and largely due to China-specific factors that are exogenous to US firms. In particular, Bloom et al. (2016) and Autor et al. (2015) suggest that import growth from China was not driven by automation. The magnitude and speed of Chinese productivity growth and the exogeneity of political events that spurred such growth should persuade us that a major portion of Chinese imports to the US and high-income countries can be attributed to exogenous factors specific to China. By including various

[17]Trade liberalization in Bernard, Redding, and Schott (2011) is export liberalization, not the import liberalization that I study here. A new model of product switching in response to import liberalization would require additional structures in Antras, Fort, and Tintelnot (2017).

[18]Still, since this industry-level specification cannot include establishment-level controls and fixed effects, it is hard to say whether establishment-level or industry-level specification is better. There are advantages and disadvantages to both approaches.

industry-level controls, I also account for concurrent changes in US manufacturing during this period, such as automation and computerization.

2.2 NETS

NETS Overview

I use the National Establishment Time Series (NETS), which comes from extensive data gathering efforts of Dun & Bradstreet and Walls & Associates. NETS covers a near-universe of US establishments from 1990 to 2015.[19] An establishment is defined as a business location having a unique, separate, and distinct operation. I make use of its annual information on employment, industry[20], export and import status, headquarter, county, and age.

Each establishment is assigned a 9-digit identification number called a Data Universal Numbering System (DUNS) number. A DUNS number follows each establishment over time irrespective of changes, such as mergers, acquisitions, and changes of industry. A DUNS number is not reused if an establishment goes out of business. The hierarchical relationship between a headquarter and its branch or subsidiary can be tracked by looking at the headquarter variable, which is available in all years. Using this variable, I can construct firm-level, as opposed to establishment-level, measures.

Coverage is one of NETS's great strengths. In 1991, 10,272,841 establishments were included in the data. I drop every establishment that has ever been educational, governmental, noncommercial, or a nonprofit because they are not likely to respond to economic incentives.

A number of works have compared NETS with government statistics (e.g., Neumark et al. 2007, Barnatchez, Crane, and Decker 2017b).[21] The implications of these works are twofold. First, NETS is remarkably comprehensive, and many of its patterns are largely similar to those found in government statistics. Second, discrepancies between NETS and government statistics, when they occur, are not necessarily due to a measurement error in NETS. Such discrepancies might well be due to NETS' conceptual uniqueness. See Appendix A.2 for more details.

I perform additional quality checks. I compare NETS and government statistics regarding import and export variables, conduct manual checks on industry and address information, and confirm the consistency

[19] As a credit rating company, Dun & Bradstreet's profit depends on the accuracy of the data, and so it has a strong market incentive to maintain up-to-date and accurate information. As Neumark, Zhang, and Wall (2007), Kolko and Neumark (2008), Barnatchez, Crane, and Decker (2017b), and other reports note, NETS's range of sources of information is extensive. See Appendix A.1 for more details.

[20] An important advantage of NETS over official statistics is that its industry codes have been maintained in a time-consistent manner. See Appendix A for more details.

[21] Recent economics papers that use NETS, such as Rossi-Hansberg, Sarte, and Trachter (2018) and Asquith et al. (2019), include further details on NETS.

of SIC codes. See Appendix A.3 and A.4 for more details.

Recently, Crane and Decker (2019) raised concerns about NETS's entry and employment dynamics (while still acknowledging the accuracy of employment statics). For three reasons their concerns are of limited relevance for my work.

First, it is important to highlight that their own previous paper (Barnatchez, Crane, and Decker 2017b) showed that *static* employment information is remarkably close to official sources, despite differences in coverage and innate ambiguity in industry classifications. For the major outcome variables in this paper (namely exporter and importer status, industry switching, exit, building affiliates in China), employment is used *statically* but not dynamically. For these margins of adjustments, the only instance where employment is used is when the initial 1991 employment level is included just as a control or regression weight.

Second, even when I study employment dynamics (as opposed to statics), I examine the long horizon, which, according to the literature, improves NETS's reliability significantly. Neumark et al. 2007 compare NETS and QCEW regarding dynamic employment *changes* by industry and county. They find that examining the long horizon significantly increases their correlation. For example, the year-by-year correlation is 0.528, while the three-year correlation is 0.864. My work uses a 16-year-long horizon. Existing works that use NETS, such as Rossi-Hansberg, Sarte, and Trachter (2018) and Asquith et al. (2019), also justify the reliability of their estimates on the basis of the high correlation between NETS and the administrative dataset over the long horizon. Moreover, even the low correlation in year-by-year change does not immediately imply an error in NETS.

Third, my analysis does not rely on the dynamic entry margin, because I include an establishment in the sample only if it existed in 1991. Therefore, Crane and Decker (2019)'s concerns about entry information are not relevant to these sections. Furthermore, the problem with entry dynamics in NETS mostly arises after 2008, whereas my time frame, like that of Autor, Dorn, and Hanson (2013) and Autor et al. (2014), includes the years until 2007. For example, Barnatchez, Crane, and Decker (2017b) and Crane and Decker (2019) show that NETS's and BDS's young firm employment shares remained remarkably similar until 2007, although in 2008 they started to diverge. Both series displayed a modestly declining trend from 1996 to 2007, hovering between 12% to 14~15%, and the per-year difference between NETS and BDS during this period remained 0% to 2% until 2007.

2.3 Summary Statistics

Table 2 reports summary statistics for two sets of samples. The first upper panel is concerned with the sample of all manufacturing establishments that were operating in 1991. The second lower panel takes the

Table 2: Summary Statistics

Manufacturing establishments operating in 1991 (Obs. = 583994)							
Variable	Mean	S.D.	P10	Median	P90	Variable	Mean
Emp growth 1991-2007	-0.95	1.13	-2	-1.33	0.57	1{Exit by 2007}	0.486
Mfg emp growth 1991-2007	-1.03	1.12	-2	-2	0.5	1{Exporter$_{i,1991}$}	0.046
Employment in 1991	37.95	215.87	1	6	66	1{Importer$_{i,1991}$}	0.003

Manufacturing establishments in 1991, that survive until 2007 (Obs. = 299921)							
Variable	Mean	S.D.	P10	Median	P90	Variable	Mean
Emp growth 1991-2007	0.05	0.66	0.72	0.00	0.93	1{Exporter$_{i,1991}$}	0.052
Mfg emp growth 1991-2007	-0.12	0.84	-1.45	0.00	0.86	1{Exporter$_{i,2007}$}	0.170
Employment in 1991	38.74	235.67	1	6	65	1{Importer$_{i,1991}$}	0.003
Employment in 2007	39.23	179.01	1	7	77	1{Importer$_{i,2007}$}	0.044
Mfg employment in 2007	37.09	174.20	1	6	75	1{Retail-Wholesale$_{i,2007}$}	0.041
						1{Commercial service$_{i,2007}$}	0.018

Notes: The data comes from merging National Establishment Time Series (NETS). The first higher panel is concerned with the sample of all manufacturing establishments that were operating in 1991. The second lower panel takes the sample of manufacturing establishments that existed in 1991 and continued to 2007. Employment-related variables are aligned on the left panel, whereas indicator variables are on the right panel. Importer and exporter statuses are at the establishment-level, not at the firm-level. Employment and manufacturing employment growth are defined according to Davis, Haltiwanger, and Schuh (1998). $1\{\cdot\}$ denotes a binary indicator.

sample of manufacturing establishments that existed in 1991 and continued to 2007. Employment-related variables are aligned on the left panel, whereas indicator variables are on the right panel. Employment and manufacturing employment growth are defined according to Davis, Haltiwanger, and Schuh (1998). Note that importer and exporter statuses are at the establishment-level, not at the firm-level as in US Census LFTTD.[22]

As is well-documented in the literature (e.g., Bernard, Jensen, Redding, and Schott 2018), only very few businesses engage in importing or exporting. Still, these figures might look too small. That is partly because NETS also includes individual proprietors and self-employment which rarely engage in exporting and importing. In the sample of those that continue until 2007, the share of exporters and importers surges dramatically.

By 2007, 4.1% and 1.8% of the continuers become retail-wholesalers and commercial servicers, respectively. Partly due to this switching, manufacturing employment growth rate is lower than overall employment growth rate in both samples. Particularly in the sample of continuers, the manufacturing employment declines whereas overall employment increases.

[22]In a separate note, titled "Within-Firm Across-Establishment Allocation of International Trade Activity," whose tables are available upon request, I document the patterns that this establishment-level information displays. Even within a firm, the ranking of the likelihood of an establishment being an exporter is manufacturers, wholesalers, and non-wholesale non-manufacturers. Again even within a firm, the ranking of the likelihood of an establishment being an importer is wholesalers, manufacturers, and non-wholesale non-manufacturers.

3 Baseline Results

3.1 Key Establishment-Level Margins of Adjustments

In Table 3, each column represents a distinct outcome variable. The dependent variables in Table 3 are concisely summarized in a table in the previous section:[23]

Table 3: Baseline Results

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.8***	1.0***	0.4**	0.1	1.8**	0.8**
	(0.5)	(0.4)	(0.2)	(0.1)	(0.8)	(0.4)
ΔIP^U	-0.8**	-0.2	-0.6***	0.0	0.5	0.6**
	(0.4)	(0.2)	(0.1)	(0.1)	(0.6)	(0.3)
ΔIP^D	3.1***	0.2	0.8***	0.9***	1.5*	0.9**
	(0.6)	(0.2)	(0.2)	(0.2)	(0.8)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: For column 1, the sample is the near-universe of US manufacturing establishments in 1991. For columns 2 to 6, the sample is the near-universe of US manufacturing establishments that continued to exist from 1991 to 2007. The dependent variables are defined in Table 1. Estimates are from the establishment-level 2SLS regressions based on equation (6). Observations are not weighted. The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. Establishment-level controls and fixed effects include 1991 employment, age, state, and import & export status. Industry-level controls and fixed effects include 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Sanderson–Windmeijer F-Statistics (Sanderson and Windmeijer 2016) in column 1 are 89.3, 380.7, and 2026.7 for ΔIP, ΔIP^U, and ΔIP^D, respectively. Sanderson–Windmeijer F-Statistics in columns 2 to 6 are 111.6, 407.1, and 1684.0 for ΔIP, ΔIP^U, and ΔIP^D, respectively. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Direct exposure

The row marked by ΔIP indicates the response of continuing US manufacturers directly exposed to China shock. Although they are more likely to exit, they also are more likely to become importers, retail-wholesalers, and exporters, and they are more likely to switch industries within manufacturing, conditional upon survival. The row marked ΔIP in Table 3 reveals three baseline results about direct exposure.

First, direct exposure is associated with manufacturers becoming importers by 2007.[24] One might think

[23] Recall again that $1\{Exporter_{i,1991}\}$ and $1\{Importer_{i,t}\}$ are controlled for in regression specification 6. In column 5, $\#China_{f,1999}$ is also controlled for.

[24] Again, in the Appendix, I compare NETS and published tabulations from administrative data regarding export and import indicators. The correlation between the datasets regarding the percent of exporters and importers by NAICS 3-digit is surprisingly high despite the intrinsic ambiguity of industry classification.

that this is obvious. But it is not, because it is consistent with the idea that *US manufacturers started offshoring products that are similar to what they used to make on their own.*[25] Taking computers as an example, this finding is consistent with the idea that *US computer manufacturers started offshoring computer products that are categorized as the same SIC 4-digit industries as the computers that they used to make on their own.*

Again, the positivity of the coefficient is not an obvious result. This positive correlation would not arise if the initial non-manufacturers are the ones that import computers from China to the US because non-manufacturers are not included in the sample. or The positive correlation would not arise if establishments that entered after 1991 were the ones that imported computers from China to the US because the sample does not include them. The coefficient would be negative if computers were imported by manufacturers whose 1991 industry was not computer manufacturing. However, the coefficient will be indeed positive if computer manufacturers are the ones offshoring computers from China. This is important to emphasize. If US firms did not view this circumstance as an offshoring opportunity, there is no bigger incentive for US computer manufacturers to become importers than US manufacturers of other goods or non-manufacturers.[26]

The economic impact of direct exposure is sizeable. Although the average of the outcome variable is merely 4.1, one standard deviation increase in the direct exposure is correlated with an increase of a 1 percentage point increase in the likelihood of becoming an importer in 2007.

Second, direct exposure is associated with manufacturers becoming retail-wholesalers by 2007. One standard deviation increase in sectoral direct exposure is associated with a 0.4 percentage point increase in the share of retailers and wholesalers in 2007. This business-level finding complements the *geographic area-level* study on non-manufacturing employment growth in affected commuting zones undertaken by Bloom, Handley, Kurman, and Luck (2019) and Faber, Sarto, and Tabellini (2019).

Intuitively, manufacturers in an industry could switch to retailers and wholesalers for two reasons: the manufacturers are importing products they formerly produced; or importing is conducted by other establishments in the industry.

The upper left graph of Figure 3 is consistent with the first cause. The residuals from the regression from the importer margin and the residuals from the regression from the wholesaler margin are positively correlated (0.35). That is, imagine that industries A and B are exposed to the *same* growth of import penetration, but suppose that manufacturers in industry A have a higher likelihood of becoming an importer

[25]This is also consistent with the offshoring pattern that Bernard, Fort, Smeets, and Warzynski (2020) document using Danish data. They find that firms engage in offshoring in a way that they "increase their imports of the same detailed goods they produce domestically".

[26]Again, the limitation of these findings is that my dataset does not contain information about the destination of exports, the origin country of imports, or export and import products. However, these findings remain consistent with an economic story of offshoring and global expansion.

than those in industry B. The upper left graph of Figure 3 indicates that establishments in industry A would have a higher likelihood of becoming a wholesaler than those in industry B. This is consistent with the idea that importing begets wholesaling. As the upper right graph of Figure 3 shows, an analogous pattern does not exist for the margin of becoming a retailer.

Third, direct exposure is associated with manufacturers becoming exporters by 2007. This is best rationalized by recalling the finding about the importer margin. Importing can increase efficiency through foreign intermediate goods (Amiti and Konings 2007; Kasahara and Rodrigue 2008; Topalova and Khandelwal 2011; Halpern, Koren, and Szeidl 2015). Then, as in the model of Kasahara and Lapham (2013) and Antras, Fort, and Tintelnot (2017), the increased productivity due to global sourcing would help manufacturers self-select into exporting. Other examples where importing makes exporting more profitable are vertical specialization (Hummels, Ishii, and Yi 2001) and carry-along trade (Bernard, Blanchard, Van Beveren, and Vandenbussche 2019). The lower left graph of Figure 3 provides additional support for the close connection between importer and exporter margins. That is, there is a strong correlation between the residuals from regressing the importer margin on China shock and residuals from regressing exporter margin on China shock. This is consistent with the idea that importing begets exporting.

Fourth, direct exposure is associated with manufacturers switching industries within manufacturing. This can be rationalized as an attempt to avoid import competition. In fact, in subsection 3.1, I show that the within-manufacturing switching occurs toward industries that are lesser-hit by China shock. This is also consistent with anecdotal evidence from Burlington Coat Factory, whose 10-K report explicitly cites China shock as its reason for switching to product lines less exposed to import penetration. Alternatively, switching can be a sign of quality upgrading undertaken to avoid import competition or to introduce new products using new inputs (Khandelwal 2010; Amiti and Khandelwal 2013; Medina 2017; Colantone and Crinò 2014; Orr 2020).[27] More generally, industry switching could be a sign of general restructuring due to adjustments introduced so far. The lower right graph of Figure 3 provides additional support for the connection between the margin of becoming an importer and the margin of switching industries within manufacturing.

Industry switching as a response to direct exposure is an establishment-version of Autor et al. (2014), who find that people who in 1991 worked in manufacturing industries that underwent a greater import penetration from China between 1991 and 2007 are more likely to spend less time in their initial two-digit SIC industries. My results and those of Autor et al. (2014) suggest that China shock induces both workers and businesses to switch industries.

[27] This is consistent with a US Steel anecdote, whose 10-K document complains about import competition and states that the company switched its focus to high value-added products.

Downstream exposure

The row marked by ΔIP^D indicates the response of continuing US manufacturers in sectors that buy from the directly exposed sectors–i.e., it shows the adjustment to downstream exposure. Although these manufacturers are more likely to exit, they are also more likely to become retailers, wholesalers, commercial service businesses, or exporters, and they are also more likely to switch industries within manufacturing, conditional on survival.

First, downstream exposure is associated with the manufacturers' exits. This outcome is inconsistent with the hypothesis that downstream manufacturers would grow thanks to imported inputs. However, if the manufacturers in some industries become wholesalers and retailers on their own, the supply chain will skip the previous downstream manufacturers, leading to their exits. Acemoglu et al. (2016b) find no impact of downstream exposures of Chinese imports on *industry-level* employment. They argue that this could be because the relationship-specific productivity of downstream businesses was lost due to Chinese imports. My narrative that relates the third and fourth points suggests that the loss of relationship-specific productivity could have occurred because directly exposed manufacturers became wholesalers and retailers on their own.

Second, remarkably, downstream-exposed manufacturers are not more likely to become importers. Yet, they are still more likely to become retailers and wholesalers. This is consistent with engaging in indirect sourcing rather than directly importing on their own. Using Belgian data, Dhyne, Kikkawa, Mogstad, and Tintelnot (2020) showed that indirect sourcing is prevalent.

Third, downstream exposure is associated with the manufacturers becoming exporters. Again using the same reasoning applied to direct exposure, this is consistent with the idea that obtaining foreign inputs make the businesses efficient enough to start exporting. The unreported graphs for downstream exposure, that are analogous to Figure 3, also display a high correlation between the residuals from importer margin and those from exporter margin.

Fourth, downstream exposure is associated with the manufacturers switching industries in manufacturing.

Upstream exposure

The row marked by ΔIP^U indicates the response of continuing US manufacturers in sectors that sell to the directly exposed sectors–i.e., the adjustment to upstream exposure.

First, in the next section, in Table 12, I show that the *negative* impact of upstream exposure on importing is economically and statistically significant for medium-sized to large manufacturers. Extremely small establishments tend not to engage in importing. But whether medium-sized or large manufacturers decide to import will depend on whether domestic businesses are willing to buy the imported goods. Second, upstream exposure is also associated with the manufacturers being less likely to become retail-wholesalers and commercial servicers.

These two effects most likely can be attributed to the loss of US domestic buyers. For example, import penetration in garments shrinks US garment manufacturing; thus, it is unprofitable to import fabrics to the US or to try to sell fabrics in the US.[28]

Third, US manufacturers that experience upstream exposure become more likely to switch within manufacturing. This is likely due to the motive for avoiding import competition hitting their buyers. This motive is consistent with an anecdotal evidence from Cone Mills cited in Introduction, whose 10-K report explicitly states that import penetration hitting certain garment products caused the company to switch to fabrics (upstream to garments) not used in such garments.

The apparent negative association between upstream exposures and exit probability (column 1) is not robust when I do not include the dummy for ten sub-industries. A cautious interpretation would be that I do not find either positive or negative strong impacts of upstream exposures on establishment exit.

Direction of Industry Switching

In this subsection, I show that industry switchers generally move toward industries that are less exposed to China shock.[29] Take the example of Monarch Services, which, according to NETS data, switched from "Games & Toys" industry to "Periodicals" industry in 2000.[30] Since "Games & Toys" experienced higher growth of import penetration from China between 1991 to 2007 than "Periodicals", we can write that $\Delta IP_{\text{Game},91\sim07} > \Delta IP_{\text{Periodicals},91\sim07}$.

Figure 2 averages across all such manufacturers who switched to another manufacturing industry. I take the sample of all establishments that (1) were manufacturers in both 1991 and 2007, and (2) whose SIC 4-digit industry in 2007 was different than in 1991. Those that did not switch industries or that switched to non-manufacturing are not included. Then I depict the average China shock ΔIP_{jt} in each year based on establishments' industry of affiliation. Since Figure 2 is derived from the sample of continuing establishments,

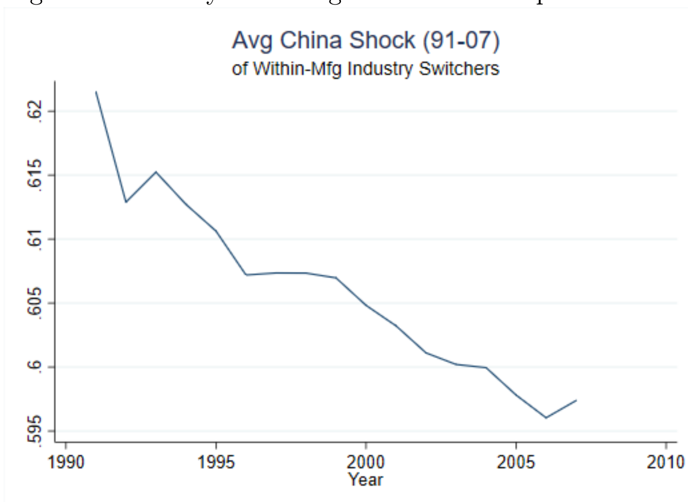
[28] Table 16 indeed shows that garments industries have been highly exposed to direct China shock, whereas fabrics industries have been heavily exposed indirectly by upstream propagation of the direct shock.

[29] Again, the accuracy of the industry information in NETS is supported by the existing literature and multiple additional checks summarized in section 2.2.

[30] I verified the accuracy of this information about this industry switching. Both the origin and destination industries are accurate, and the timing of industry switching is accurate. Baltimore Sun reports in 1999 that "Monarch Services (...) best known as a maker of elaborate board games (...) moving forward with new plans for their sole remaining venture -- Girls' Life magazine." This adds confidence to NETS data accuracy.

the exit margin is not present in this figure. The clearly declining trend implies that within-manufacturing industry switchers generally moved toward less-exposed industries.

Figure 2: Industry Switching Toward Less-Exposed Sectors



Notes: Each point in the graph takes the same sample: establishments that (1) were manufacturers both in 1991 and 2007, and (2) whose SIC 4-digit industry in 2007 was different from that in 1991. Those that did not switch industries or that switched to non-manufacturing are not included. Y-axis in year t corresponds to the average of direct exposure $\Delta IP_{j(i)t}$ where the industry $j(i)$ of establishment i could be different in each year.

3.2 Establishment-Level Employment Structure

Next, Table 4 turns to the establishment-level employment structure.

Table 4: Employment Structure at Establishment-Level

Outcome	Emp growth	Mfg emp growth	Emp growth among continuers	Mfg emp growth among continuers
	(1)	(2)	(3)	(4)
ΔIP	-0.042***	-0.041***	-0.010***	-0.015***
	(0.010)	(0.011)	(0.003)	(0.006)
ΔIP^U	0.015*	0.026***	-0.002	0.021***
	(0.008)	(0.008)	(0.004)	(0.006)
ΔIP^D	-0.060***	-0.075***	0.007	-0.035***
	(0.012)	(0.013)	(0.004)	(0.008)
All controls	✓	✓	✓	✓
$Avg(Y)$	-0.946	-1.034	0.052	-0.119
F for ΔIP	89.3	89.3	111.6	111.6
F for ΔIP^U	380.7	380.7	407.1	407.1
F for ΔIP^D	2026.7	2026.7	1684.0	1684.0
N	583994	583994	299921	299921

Notes: The sample for columns 1 and 2 is the near-universe of US manufacturing establishments that existed in 1991. The sample for the other columns is restricted to continuers from 1991 to 2007. For columns 1 and 3, the dependent variable is establishment-level employment growth rate defined by Davis, Haltiwanger, and Schuh (1998). For columns 2 and 4, the dependent variable is establishment-level manufacturing employment growth rate again defined by Davis, Haltiwanger, and Schuh (1998). The dependent variable of the last column is the change in establishment-level manufacturing employment shares. Estimates are from the establishment-level 2SLS regressions based on equation (6). The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. Establishment-level controls and fixed effects include 1991 employment, age, state, and import & export status. Industry-level controls and fixed effects include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Sanderson–Windmeijer F-Statistics for all three regressors are reported. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Let $L_{i,t}$ and $L_{i,t}^{Mfg}$ denote the employment and manufacturing employment of establishment i in year t, respectively. In columns 1 and 3, the dependent variable is employment growth rate defined by Davis, Haltiwanger, and Schuh (1998). That is,

$$\frac{2\left(L_{i,2007}-L_{i,1991}\right)}{L_{i,2007}+L_{i,1991}}. \tag{7}$$

Analogously, in columns 2 and 4, the dependent variable is manufacturing employment growth rate defined by Davis, Haltiwanger, and Schuh (1998). That is,

$$\frac{2\left(L_{i,2007}^{Mfg}-L_{i,1991}^{Mfg}\right)}{L_{i,2007}^{Mfg}+L_{i,1991}^{Mfg}}. \tag{8}$$

Since the first two columns include both eventual exiters and continuers, they involve, in large part, the exit margin in column 1 of Table 3. Consequently, the signs of the coefficients are consistent with them: Both overall employment and manufacturing employment decline when they are exposed to direct or downstream shock. The apparent employment gain from upstream exposure (column 1) is not robust when I do not include the dummy for ten sub-industries. A cautious interpretation would be that I do not find either a positive or a negative strong impact of upstream exposures on overall employment. Nevertheless, since upstream exposures suppress industry switching toward non-manufacturing, they lead to gains in manufacturing employment (column 2).

Columns 3 and 4 take the sample of continuers only. Here, only direct exposure has a significant negative impact. However, in the case of manufacturing employment growth, shown in column 4, the effect of industry switching toward non-manufacturing (shown in columns 3 and 4 of Table 3) is incorporated. Consequently, for manufacturing employment in column 4, the negative impact of direct shock is even more pronounced than in column 3; moreover, there is a strong negative impact of downstream shock, and a positive impact of upstream shock.

Discussion in Relation to Manufacturing Employment

My results have two implications for the important literature on manufacturing employment declines (reviewed in Fort, Pierce, and Schott 2018b and Abraham and Kearney 2018).

First, my results imply that it is important to incorporate input-output linkages in analyses of manufacturing employment declines. The literature has mainly focused on the negative impact of direct exposure on the manufacturing employment of affected firms and establishments. However, I show that upstream exposure had a positive impact on the establishments that were already operating in 1991 (the row marked ΔIP^U, columns 2 and 4 of Table 4). This will be further confirmed in my firm-level (as opposed to establishment-level) results in Tables 10 and 11. To my knowledge, this is a new channel in the literature.

Second, I relate China shock to industry switching to retail, wholesale, and service. Fort, Pierce, and Schott (2018b) find that the share of non-manufacturing employment at manufacturing firms steadily increased from 1977 to 2012, including during the period between 1991 and 2007. They also find that one-third of this increase occurred in retail, while another one-third occurred in professional services. However, they do not indicate whether trade or technology was responsible for this trend. Similarly, using Danish data, Bernard, Smeets, and Warzynski (2017) find that industry switching from manufacturing to services accounts for an important fraction of Danish manufacturing employment declines.

4 Decomposition of Industry-Level Employment Response

This section links the establishment-level margins of adjustments to aggregate employment outcomes. The first dependent variable is the industry-level employment growth rate as defined by Davis, Haltiwanger, and Schuh (1998):

$$\frac{L_{j,2007} - L_{j,1991}}{0.5(L_{j,2007} + L_{j,1991})}.$$

Column 1 of Table 5 reports the impact of the three measures of trade exposure on the industry employment growth. The direct exposure clearly has a negative impact on industry total employment. Upstream and downstream exposures have only a weak indication of a negative association.

This change in the employment of industry j can be decomposed into eight components. These components are defined by the type of establishment-level margins of adjustments.

Four components contributed to employment growth in industry j: establishment entry, switching from non-manufacturing to j, switching from non-j manufacturing to j, and job creation at establishments that operated in industry j in both 1991 and 2007. The employment growth that can be accounted for by these components are denoted by $L^{entry}_{j,2007}$, $L^{\text{NonMfg}\to j}_{j,2007}$, $L^{\text{Non}j\text{Mfg}\to j}_{j,2007}$, and $L^{+}_{j,1991,2007}$, respectively.

Four components contributed to employment losses in industry j: establishment exit, switching from j to non-manufacturing, switching from j to non-j manufacturing, and job destruction at establishments that operated in industry j in both 1991 and 2007. The employment losses that can be accounted for by these components are denoted by $L^{exit}_{j,1991}$, $L^{j\to\text{NonMfg}}_{j,1991}$, $L^{j\to\text{Non}j\text{Mfg}}_{j,1991}$, and $L^{-}_{j,1991,2007}$, respectively.

Then, the employment growth rate in industry j can be decomposed as follows:[31]

$$\begin{aligned}&\frac{L_{j,2007} - L_{j,1991}}{0.5(L_{j,2007} + L_{j,1991})}\\ =&\frac{\left(L^{entry}_{j,2007} + L^{\text{Non-Mfg}\to j}_{j,2007} + L^{\text{Non-}j\text{-Mfg}\to j}_{j,2007} + L^{+}_{j,1991,2007}\right) - \left(L^{exit}_{j,1991} + L^{j\to\text{Non-Mfg}}_{j,1991} + L^{j\to\text{Non-}j\text{-Mfg}}_{j,1991} + L^{-}_{j,1991,2007}\right)}{0.5(L_{j,2007} + L_{j,1991})}.\end{aligned} \tag{9}$$

Columns 2 to 9 of Table 5 report each component. Columns 2 to 5 correspond to the first four terms in equation 9. Columns 6 to 9 correspond to the last four terms in equation 9. Consequently, the sum of coefficients from columns 2 to 5, minus the sum of coefficients from columns 6 to 9, equals the coefficient in

[31] Again, this decompositional analysis differs from Bloom, Handley, Kurman, and Luck (2019) in two respects. First, they use region-level measure of trade exposure, rather than industry-level. As discussed in Acemoglu et al. (2016b), region-level measures capture different channels than industry-level measures. Second, they do not analyze upstream and downstream exposures. Third, the components of within-manufacturing switching (in and out) are missing in their analysis.

column 1.

Table 5: Industry-Level Employment Growth Decomposition

		Components that cause emp growth				Components that cause emp declines			
	Total	Entry	From Non-Mfg	Mfg switch in	Job creation	Exit	To Non-Mfg	Mfg switch out	Job destruction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔIP	-11.0***	-2.3**	-0.0	-0.2	-1.0*	5.9***	0.3	0.1	1.2
	(3.5)	(1.0)	(0.2)	(0.7)	(0.6)	(1.7)	(0.4)	(0.5)	(0.8)
ΔIP^U	-0.4	-0.7	-0.5***	0.4	0.4	-0.1	-0.8**	0.7*	-0.0
	(2.0)	(0.8)	(0.1)	(0.4)	(0.3)	(1.0)	(0.3)	(0.4)	(0.4)
ΔIP^D	-1.0	2.5***	0.2	0.2	-0.4	4.1***	0.6	0.3	-1.6**
	(2.6)	(0.9)	(0.2)	(0.4)	(0.4)	(1.2)	(0.4)	(0.5)	(0.7)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
$Avg(Y)$	-16.8	36	4.2	7.6	12.8	52.9	3.7	8	12.9

Notes: $N = 392$. The industry-level employment growth rate (as defined by Davis, Haltiwanger, and Schuh (1998)) is reported in column 1. Columns 2 to 9 decompose this into eight components discussed in the main body of the text. Columns 2 to 5 (6 to 9) report the components that contribute to the growth (decline) of employment. Consequently, the sum of coefficients from columns 2 to 5, minus the sum of coefficients from columns 6 to 9, equals the coefficient in column 1. Regressions are weighted by industry-level initial employment. The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Sanderson–Windmeijer F-Statistics (Sanderson and Windmeijer 2016) are 65.6, 408.6, and 1976.8 for ΔIP, ΔIP^U, and ΔIP^D, resectively. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The negative impact of direct exposure is mainly due to the significantly suppressed entry (column 2), significantly higher exit (column 6), and somewhat suppressed job creation at continuing establishments (column 5).

Although the total impact of upstream shock is not clear in either direction, switching from non-manufacturing to manufacturing is suppressed (column 3), and switching from manufacturing to non-manufacturing is also suppressed (column 7). These two effects largely cancel one another. The within-manufacturing switching out (column 8) is particularly significant as a response to upstream exposure, whereas it is not so pronounced as a response to either direct or downstream exposure.

The total impact of downstream exposure on employment is not clear, although the coefficient is negative (column 1). This is because entry (column 2) and exit (column 6) are simultaneously suppressed. This is consistent with Acemoglu et al. (2016b)'s hypothesis that there are two counteracting channels. They report that there is no clear indication that downstream exposure has either a positive or negative impact on employment, which is consistent with column 1 of Table 5.[32]

[32] Their analysis was at the industry-level, and they could not perform decompositional analysis as I do.

Acemoglu et al. (2016b) rationalize this by arguing that there are two counteracting channels. First, downstream industry will benefit from cheap inputs from China. Second, however, they will be hurt because relationship-specific production will be negatively affected. My decomposition provides support for their rationalization. The enhanced entry (column 2) is consistent with the first channel of benefiting from cheap inputs. The higher exit (column 6) is consistent with the second channel of hampered relationship-specific production. Newly entering businesses will be free from the concern of the second channel because they do not have relationship-specific production when they enter the market.

5 Heterogeneous Response

In this section, I interact all three types of exposures with age and employment. Table 6 and 7 reveal that there is a clear dependence for exporting the margin of adjustment. Note that there are three distinct concepts of heterogeneity:

1. The age and size of an establishment in 1991 is correlated with its *being* an exporter or an importer in 1991.

2. The age and size of an establishment in 1991 is correlated with its *becoming* an exporter or an importer by 2007 (rows "Emp" and "Age").

3. The age of an establishment in 1991 is correlated with the *effect of trade shocks on becoming* an exporter or an importer by 2007 (rows "$\Delta IP_{j(i)}$***Age**", "$\Delta IP^{U}_{j(i)}$***Age**", and "$\Delta IP^{D}_{j(i)}$***Age**").

I confirm all three types of heterogeneity. The first point, the static dependence on either size or age[33], has been documented in the literature numerous times (e.g., Pavcnik 2002; Trefler 2004; Bernard, Jensen, and Schott 2006b; Melitz and Trefler 2012). However, to the best of my knowledge, the third point has not been confirmed in the literature.

The second point can be seen by the rows titled "Age" and "Emp" in Table 6. Even when both age and employment are included, in the last column, the clear correlation is still maintained. An establishment 10 years older is 1.45 (0.45) percentage points more likely to become an exporter (importer) by 2007. An establishment that had 10 more employees in 1991 is 0.1 (0.08) percentage points more likely to become an exporter (importer) by 2007.

The third point can be seen from the interaction between trade exposures and age. For exporting margin, the impact of upstream and downstream shocks is greater for older establishments. To the best of my knowledge, this channel is uninvestigated both empirically and theoretically. For the importing margin, the impact of direct exposure is greater for older establishments. To the extent that age capture productivity, it is consistent with global sourcing models with heterogeneous firms (Antras and Helpman 2004; Antras, Fort, and Tintelnot 2017).

[33]This result is unreported in the table, but the result is available upon request.

Table 6: Impact of China Shock on US Exporting with Interactions

	(1)	(2)	(3)
$\Delta IP_{j(i)}$	1.515**	1.718**	1.513**
	(0.692)	(0.766)	(0.694)
$\Delta IP^U_{j(i)}$	-0.245	0.340	-0.268
	(0.551)	(0.619)	(0.556)
$\Delta IP^D_{j(i)}$	1.254	1.588*	1.258
	(0.774)	(0.830)	(0.772)
Age	0.145***		0.144***
	(0.013)		(0.013)
$\Delta IP_{j(i)}$***Age**	0.026		0.026
	(0.019)		(0.020)
$\Delta IP^U_{j(i)}$***Age**	0.041***		0.037***
	(0.013)		(0.012)
$\Delta IP^D_{j(i)}$***Age**	0.042**		0.044**
	(0.017)		(0.017)
Emp	0.009***	0.009***	0.010***
	(0.002)	(0.002)	(0.002)
$\Delta IP_{j(i)}$***Emp**		0.001	0.000
		(0.001)	(0.002)
$\Delta IP^U_{j(i)}$***Emp**		0.002	0.003
		(0.002)	(0.002)
$\Delta IP^D_{j(i)}$***Emp**		-0.003***	-0.001
		(0.001)	(0.001)
All control/f.e.	✓	✓	✓
N	278013	303556	278013

Notes: The sample is the near-universe of US manufacturing establishments that continued to exist from 1991 to 2007. The dependent variable is the binary indicator of exporter status in 2007 minus that in 1991. Note again that the binary exporter status in 1991 is controlled for. Estimates are from the establishment-level 2SLS regressions of equation (6). "Age" denotes establishment age in 1991. "Emp" denotes establishment employment in 1991. The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. The regressions are not weighted. Establishment-level controls and fixed effects include 1991 state and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Impact of China Shock on US Importing with Interactions

	(1)	(2)	(3)
$\Delta IP_{j(i)}$	0.371	0.938**	0.355
	(0.224)	(0.379)	(0.221)
$\Delta IP^U_{j(i)}$	-0.263	-0.258	-0.264
	(0.198)	(0.242)	(0.206)
$\Delta IP^D_{j(i)}$	0.377**	0.287	0.385**
	(0.186)	(0.254)	(0.183)
Age	0.048***		0.048***
	(0.005)		(0.004)
$\Delta IP_{j(i)}$***Age**	0.033***		0.030**
	(0.012)		(0.012)
$\Delta IP^U_{j(i)}$***Age**	0.006		0.005
	(0.006)		(0.005)
$\Delta IP^D_{j(i)}$***Age**	-0.006		-0.004
	(0.006)		(0.006)
Emp	0.007***	0.012***	0.008***
	(0.001)	(0.002)	(0.002)
$\Delta IP_{j(i)}$***Emp**		0.003	0.003
		(0.002)	(0.002)
$\Delta IP^U_{j(i)}$***Emp**		0.001	0.001
		(0.002)	(0.001)
$\Delta IP^D_{j(i)}$***Emp**		-0.003**	-0.001
		(0.001)	(0.001)
All control/f.e.	✓	✓	✓
N	278013	303556	278013

Notes: The sample is the near-universe of US manufacturing establishments that continued to exist from 1991 to 2007. The dependent variable is the binary indicator of importer status in 2007 minus that in 1991. Note again that the binary importer status in 1991 is controlled for. Estimates are from the establishment-level 2SLS regressions of equation (6). "Age" denotes establishment age in 1991. "Emp" denotes establishment employment in 1991. The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. The regressions are not weighted. Establishment-level controls and fixed effects include 1991 state and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table 8, the dependent variable is the employment growth rate of an establishment defined by Davis, Haltiwanger, and Schuh (1998). The sample includes not only continuers but also those that exited by 2007. Those that exited by 2007 are assigned zero employment in 2007. The growth rate defined in Davis, Haltiwanger, and Schuh (1998) is particularly appropriate when including exiters and survivors. Reading the first three rows, direct and downstream shocks clearly have a negative impact, whereas the upstream exposure has a positive impact. This is consistent with the result on exit in the baseline result reported in Table 3.

The main lesson from Table 8 is that the negative impact of direct exposure on employment growth is greater for young and large businesses (as indicated by row $\Delta IP_{j(i)}$***Age** and $\Delta IP_{j(i)}$***Emp**). If age captures productivity, it is consistent with the literature. It has been repeatedly shown in the literature that low-productivity plants are more likely to exit due to some episodes of trade liberalization (e.g., Trefler 2004; Bernard, Jensen, and Schott 2006b). However, age is potentially distinct from productivity in this context: a large theoretical literature on firm dynamics since Jovanovic (1982) predicts that even among businesses that have identical productivities, young firms are more likely to exit.

Business age is a significant determinant of various outcomes in the firm dynamics literature. Therefore, my finding on interaction with age raises new hypotheses in connection with firm dynamics. For example, Autor, Dorn, Hanson, Pisano, and Shu (2019b) find that China shock is associated with lower innovation in affected industries, but they do not identify the exact mechanism. However, in light of the prediction of Akcigit and Kerr (2018) that "younger firms are more R&D and patent intensive than older firms" (page 21), my finding that young businesses are driven out by China shock could partly explain Autor, Dorn, Hanson, Pisano, and Shu (2019b).

The interaction with employment is particularly surprising.[34] However, it is consistent with the theory of Holmes and Stevens (2014), who posit that large producers make standardized goods, whereas small ones make specialty goods, and therefore large establishments are most affected by China shock. They provide empirical support for their theory by showing that industries hit by China shock experience a greater decline in locations that have large plants. But their empirical analysis is not at the plant-level, and therefore it could not include other correlates of establishment size, such as age. This means, in principle, they could not distinguish between large and old establishments. Table 9 provides roughly the same result. The positive impact of direct exposure on exit is greater for young and large businesses (as indicated by row $\Delta IP_{j(i)}$***Age** and $\Delta IP_{j(i)}$***Emp**).

By interpreting the result as supportive of Holmes and Stevens (2014), I provide a managerial policy implication: that businesses in high-income countries can avoid import competition from low-income countries by producing specialty goods. Other strategies that businesses can take to be shielded from import competition include building R&D stock (Hombert and Matray 2018), operating in areas where banking

[34]I circulated this finding in internal seminars at the University of Chicago as early as April 2019 (Trade Working Group), and in external conference as early as February 2020 (AEF conference). At the suggestion of Jonathan Dingel at the April 2019 seminar, I provided the interpretation based on Holmes and Stevens (2014). Later, in their July 2020 working paper, Argente, Moreira, Oberfield, and Venkateswaran (2020) reported a similar result using the same NETS data. To the best of my knowledge, I am the first to circulate this finding from NETS data. Moreover, there are several other differences. First, my result is based on the period 1991-2007, whereas their result is based on the period 2006-2015, which largely overlaps with the Great Recession and Great Trade Collapse. Second, since age and size are correlated, I show the robustness of my result by including age interaction and size interaction simultaneously, which they do not seem to have done. Third, I include upstream and downstream exposures, and plus their interactions with age and size, to further check the robustness of my finding. Fourth, I provide an interpretation based on Holmes and Stevens (2014), whereas they provide a new theory of scalable expertise.

Yet, there are at least two aspects that they have, but that I do not have. First, they also complemented the result using Nielsen data (for the period 2006-2015). Second, they provide a different explanation, based on scalable expertise, that applies to any sort of demand shock. They are the first to introduce the mechanism based on scalable expertise.

sector is deregulated (Hoffmann and Ruslanova 2020), using service inputs (Bamieh, Fiorini, Hoekman, and Jakubik 2020), and product innovation strategies (Kueng, Li, and Yang 2016).

Table 8: Impact of China Shock on Employment Growth with Interactions

	(1)	(2)	(3)
$\Delta IP_{j(i)}$	-4.310***	-3.425***	-4.270***
	(1.103)	(0.935)	(1.110)
$\Delta IP^U_{j(i)}$	2.584***	2.196***	2.614***
	(0.858)	(0.779)	(0.866)
$\Delta IP^D_{j(i)}$	-5.010***	-5.068***	-5.011***
	(1.214)	(1.184)	(1.220)
Age	0.203***		0.204***
	(0.028)		(0.028)
$\Delta IP_{j(i)}$***Age**	0.038		0.043*
	(0.024)		(0.024)
$\Delta IP^U_{j(i)}$***Age**	-0.063***		-0.059***
	(0.023)		(0.022)
$\Delta IP^D_{j(i)}$***Age**	-0.019		-0.022
	(0.030)		(0.031)
Emp	-0.012***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.003)
$\Delta IP_{j(i)}$***Emp**		-0.004**	-0.005**
		(0.002)	(0.002)
$\Delta IP^U_{j(i)}$***Emp**		-0.003	-0.003
		(0.002)	(0.003)
$\Delta IP^D_{j(i)}$***Emp**		0.002	0.002
		(0.001)	(0.002)
All control/f.e.	✓	✓	✓
N	523428	637743	523428

Notes: The sample is the near-universe of US manufacturing establishments that existed in 1991. The dependent variable is employment growth rate of an establishment defined by Davis, Haltiwanger, and Schuh (1998). Note again that the sample includes not only continuers but also those that exited by 2007. Those that exited by 2007 are assigned zero employment in 2007. Note again that the binary importer status in 1991 is controlled for. Estimates are from the establishment-level 2SLS regressions of equation (6). "Age" denotes establishment age in 1991. "Emp" denotes establishment employment in 1991. The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. The regressions are not weighted. Establishment-level controls and fixed effects include 1991 state and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Impact of China Shock on US Exit with Interactions

	(1)	(2)	(3)
$\Delta IP_{j(i)}$	2.037***	1.577***	2.032***
	(0.563)	(0.498)	(0.566)
$\Delta IP^U_{j(i)}$	-1.016**	-1.065***	-1.014**
	(0.414)	(0.374)	(0.417)
$\Delta IP^D_{j(i)}$	2.936***	2.700***	2.953***
	(0.578)	(0.583)	(0.579)
Age	-0.211***		-0.208***
	(0.010)		(0.010)
$\Delta IP_{j(i)}$***Age**	-0.030**		-0.031**
	(0.012)		(0.012)
$\Delta IP^U_{j(i)}$***Age**	0.011		0.010
	(0.010)		(0.010)
$\Delta IP^D_{j(i)}$***Age**	-0.016		-0.013
	(0.011)		(0.011)
Emp	-0.003***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)
$\Delta IP_{j(i)}$***Emp**		0.001	0.001*
		(0.001)	(0.001)
$\Delta IP^U_{j(i)}$***Emp**		0.001*	0.000
		(0.001)	(0.001)
$\Delta IP^D_{j(i)}$***Emp**		0.000	-0.001**
		(0.001)	(0.001)
All control/f.e.	✓	✓	✓
N	523428	637743	523428

Notes: The sample is the near-universe of US manufacturing establishments that existed in 1991. The dependent variable is the binary indicator that is 1 if the establishment exited by 2007. Estimates are from the establishment-level 2SLS regressions of equation (6). "Age" denotes establishment age in 1991. "Emp" denotes establishment employment in 1991. The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). All three regressors are standardized to have mean 0 and standard deviation 1. The regressions are not weighted. Establishment-level controls and fixed effects include 1991 state and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6 Firm-Level Analog

The baseline results are reported at the level of establishments rather than firms. This is so for at least two reasons. First, an establishment is a more granular unit than a firm. Second, the assignment of trade exposure is more straightforward because different establishments in the same firm often have different industries. However, an argument that favors analysis at the level of firms contends that firms are the ultimate decision-makers. In this section, I provide results from firm-level analysis.

Firm-Level Exposures

A firm may have multiple establishments. Since a firm could be the actual unit of decision making, I also construct a firm-level China shock. If a firm is a single-unit, or if it is a multi-unit with identical industries, the calculation of firm-level shock is straightforward. For multi-unit multi-industry firms, I use employment weights to construct the firm-level shock. Again, let $\Delta IP_{j(i)}$ denote the China shock experienced by an establishment i whose SIC 4-digit industry is j. Then the firm-level China shock ΔIP_f of firm f is defined as

$$\Delta IP_f = \sum_{i \in E_f} w_{if} \Delta IP_{j(i)} \tag{10}$$

where E_f is the set of establishments that belonged to firm f in 1991 and w_{if} is the employment share of establishment i in firm f in 1991. Note that some of the establishments could be non-manufacturers for which the measure of trade exposure $\Delta IP_{j(i)}$ is not defined. There are two ways to deal with this issue. First, I can restrict the sample to firms that consist only of manufacturing. Second, I can include all firms with at least one manufacturing establishment, but let non-manufacturing establishments take a zero value of trade exposure. I present the regression results of both approaches.

Upstream and downstream firm-level shocks ΔIP^U_f and ΔIP^D_f are constructed in the same manner that $\Delta IP^U_{j(i)}$ and $\Delta IP^D_{j(i)}$ were constructed:

$$\Delta IP^U_f = \sum_{i \in E_f} w_{if} \Delta IP^U_{j(i)} \text{ and } \Delta IP^D_f = \sum_{i \in E_f} w_{if} \Delta IP^D_{j(i)}. \tag{11}$$

Instruments for ΔIP_f, ΔIP^U_f, and ΔIP^D_f are constructed in a similar way:

$$\begin{aligned} \Delta IPO_f &= \sum_{i \in E_f} w_{if} \Delta IPO_{j(i)} \\ \Delta IPO^U_f &= \sum_{i \in E_f} w_{if} \Delta IPO^U_{j(i)} \\ \Delta IPO^D_f &= \sum_{i \in E_f} w_{if} \Delta IPO^U_{j(i)}. \end{aligned} \tag{12}$$

This shift-share way of aggregating establishment-level variables to the firm-level is common in applied macroeconomics and IO literature.

Firm-Level Empirical Model

When the unit of observation is a firm rather than an establishment, the empirical specification is

$$Y_f = \beta_0 + \beta_1 \Delta IP_f + \beta_2 \Delta IP_f^U + \beta_3 \Delta IP_f^D + \beta_4 \mathbf{X}'_{f,0} + \beta_5 \mathbf{Z}'_{f,0} + e_f, \tag{13}$$

where ΔIP_{ft} is the firm-level China shock constructed as in equation (10). The regressors are instrumented by ΔIPO_f, ΔIPO_f^U, and ΔIPO_f^D as defined in (12). $\mathbf{X}'_{f,0}$ is the firm-level analogue of $\mathbf{X}_{i,0}$. It includes initial year firm-level employment, firm-level age (age of the oldest establishment), the region of the largest establishment, the number of establishments in a firm, and an import (export) status indicator that equals 1 if at least one of its establishments is importing (exporting). $\mathbf{Z}'_{f,0}$ is the firm-level analogue of $\mathbf{Z}'_{j(i),0}$. In NETS, as in US Census data, industry is defined at the establishment-level, not at the firm-level. There are multiple ways to define the firm-level analogue. One element of $\mathbf{Z}'_{f,0}$ is 10 manufacturing industries dummies, which are categorical variables. In this case, the categorical variable of the largest manufacturing establishment in each firm f is assigned to the firm.[35] All other variables in $\mathbf{Z}'_{f,0}$ are continuous. In this case, the weighted average of the industry-level controls, in which the weights are employment shares of each establishment, is assigned to the firm.

Outcomes for the sample that contains both exiters and continuers

Table 10 reports the firm-level results for three margins: exit, employment growth, and manufacturing employment growth.[36] However, since a firm may include non-manufacturing establishments, and since China shock is not assigned for non-manufacturing industries, I need to make a judgement on how to treat them in the firm-level analysis. In columns 1 to 3, I assign $\Delta IP_{j(i)} = \Delta IP_{j(i)}^U = \Delta IP_{j(i)}^D = 0$ to non-

[35] A concrete example would be a firm that has a manufacturing establishment 1 (E1) with 20 employees, a manufacturing establishment 2 (E2) with 30 employees, and a non-manufacturing establishment 3 (E3) with 50 employees. In this case, establishment 2 is the one with the biggest manufacturing employment. Therefore, the subindustry dummy of establishment 2 is assigned to this firm. The fact that non-manufacturing establishment is the largest is not of a big concern because I also control for the share of manufacturing employment.

[36] Employment and manufacturing employment growth are defined analogously to the establishment measures of 7 and 8. Let $L_{f,t}$ and $L_{f,t}^{Mfg}$ denote the employment and manufacturing employment at firm f in year t, respectively. In columns 2 and 5, the dependent variable is employment growth rate defined by Davis, Haltiwanger, and Schuh (1998). That is,

$$\frac{2\left(L_{f,2007} - L_{f,1991}\right)}{L_{f,2007} + L_{f,1991}}. \tag{14}$$

Analogously, in columns 3 and 6, the dependent variable is manufacturing employment growth rate defined by Davis, Haltiwanger, and Schuh (1998). That is,

$$\frac{2\left(L_{f,2007}^{Mfg} - L_{f,1991}^{Mfg}\right)}{L_{f,2007}^{Mfg} + L_{f,1991}^{Mfg}}. \tag{15}$$

manufacturing establishments when calculating the firm-level measures defined in (10) and (11). In columns 4 to 6, I only take the sample of manufacturing firms that consist only of manufacturing establishments. In the second case, the coverage is smaller than the first, but the concept of trade exposure is clearer.

In both sets of the sample, I find that the establishment-level results in Table 4 carry over. The direct exposure and downstream exposure are associated with more exits, lower overall employment growth, and lower manufacturing employment growth in this sample that contains exiters.[37] On the other hand, upstream exposure is associated with less exits and higher manufacturing employment growth.

Table 10: Firm-Level Outcomes (Exiters + Continuers Sample)

	Firms with at least one manufacturing establishment in 1991			Firms consisting only of manufacturing establishments in 1991		
	Exit	Emp growth	Mfg emp growth	Exit	Emp growth	Mfg emp growth
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP_f	1.617***	-0.038***	-0.035***	1.638***	-0.038***	-0.037***
	(0.482)	(0.010)	(0.010)	(0.487)	(0.010)	(0.010)
ΔIP_f^U	-0.789**	0.013*	0.025***	-0.791**	0.013*	0.023***
	(0.365)	(0.007)	(0.008)	(0.375)	(0.007)	(0.007)
ΔIP_f^D	2.604***	-0.050***	-0.061***	2.623***	-0.050***	-0.065***
	(0.546)	(0.011)	(0.012)	(0.559)	(0.012)	(0.012)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	47.482	-0.916	-1.007	47.598	-0.914	-1.001
N	506003	506003	506003	485470	485470	485470

Notes: In columns 1 to 3, the sample is the near-universe of US manufacturing firms that operated in 1991. Manufacturing firms are firms that have at least one manufacturing establishment. In columns 4 to 6, the sample is further restricted to firms that consisted only of manufacturing establishments in 1991. For the exit margins in columns 1 and 4, the dependent variable is 100 if the firm exited by 2007, 0 otherwise. Employment growth (columns 2 and 5) and manufacturing employment growth (columns 3 and 6) are defined in 14 and 15, respectively, following Davis, Haltiwanger, and Schuh (1998). Since the sample includes those that exit by 2007, the exiters' employment and manufacturing growth rates are -2 according to Davis, Haltiwanger, and Schuh (1998). Firm-level regressors ΔIP_f, ΔIP_f^U, and ΔIP_f^D (defined in (10) and (11)) are instrumented by ΔIPO_f, ΔIPO_f^U, and ΔIPO_f^D (defined in (12)). All three regressors are standardized to have mean 0 and standard deviation 1. Firm-level controls and fixed effects include 1999 employment, domestic manufacturing employment shares, state of the largest establishment, age, the number of establishments in a firm, and import & export status. Industry-level controls include the share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. In columns 1 to 3, Sanderson–Windmeijer F-Statistics (Sanderson and Windmeijer 2016) are 93, 395, and 2027 for ΔIP_f, ΔIP_f^U, and ΔIP_f^D, respectively. In columns 4 to 6, they are 93, 383, and 1923. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[37] Although my result on the impact of direct exposure on firm-level employment growth (row ΔIP, columns 2 and 5) has an expected negative sign and it is consistent with many related findings from US (e.g., Bernard, Jensen, and Schott 2006a) and other countries (e.g., Mion and Zhu 2013 (Belgium), Ekholm, Moxnes, and Ulltveit-Moe 2012 (Norway)), the result in Magyari (2017) is the opposite of mine. My result is more consistent with what Autor, Dorn, and Hanson (2013) and Fort, Pierce, and Schott (2018b) would expect.

Table 11: Firm-Level Outcomes (Continuers Sample)

	Firms with at least one manufacturing establishment in 1991				Firms consisting only of manufacturing establishments in 1991			
	Emp growth	Mfg emp growth	Exporter	Importer	Emp growth	Mfg emp growth	Exporter	Importer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔIP_f	-0.008**	-0.008*	1.891**	0.714**	-0.007*	-0.011**	1.926**	0.758***
	(0.004)	(0.005)	(0.785)	(0.287)	(0.004)	(0.005)	(0.763)	(0.284)
ΔIP_f^U	-0.005	0.021***	0.373	-0.222	-0.006	0.016**	0.405	-0.100
	(0.005)	(0.006)	(0.619)	(0.215)	(0.005)	(0.006)	(0.590)	(0.138)
ΔIP_f^D	0.009*	-0.025***	1.672**	0.044	0.010**	-0.030***	1.649**	0.184
	(0.005)	(0.007)	(0.787)	(0.219)	(0.005)	(0.007)	(0.767)	(0.166)
All controls	✓	✓	✓	✓	✓	✓	✓	✓
$Avg(Y)$	0.064	-0.109	11.111	3.66	0.072	-0.093	10.667	2.804
N	265733	265733	265733	265733	254390	254390	254390	254390

Notes: In columns 1 to 3, the sample is the near-universe of US manufacturing firms that continued from 1991 to 2007. Manufacturing firms are firms that have at least one manufacturing establishment. In columns 4 to 6, the sample is further restricted to firms that consisted only of manufacturing establishments in 1991. Employment growth (columns 1 and 5) and manufacturing employment growth (columns 2 and 6) are defined in 14 and 15, respectively, following Davis, Haltiwanger, and Schuh (1998). The dependent variables in columns 3, 4, 7, and 8 are firm-level exporter or importer status in 2007. Firm-level regressors ΔIP_f, ΔIP_f^U, and ΔIP_f^D (defined in (10) and (11)) are instrumented by ΔIPO_f, ΔIPO_f^U, and ΔIPO_f^D (defined in (12)). All three regressors are standardized to have mean 0 and standard deviation 1. Firm-level controls and fixed effects include 1999 employment, domestic manufacturing employment shares, state of the largest establishment, age, the number of establishments in a firm, and import & export status. Industry-level controls include the share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. In columns 1 to 4, Sanderson–Windmeijer F-Statistics (Sanderson and Windmeijer 2016) are 111, 426, and 1688 for ΔIP_f, ΔIP_f^U, and ΔIP_f^D, respectively. In columns 5 to 8, they are 110, 410, and 1577. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Outcomes for the sample that contains only continuers

In Table 11, I restrict the sample to the manufacturing firms that continued to operate from 1991 to 2007. Employment and manufacturing employment growth rates are again defined as in 7 and 8, but a firm will be regarded as missing, rather than being assigned -2, if it is not a continuer. As in 10, I consider two sets of samples. Several patterns stand out.

First, directly-exposed continuing firms are more likely to become importers and exporters, but their employment and manufacturing employment growth are negatively affected. One might think this is counter-intuitive given that importing and exporting are often associated with firm growth, but this is consistent with the offshoring explanation that I have provided. The offshorers' labor demand for US employment will shrink.

Second, continuing firms exposed to downstream shock are more likely to become exporters, and they gain employment but lose manufacturing employment.[38] This is consistent with my establishment-level finding that downstream manufacturers tend to become exporters and switch to retailers, wholesalers, and commercial servicers. In so doing, although their manufacturing employment naturally decline, overall firm-level employment goes up.

Third, upstream exposure is positively associated with manufacturing employment growth. This is consistent with the baseline establishment-level result that upstream exposure is negatively associated with becoming retailers and wholesalers. The effect on total employment is indeterminate.

7 Extensions

7.1. Weighted Regression for Key Margins of Adjustment

The baseline results in Table 3 are unweighted. Unweighted regression has advantages and disadvantages. It is advantageous in the respect that the result does not critically depend on a few extremely large establishments. It is disadvantageous when we are particularly interested in relatively large establishments that play an important role in the aggregate economy. Particularly when the adjustment patterns depend on size, the two types of analyses complement each other to produce the whole picture.

Table 12 reports the results when the observations are weighted by their initial 1991 employment.[39] Several points are noteworthy.

[38] The employment gains of downstream firms are consistent with Wang, Wei, Yu, and Zhu (2018) although their measure of downstream shock uses intermediate input imports instead of total imports.

[39] Initial employment is not the only weight that can roughly proxy the significance of an establishment or a firm. For example, worth or net worth could be another quantity appropriate as a weight. However, only employment is reliably available for all establishments in the dataset.

Table 12: Baseline Results (Weighted by 1991 Employment)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	2.3***	3.0***	0.4	0.4*	1.5**	0.4
	(0.7)	(1.1)	(0.3)	(0.2)	(0.7)	(0.6)
ΔIP^U	-0.1	-1.4***	-0.3	-0.3	0.8	1.0*
	(0.4)	(0.5)	(0.3)	(0.3)	(0.6)	(0.6)
ΔIP^D	2.8***	-1.0	-0.2	1.2***	-0.8	1.7**
	(0.6)	(0.7)	(0.2)	(0.2)	(0.8)	(0.7)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	47.6	20.7	3.2	1.5	22.0	14.2
F for ΔIP	68.5	118.6	118.6	118.6	118.6	118.6
F for ΔIP^U	450.5	485.7	485.7	485.7	485.7	485.7
F for ΔIP^D	2221.9	2263.2	2263.2	2263.2	2263.2	2263.2
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from 12 is that now the regressions are weighted by their initial employment in 1991. For column 1, the sample is the near-universe of US manufacturing establishments in 1991. For columns 2 to 6, the sample is the near-universe of US manufacturing establishments that continued to exist from 1991 to 2007. The dependent variables were defined in Table 1. Estimates are from the establishment-level 2SLS regressions based on equation (6). The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). Establishment-level controls and fixed effects include 1991 employment, age, state, and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Sanderson–Windmeijer F-Statistics for all three regressors are reported. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In column 2, upstream exposure is strongly negatively associated with being an importer by 2007. This association was not statistically significant in the unweighted regression. In fact, there is a strong size dependence. As is widely assumed in the theoretical literature, there is a fixed cost of foreign sourcing (Antras, Fort, and Tintelnot 2017). Thus, it is understandable that small manufacturers tend not to become importers, whether or not their industries are upstream-exposed (i.e., whether the industries that their industries mainly sell to experience a surge of import growth from China). However, large manufacturers may start to import when their industry finds an opportunity for foreign sourcing. However, as observed in the baseline section, upstream exposure removes US domestic demand for upstream manufacturers. Therefore, large upstream manufacturers become even less likely to start importing.

Again in column 2, downstream exposure is uncorrelated with becoming an importer. In fact, the coefficient is negative, albeit insignificantly so, which strengthens the finding in the unweighted regression. Contrary to popular belief, original downstream manufacturers are not main drivers of the import growth from China. Instead, the pattern is more consistent with indirect sourcing of downstream manufacturers.[40]

In column 3, there is no clear pattern, either positively or negatively, for the margin of becoming retailers or wholesalers. The unweighted result in Table 3 shows that direct exposure and downstream exposure are strongly positively associated with becoming retailers, whereas upstream exposure is strongly negatively associated with that outcome. The null result in the weighted version is driven especially by the tendency of large manufacturers to not become retailers, which is intuitively understandable.

In column 4, now direct exposure is positively associated with becoming a commercial service provider, but the result is not robust across specifications. The weak indication needs to be interpreted with caution.

In column 6, although the result is maintained for upstream and downstream exposures, the direct exposure is not clearly associated with switching industry within manufacturing. There is some indication that huge establishments do not respond to direct exposure in this way.

7.2. Weighted Regression for Employment Structure

Table 13 reports the weighted version of Table 4. Direct exposure still has a strong negative impact on employment growth and manufacturing employment growth. Since the positive employment impact of upstream exposure reported in Table 4 is relatively weaker for large establishments, both economic and statistical significance weakens in this weighted version. Downstream exposure is still negatively associated with employment growth and manufacturing employment growth, but the significance of the impact vanishes

[40]Again, a caveat is that my dataset does not provide information on the source country of import. Therefore, I cannot categorically reject the possibility that the effect that I observe is the effect on import from non-China foreign countries. Nevertheless, I provide the rationalization that is consistent with my findings.

for continuing establishments.

Table 13: Employment Structure at Establishment-Level

Outcome	Emp growth (1)	Mfg emp growth (2)	Emp growth among continuers (3)	Mfg emp growth among continuers (4)
ΔIP	-0.062***	-0.059***	-0.048**	-0.049**
	(0.019)	(0.018)	(0.023)	(0.023)
ΔIP^U	0.003	0.010	0.000	0.016*
	(0.008)	(0.008)	(0.007)	(0.008)
ΔIP^D	-0.050***	-0.053***	-0.008	-0.020
	(0.013)	(0.013)	(0.014)	(0.014)
All controls	✓	✓	✓	✓
$Avg(Y)$	-1.13	-1.176	-0.34	-0.427
F for ΔIP	68.5	68.5	118.6	118.6
F for ΔIP^U	450.5	450.5	485.7	485.7
F for ΔIP^D	2221.9	2221.9	2263.2	2263.2
N	583994	583994	299921	299921

Notes: The only difference from Table 4 is that now the regressions are weighted. The sample for columns 1 and 2 is the near-universe of US manufacturing establishments that existed in 1991. The sample for the other columns is restricted to continuers from 1991 to 2007. For columns 1 and 3, the dependent variable is establishment-level employment growth rate defined by Davis, Haltiwanger, and Schuh (1998). For columns 2 and 4, the dependent variable is establishment-level manufacturing employment growth rate again defined by Davis, Haltiwanger, and Schuh (1998). The dependent variable of the last column is the change in establishment-level manufacturing employment shares. Estimates are from the establishment-level 2SLS regressions based on equation (6). The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). Establishment-level controls and fixed effects include 1991 employment, age, state, and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, 1976-1991 changes in industry share in US employment, and 10 dummies that classify SIC four-digit industries. Sanderson–Windmeijer F-Statistics for all three regressors are reported. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7.3. Local Reallocation and Demand Effects

The China shock literature uses either industry-level exposure or geographic region-level exposure (usually at the commuting-zone level). These two shocks capture different mechanisms. The shock at the local area additionally captures the general equilibrium effects, such as local reallocation and demand effects. In an unreported table, I find that the response to commuting-zone-level shock is smaller than the response to industry-level shock, or often it is simply null. This is rationalizable since it is implausible that an establishment will respond more strongly to the shock hitting other industries that affect the region they are located in. That is especially true because they are manufacturers who produce tradable goods that do not necessarily depend on local demand.

7.4. Including Each Shock Separately

So far I have included three types of measures simultaneously: direct, upstream, and downstream exposures defined in (1), (2), and (3), respectively. In Table 18, I show the results from regressions in which each exposure is included separately rather than jointly. Here, the baseline restuls are mostly borne out except for two results. First, the impact of downstream exposure on becoming importers turns statistically significant. Second, the impact of upstream exposure on within-manufacturing industry switching turns statistically insignificant. However, I maintain my interpretation on the results from the baseline regression where the three exposures are jointly included since I want to distinguish between the impacts of each type of exposures.

7.5. Dropping Headquarters Switchers between 1991-2007

Columns 1 to 6 of the baseline result could be partly driven by establishments switching their headquarters. Rather than being a threat to identification, mergers and acquisitions could be genuine mechanisms through which the esablishment-level adjustments occur. Nonetheless, it is of interest to check to what extent the results come from the establishments that change their headquarters between 1991-2007. Table 19 reports the result. The only difference from Table 3 is that now I do not include headquarter switchers between 1991-2007.[41]

The results mostly do not change. The sole exception is seen in column 6: partly due to the loss of the number of observations, the standard error increases so that now there is no significant sign that upstream manufacturers respond by switching industries within manufacturing. This result could also mean that the mechanism through which upstream manufacturers switch industries partly occurs when these establishments are bought by another business entity.

7.6. Concerns on Spurious Industry Switching

A spurious change in the industry classification of a multi-product establishment could occur because of a temporary change in its product mix. However, such a random change in industry, which is irrelevant to any shock, will create a bias *against* finding an impact of trade shocks on industry switching. Despite this possibility, I find a strong impact in the baseline result. Nevertheless, I tackle this concern by re-running regressions after dropping all establishments that switched SIC 4-digit industry more than 3 times between

[41] In NETS, each establishment has information about an establishment identifier of its headquarter establishment. Moreover, NETS' establishment identifier is dynamically consistently maintained, and is not reused after it goes inactive.

1991-2007 (less than 0.2% of the sample), and also all establishments that ever reverted back to their original industry (about 1.2% of the sample). As Table 21 shows, every result is qualitatively unchanged.

7.7. Overall Industry Switching

So far, I decomposed the overall industry switching into three categories: switching to retail and wholesale, to commercial service, and switching within manufacturing. It is of a separate interest to see how China shock is associated with overall industry switching.

Table 17 shows the result. Switching SIC 1-digit corresponds to switching to any sort of non-manufacturing. The pattern is consistent with the switching to retail, wholesale, and commercial service that was documented in Table 3. Although there are various non-manufacturing industries that were not considered in the baseline results[42], switching to those industries is not important enough to wash out the impact found in baseline Table 3.

Switching SIC 2, 3, and 4-digit industries entails both switching to non-manufacturing and switching within manufacturing. In columns 2, 3, and 4, it is expected that direct and downstream exposures will still have positive coefficients since we have seen from Table 3 that the two types of switching have direction for direct and downstream exposures. However, in Table 3, the two types of switching have the opposite signs. In columns 2, 3, and 4, the total effect turns out to be indeterminate.

7.8. Extensive Margin of Importing and Exporting

In the baseline regression, for the importing (exporting) margin, I included both those which were importers (exporters) and those that were not importers (exporters). However, in international trade theories, the fixed cost of importing (Antras, Fort, and Tintelnot 2017) and the fixed cost of exporting (Melitz 2003) are important for theoretically replicating empirical patterns. Thus, it is worthwhile to isolate the extensive margin only. Table 23 reports a result that is qualitatively the same as the baseline result in Table 3 and its weighted version in Table 12.

[42] i.e., agriculture, forestry, fishing, mining, construction, transportation, communications, electric, gas, sanitary services, finance, insurance, real estate, and non-commercial services.

7.9. Restricting to Establishments in Single-Manufacturing-Industry Firms

In Hyun, Park, and Smirnyagin (2020b), I and my coauthors show that China shock may propagate from one establishment to other establishments in the same firm through an internal firm network channel. If this indirect channel is present for the margins of the adjustments that the current paper considers, then it is not clear whether the effect I found is a result of this indirect shock or of the three types of exposures I have used. To show that the three types of exposures do result in business-level adjustments I have showed so far, Tables 24 and 25 restrict the sample to the establishments that, in 1991, belonged to a firm that had a single SIC 4-digit manufacturing industry in 1991. About 90% of sample is maintained. Although the sample shrank, the qualitative results of Tables 3 and 4 remain unchanged. The only conspicuous difference is that the impact of downstream exposure on the employment growth of continuing establishments becomes statistically significant, but because of the lack of robustness, I do not interpret this as having a reliable association.

7.10. Restricting to Establishments That Never Switched Industries

Industry switching of some establishments in the sample might affect the estimates for other margins of adjustments, which is a concern that is shared with the existing literature. I check if my results are vulnerable to this concern. In Table 26, I drop every establishment that has ever switched their industry between 1991 and 2007, and I check the margins of adjustments that are not about industry switching. Every qualitative result is maintained.

7.11. Dropping Industries That Faced a Large Import Demand Shock from High-Income Countries

By using the popular instrument (4), I tackle the first-order concern that the import growth from China might have been partially driven by US demand shock. In the literature that uses the instrument (4), the common identifying assumption is that import demand shocks are not correlated across high-income countries.[43] To provide robustness to this assumption, Autor, Dorn, and Hanson (2013) show that their

[43]Nevertheless, I argue again that there are two strong reasons to infer that the import growth from China was primarily due to China's supply shock rather than US demand shock. First, the imports from China were made possible by China's political and economic reforms. Second, the steep imports to the US came primarily from China, but not so much from other low-income countries, which is not what one would expect if the imports were precipitated by US demand shock.

results are insensitive to dropping several industries that have faced a large import demand shock from high-income countries. I conduct an analogous exercise.

First, I drop the establishments whose 1991 industry were steel, flat glass, or cement. I do so because many high-income countries experienced housing booms between 2000 to 2007, which could have caused to the demand for construction materials. Second, I drop the establishments that produced electronic computers in 1991 because IT innovations between 1991 and 2007 might have correlated demand shocks for computers across high-income countries. Third, I additionally drop the establishments whose 1991 products were apparel, footwear, and textiles.

Table (27) shows that the qualitative results are unchanged. Both the economic and statistical significance remain despite the fewer observations.

7.12. Probit

Following suggestions from the applied econometric literature, such as Angrist and Pischke (2008), I used the linear probability model. Nevertheless, I show the results from instrumented probit regressions in Table 28. The qualitative results are maintained. In fact, the statistical significance for the effect of downstream exposure on becoming importers turns significant. However, to remain conservative, I maintain that I have not found enough evidence that downstream manufacturing establishments respond by engaging in importing on their own.

7.13. Clustering at SIC 4-digit or at SIC 2-digit

I followed the literature which usually clusters standard errors at SIC 3-digit (e.g., Autor, Dorn, Hanson, and Song 2014). However, Abadie, Athey, Imbens, and Wooldridge (2017) would suggest clustering at the level of the shock, i.e., SIC 4-digit. Table 29 displays baseline results while clustering at SIC 4-digit level. The results barely change. Moreover, although it is not justified by Abadie, Athey, Imbens, and Wooldridge (2017), for curious readers, I present the results from clustering at SIC 2-digit in Table 30. The results barely change.

7.14. Upstream and Downstream Exposures with Diagonals

My construction of upstream and downstream exposures does not include sales from and to a firm's own industries. That is, diagonal entries in the input-output matrix were not included in the construction of upstream and downstream exposures. This is because of the high correlation between exposures (especially the correlation between direct exposure and downstream exposure). Since I include all three exposures simultaneously, not excluding the diagonal entries in the construction of upstream and downstream exposures will make it unclear which of the three exposures is driving the result.

Nevertheless, in Table 31, I provide the results from regressions where upstream and downstream exposures are constructed without dropping diagonal entries (sales to the same SIC 4-digit industry). Compared to the baseline results, the direct exposure loses statistical significance for the margins of exiting, switching to retail and wholesale, and switching within manufacturing. Upstream exposure loses statistical significance for the margin of switching within manufacturing. Downstream exposure loses statistical significance for the margins of exporting and switching within manufacturing. However, again, I argue that it is a better practice to remove the diagonal entries when including all three exposures jointly in one regression because otherwise the correlation between exposures blurs the distinctive effect of each individual exposure even when an effect exists.

7.15. Industry Fixed Effects at Different Levels

On top of the various industry-level controls, I included 10 industries dummies that classify 392 SIC 4-digit industries into 10 groups, in line with Autor, Dorn, Hanson, and Song (2014) and Acemoglu et al. (2016b). Alternatively, in Table 32, I display the results when SIC 2-digit fixed effects are included. When the 10 industry dummies were included in the baseline, the negative impact of upstream exposure on being an importer in 2007 obtained statistical significance only in the weighted regression. However, when the SIC 2-digit fixed effects are included, it is significant even if the regression is not weighted. Also, the impact of upstream exposure on switching manufacturing industries becomes noticeably imprecise.

Having SIC 3-digit level fixed effect loses much of cross-industry variation. Among 135 SIC 3-digit industries, 54 of them has only one SIC 4-digit industry. Therefore, there is no variation in trade shock for those 54 industries if I include SIC 3-digit fixed effect. Also, 19 SIC 3-digit industries have only two SIC 4-digit industries, and in many cases there is little variation in China shock between the two.

7.16. Net Imports

In the baseline regression, I used import penetration, rather than net import growth. Using net imports as the measure of exposure will suffer from a few problems. China occupied the downstream portion of the global supply chain, especially during the early stage of opening their economy. In this case, the measure of the direct export from the US to China might not capture, say, exports from the US to Korea, which are then used for exports from Korea to China. This is an important reason why the literature on China shock mostly focuses on import penetration, rather than net imports. Nonetheless, in Table 33, I show the results when using net imports instead. Many of the results that I rationalized based on the logic of foreign sourcing changes.

7.17. Imports from All Low-Income Countries

China accounts for over 90% of the growth of imports from low-income countries to the US during the period under consideration. Therefore, it is implausible that the imports from China are merely replacing pre-existing imports from low-income countries, not being spurred by China's positive supply shock. Nonetheless, Table 34 reruns the baseline regressions using the import penetration from all low-income countries, not just from China. The results barely change.

8 Conclusion

I find a series of facts that can be coherently understood to be a consequence of the supply-shock-driven component of import growth from China to the US. The rise of Chinese imports provides a useful stage for an empirical analysis that isolates the supply shock of a source country. This is so because the impetus for China's integration into the global economy and its technological development can be largely attributed to internal politics within the Communist Party of China, which was exogenous to the US. I further isolate the supply-shock component by using the now popular instrument.

I find evidence suggesting *own-product offshoring* in industries experiencing surging imports from China. However, other evidence is consistent with the situation where input sourcing largely occurs indirectly from US importers, rather than directly from China. Manufacturers which do not make these adjustments face intensified import competition, which leads to a higher likelihood of exits in the directly exposed and downstream industries. But manufacturers that survived are more likely to export, consistent with the idea that global sourcing can enhance firms' efficiency enough to allow them to export. Another consequence is that their upstream businesses lose their US domestic demand, and so they are less likely to become importers, retailers, and wholesalers. All three types of shocks induce within-manufacturing industry switching.[44]

Consistent with the pattern of industry switching, direct and downstream exposures lead to a decline of manufacturing employment shares, whereas upstream exposures lead to an increase of them. By showing that pre-exposure industry input-output structure matters for the manufacturing employment adjustments of continuing firms, this finding contributes to the important literature that associates the US aggregate manufacturing employment declines with import penetration (Autor, Dorn, and Hanson 2013, Pierce and Schott 2016b, Fort, Pierce, and Schott 2018b).

This paper inspires at least six lines of promising future research. First, it can guide theory. As noted above, recent theories (Antras, Fort, and Tintelnot 2017; Bernard, Jensen, Redding, and Schott 2018) suggest that it is useful to empirically analyze various margins of adjustments in one paper, as I do in this paper. However, a model that explain my findings coherently does not exist. The theoretical literature could be enriched by capturing facts in this paper.

Second, will the US-China trade war and the Covid-19 pandemic reverse the business-level adjustments that I find? How much of the existing findings on the US-China trade war (e.g., Amiti, Redding, and Weinstein 2019; Bellora and Fontagné 2019; Cavallo, Gopinath, Neiman, and Tang 2019; Fajgelbaum, Goldberg, Kennedy, and Khandelwal 2020; Waugh 2019) come from the business-level adjustments in this paper? The unprecedented nature and history-defining significance require us to use relevant information from the past to cope better with it better.

Third, how do business-level adjustments intermediate labor market outcomes and social or political outcomes of China shocks?[45] For example, what happens to job flows and wages when a manufacturer switches to retail or starts exporting due to China shock?

Fourth, the literature finds that trade shock could propagate through cross-establishment-within-firm networks (Hyun, Park, and Smirnyagin 2020b) or through cross-establishment-within-region network (Helm 2020). In a project soon to be undertaken, I will analyze how such propagation affects the industry switching and trade margin that I consider.

Fifth, my findings on heterogeneous response raise a hypothesis that the distributional consequences of China shock may in part depend on the business-level adjustments. Matched employer-employee data, such

[44] This finding on building affiliates in China used to be a part of the current paper, was circulated and presented at conferences and job talks. This part will soon appear as a separate paper.

[45] The social and political consequences of a highly exposed region and industry include Trump's election and Brexit (Autor et al. 2020; Colantone and Stanig 2018; Che et al. 2016; Dippel et al. 2017), negative health and fatality (McManus and Schaur 2016; Colantone, Crino, and Ogliari 2019; Pierce and Schott 2020), low fertility and single-motherhood (Autor, Dorn, and Hanson 2019a), and crime and violence (Dix-Carneiro, Soares, and Ulyssea 2018).

as US LEHD and German LIAB data, will help to formalize this idea. This will enrich the literature that relates firm heterogeneity to the distributional consequences of trade shock (e.g., Felbermayr, Impullitti, and Prat 2018).

Sixth, the approaches undertaken in this paper can be applied to other countries. Although the literature shows that imports from low-income countries generally cause manufacturing employment declines, the patterns and magnitude differ across countries (Dauth et al. 2014 for Germany; Ashournia et al. (2014) and Utar (2018) for Denmark; Balsvik et al. 2015 for Norway; Malgouyres 2017 for France; De Lyon and Pessoa 2020 for the UK; Branstetter et al. 2019 for Portugal). By applying the approaches in this paper beyond the US, we can better understand how businesses in countries with different institutions, industrial structures, and trading partners respond differently.

A. NETS Quality

A.1. Sources of Data

First, Dun & Bradstreet analysts conduct 100 million telephone interviews from calling centers each year. The recipients of these interviews include knowledgeable and reliable sources, such as Legal personnel, CFOs, Controllers, and CIOs at the headquarter company or one of its high-level subsidiaries.[46] Second, they also use third-party data, such as government registries and licensing data; court, tribunal, and legal filings; yellow pages; news (both paper and electronic); annual reports; Internet crawling; financial filings of public companies, public utilities, and all U.S. Secretaries of State; payment and collections information; and company websites. Third, the U.S. government contracts with D&B to manage its System for Award Management (SAM).[47] This is an important source of information for D&B data and, thus, NETS data. Businesses registered with SAM are required, under penalty of law, to update their information every year. Fourth, D&B has a license to the National Change of Address database which contains information about all changes of US addresses provided by the US Postal Service (Kolko and Neumark 2008).

A.2. NETS Quality

Neumark, Zhang, and Wall (2007) report an employment correlation of 0.994 between NETS and the Quarterly Census of Employment and Wages (QCEW) at the county level over four years. Barnatchez, Crane, and Decker (2017b) confirm that the correlation of employment between NETS and CBP is larger than 0.99, and they find that the employment correlation in state-industry-size cells also is above 0.9. This similarity is even more surprising given the large difference in the data coverage just described. Neumark et al. (2007) also find that, among 153 California biotech businesses that had founding dates on their websites and were located in the BioAbility database, the NETS entry year exactly matched their website entry year 75% of the time, 88% within one year, and 92% within two years. Given that the term "entry" is sometimes ambiguous (it could depend, for example, on whether the period of inactivity or preparation is counted), this concordance is surprisingly high. I also compared export and import indicators published by NETS and administrative data. The correlation between the datasets regarding the percent of exporters and importers by NAICS 3-digit is surprisingly high. The result is presented in Table 14 in the appendix.

Again, even the remaining gap between NETS and other datasets could be due to non-erroneous differ-

[46]Further information is available in the document "Headquarters in the NETS Database" provided by Walls & Associates.

[47]The U.S. Small Business Administration requires DUNS number for firms that bid on government contracts. The United States Department of Agriculture says "A Dun & Bradstreet Data Universal Numbering System (DUNS) number and current registration in the System for Award Management (SAM) are required for entities to receive federal payment using an Employee Identification Number (EIN) (also known as a tax identification number)." Under this system, EIN and DunsNumber are closely-related concepts.

ences in concepts. There are two main such conceptual differences: employment and establishment. The establishment-level employment in NETS include, not only regular workers, but also proprietors, independent contractors, and temporary workers supplied by other firms; the classification scheme employed by CBP does not include these concepts. Therefore, a discrepancy between NETS and CBP that arises from this conceptual difference would not necessarily imply errors in NETS data (Barnatchez, Crane, and Decker 2017b). The set of establishments included in the dataset is also non-erroneously different. Neumark, Zhang, and Wall (2007) and Barnatchez, Crane, and Decker (2017b) report that NETS has significantly more aggregate employment and number of establishments than official sources. This difference is primarily due to the fact that NETS data includes non-employer businesses. Thus, NETS reports higher counts of establishments than official sources, especially in the case of businesses that employ fewer than 5 people. This difference, of course, does not reflect errors in either dataset.

Dynamic consistency also contributes to the quality of NETS' industry information. US official statistics have switched from SIC to NAICS in 1997. NAICS also substantially switched its industry categorization in every five years since 1997 so that they have distinct NAICS 1997, NAICS 2002, NAICS 2007, and NAICS 2012 industry codes. If this issue is not adequately accounted for, it raises a significant concern for dynamic economic analyses. This led researchers to construct industry families as in Pierce and Schott (2016b) or perform imputations as in Fort and Klimek (2018a). Dun & Bradstreet, however, maintained *time-consistent* industry codes based on 1987 version of SIC even after 1997.[48] The fact that it is 1987 version of SIC that was used throughout the time period also has the advantage of having no ambiguity in matching with important SIC1987-level data such as NBER-CES Manufacturing Database (Becker, Gray, and Marvakov 2013).

A.3. NETS Quality on Trade Indicators

NETS provides an indicator for export/import status each year. I provide the first comparison between NETS and published tabulation from official sources. Using the U.S. Census Bureau's Census of Manufacturers (CM) data, Bernard, Jensen, Redding, and Schott (2007b) (hereafter BJRS (2007)) calculated the percent of exporting firms for each 3-digit NAICS manufacturing industry in 2002. Using the U.S. Census Bureau's Longitudinal Firm Trade Transactions Database (LFTTD) data, Bernard, Jensen, Redding, and Schott (2018) (hereafter BJRS (2018)) calculated the percent of exporting firms and importing firms for each 3-digit NAICS manufacturing industry in 2007.

I produced an analogous numbers using NETS. Table (14) summarizes the correlation between NETS

[48] I double-checked it. I found that there are exactly the same 1005 SIC 4-digit industries in every year from 1990 to 2015, except for "8811" , which occupied at most a tiny fraction until 2000. That is, at least some establishments exist in each 1004 SIC 4-digit category in every year, and no other SIC 4-digit code exists in every year, except for "8811."

and BJRS (2007, 2018). For the percent of exporters in 2002, the correlation between NETS and CM is 0.909 except for the last category, 339 (Miscellaneous Manufacturing).[49] Moreover, the correlation on the percent of firms by 3-digit NAICS is 0.974. Other numbers are also high. The percent of importers by NAICS 3-digit in 2002 is missing because neither BJRS (2007) nor BJRS (2018) reported it.

Table 14: Correlation between NETS and Administrative Data: NAICS-Level % of Firms, Exporters, and Importers

Measure	Source	Administrative data	Correlation
% of firms by NAICS 3-digit in 2002	BJRS (2007)	CM	0.9738
% of firms by NAICS 3-digit in 2007	BJRS (2018)	LFTTD	0.9530
% of exporters by NAICS 3-digit in 2002	BJRS (2007)	CM	0.9090
% of exporters by NAICS 3-digit in 2007	BJRS (2018)	LFTTD	0.9330
% of importers by NAICS 3-digit in 2007	BJRS (2018)	LFTTD	0.8022
% of exporter-importers by NAICS 3-digit in 2007	BJRS (2018)	LFTTD	0.8029

Notes: This table reports the correlation between NETS and statistics from administrative data published in Bernard, Jensen, Redding, and Schott (2007b) (BJRS 2007) and Bernard, Jensen, Redding, and Schott (2018) (BJRS 2018). Those are the distribution of U.S. firms across 3-digit NAICS manufacturing industries (first two rows), the share of firms in each 3-digit NAICS manufacturing industry that export (3rd and 4th rows), import (5th row), or both (last row). The percent of importers by NAICS 3-digit in 2002 is missing because neither BJRS (2007) nor BJRS (2018) reported it.

The high correlation between NETS and administrative data suggests NETS' information on export and import is highly accurate. There are three reasons why this high correlation is even more surprising than it seems. First, my NETS sample might have different coverage than BJRS sample. I dropped NETS firms that are smaller than 5 employees because it is common among research that use CM to drop "administrative records." Still, my NETS sample for this comparison may still contain proprietors and nonemployers which are not covered by the CM. Second, NETS has a considerably higher percentage of exporters in industry 339 (Miscellaneous Manufacturing) than in the BJRS's table. The most likely explanation for this difference is that NETS and administrative data use different definitions to classify businesses as "miscellaneous" manufacturing. Third, as mentioned earlier, industry classification intrinsically entails some degree of ambiguity. To sum up, the high correlation is even more surprising given the likely differences in coverage, intrinsic ambiguities of industry, and potentially different rule for categorizing as "miscellaneous."

[49] I lagged back NETS by one year because NETS takes January snapshot of D&B data gathered in previous year. The correlation without lagging by one year is 0.906.

A.4. Manual Check on Industry Information Accuracy

Table 15 uses an example to demonstrate high accuracy of industry information in NETS even at the level of SIC 8-digit. It reports the NETS industries of US Steel establishments located in 1200 Penn Ave Suite 300, Pittsburgh, and compares them with the descriptions I find on the Internet. NETS provides industry information at SIC 8-digit level, which is more granular than official statistics that provide information at SIC 4-digit level at most. Even at this highly granular level, NETS industry and Internet description coincide. Given that there is an intrinsic ambiguity in any industry classification, this can be considered highly accurate. Moreover, I use SIC 4-digit information to conduct analysis so that even in case NETS is somewhat inaccurate in its SIC 8-digit classification, my analysis will not be affected.

Table 15: Internet Verification on Industry Information

NETS Name	SIC8 in NETS	Description on Internet to confirm SIC8 is reasonable
Tracks Traffic & Mgt Svcs	Management services	(Management service, as its name suggests)
United States Steel Corp	Iron and steel products	Confirmed that US Steel actually has department called "Metals Service Center Institute" and they include iron and steel
Mobile River Terminal	Marine cargo handling	"Mobile River Terminal (MRT) Cargoes Handled: Any Bulk Commodity"[50]
Mckeesport Connecting RR	Railroad switching	"it connected the National Tube Works Co., and later U.S. Steel's National Works, to the Pennsylvania, Baltimore & Ohio and Pittsburgh & Lake Erie railroads. It also switched freight cars within the plant. Naturally, for most of its existence, McKeesport Connecting Railroad was wholly owned by U.S. Steel."[51]
Union Railroad Company	Switching & terminal svc	"The Union Railroad Company stretches from N. Bessemer, PA on the north to Clairton, PA on the south and provides switching to the heart of southwestern Pennsylvania's industrial Monongahela Valley."[52]
Elgin Joliet & Eastrn RLWY	Railroads, line-haul	"The Elgin, Joliet and Eastern Railway (reporting mark EJE) was a Class I railroad, operating between Waukegan, Illinois and Gary, Indiana."[53]

Notes: Internet verification on industry information of US Steel's establishments at *1200 Penn Ave Suite 300, Pittsburgh*. Some of the evidences that these establishments are located at *1200 Penn Ave Suite 300* can be found online at these links for Tracks Traffic & Mgt Svcs, Mobile River Terminal, Mckeesport Connecting RR, and Union Railroad Company.

[50] http://www.bluewatershipping.com/locationdetails.php?ld=195
[51] http://www.tubecityonline.com/almanac/entry_2199.php
[52] https://bit.ly/2YkYg6L
[53] https://en.wikipedia.org/wiki/Elgin,_Joliet_and_Eastern_Railway

B. Additional Tables and Figures

Table 16: Upstreamness of Fabrics Industry

	Ranking by direct shock	Ranking by upstream shock
Narrow fabric mills	133	20
Coated fabrics, not rubberized	168	4
Nonwoven fabrics	240	39
Broadwoven fabric mills, manmade	247	18
Weft knit fabric mills	256	44
Broadwoven fabric mills, wool	296	15
Tire cord and fabrics	301	16
Lace and warp knit fabric mills	334	19
Broadwoven fabric mills, cotton	391	14

Notes: All nine industries that contain "fabric" in its name are included. I order them by direct shock (1) and mark its ranking in second column, and by upstream shock (2) and mark its ranking in third column. This Table shows that fabrics industries are ranked very low for direct exposure, but high for upstream exposure.

Table 17: China Shock and Industry Switching at Four Levels

Outcome	Switch SIC 1 (1)	Switch SIC 2 (2)	Switch SIC 3 (3)	Switch SIC 4 (4)
ΔIP	0.7**	0.8**	1.1**	1.1**
	(0.3)	(0.4)	(0.5)	(0.6)
ΔIP^U	-1.1***	-0.5	-0.3	-0.5
	(0.2)	(0.4)	(0.4)	(0.4)
ΔIP^D	2.0***	2.6***	2.4***	2.9***
	(0.4)	(0.5)	(0.5)	(0.5)
All controls	✓	✓	✓	✓
$Avg(Y)$	9.7	13.5	16.4	17.7
N	299921	299921	299921	299921

Notes: The sample is the near-universe of US manufacturing establishments that continued to exist from 1991 to 2007. The dependent variables in each column is an indicator of switching industries at the level indicated by column title. Estimates are from the establishment-level 2SLS regressions based on equation (6). The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). Establishment-level controls and fixed effects include 1991 employment, age, state, and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, and 1976-1991 changes in industry share in US employment. 10 manufacturing dummies are the categorization of SIC 4-digit industries into 10 groups. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: Baseline Results (Each Shock Separately)

Outcome	Exit (1)	Be an importer (2)	Switch to rtl, whsl (3)	Switch to cml. service (4)	Be an exporter (5)	Switch in Mfg (6)
ΔIP	2.5***	1.1***	0.7**	0.2	2.1**	0.9**
	(0.8)	(0.4)	(0.3)	(0.2)	(0.9)	(0.5)
ΔIP^U	-0.9	-0.4	-0.6**	0.0	0.2	0.5
	(0.8)	(0.3)	(0.3)	(0.1)	(0.8)	(0.4)
ΔIP^D	3.4***	0.5*	0.8***	0.9***	2.1**	1.2**
	(0.7)	(0.2)	(0.2)	(0.3)	(0.8)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.4	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that now the rows for ΔIP, ΔIP^U, and ΔIP^D represent separate regressions each. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Baseline Results (Without HQ Switchers)

Outcome	Exit (1)	Be an importer (2)	Switch to rtl, whsl (3)	Switch to cml. service (4)	Be an exporter (5)	Switch in Mfg (6)
ΔIP	1.8***	0.9***	0.4**	0.0	1.8**	0.8**
	(0.5)	(0.3)	(0.2)	(0.1)	(0.8)	(0.4)
ΔIP^U	-0.9**	-0.1	-0.5***	0.0	0.5	0.5*
	(0.4)	(0.2)	(0.1)	(0.1)	(0.6)	(0.3)
ΔIP^D	3.2***	0.3	0.7***	0.8***	1.6**	0.9**
	(0.6)	(0.2)	(0.2)	(0.2)	(0.8)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	49.0	3.3	3.9	1.8	10.9	8.8
N	541896	276198	276198	276198	276198	276198

Notes: The only difference from the columns 1 to 6 of Table 3 is that the establishments that switched their headquarters between 1991-2007 are not included. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Employment Structure at Establishment-Level (Without HQ Switchers)

Outcome	Emp growth	Mfg emp growth	Emp growth among continuers	Mfg emp growth among continuers
	(1)	(2)	(3)	(4)
ΔIP	-0.042***	-0.041***	-0.009***	-0.014***
	(0.010)	(0.011)	(0.003)	(0.005)
ΔIP^U	0.016*	0.025***	-0.004	0.018***
	(0.008)	(0.008)	(0.004)	(0.006)
ΔIP^D	-0.062***	-0.075***	0.005	-0.034***
	(0.013)	(0.013)	(0.004)	(0.007)
All controls	✓	✓	✓	✓
$Avg(Y)$	-0.955	-1.039	0.05	-0.115
N	541896	541896	276198	276198

Notes: The only difference from Table 4 is that the establishments that switched their headquarters between 1991-2007 are not included. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: Baseline Results (Without Frequent Industry Switchers and Switch-Reverters)

Outcome	Exit	Be an importer	Switch to rtl, whsl	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.8***	1.0***	0.5**	0.1	1.8**	0.8**
	(0.5)	(0.4)	(0.2)	(0.1)	(0.8)	(0.4)
ΔIP^U	-0.8**	-0.2	-0.6***	0.0	0.5	0.6*
	(0.4)	(0.2)	(0.1)	(0.1)	(0.6)	(0.3)
ΔIP^D	3.2***	0.2	0.8***	0.9***	1.5*	0.9**
	(0.6)	(0.2)	(0.2)	(0.2)	(0.8)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.9	4.1	4.1	1.8	11.7	9.3
N	578871	295961	295961	295961	295961	295961

Notes: The only difference from t Table 3 is that I omit the establishments that switch SIC 4-digit industries more than 3 times between 1991-2007 and those that ever reverted back to their initial 1991 SIC 4-digit industry. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 22: Employment Structure at Establishment-Level (Without Frequent Industry Switchers and Switch-Reverters)

Outcome	Emp growth	Mfg emp growth	Emp growth among continuers	Mfg emp growth among continuers
	(1)	(2)	(3)	(4)
ΔIP	-0.042***	-0.041***	-0.010***	-0.016***
	(0.010)	(0.011)	(0.003)	(0.006)
ΔIP^U	0.015*	0.026***	-0.003	0.021***
	(0.008)	(0.008)	(0.004)	(0.006)
ΔIP^D	-0.061***	-0.075***	0.007	-0.035***
	(0.012)	(0.013)	(0.004)	(0.008)
All controls	✓	✓	✓	✓
$Avg(Y)$	-0.951	-1.038	0.051	-0.119
N	578871	578871	295961	295961

Notes: The only difference from Table 4 is that I omit the establishments that switch SIC 4-digit industries more than 3 times between 1991-2007 and those that ever reverted back to their initial 1991 SIC 4-digit industry. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 23: Becoming an importer or exporter (Extensive margin)

	Unweighted		Weighted by 1991 Employment	
Outcome	Be an importer	Be an exporter	Be an importer	Be an exporter
	(1)	(2)	(3)	(4)
ΔIP	1.1***	2.0**	3.0***	2.3**
	(0.4)	(0.8)	(1.1)	(1.0)
ΔIP^U	-0.2	0.5	-1.4***	0.7
	(0.2)	(0.7)	(0.5)	(0.7)
ΔIP^D	0.2	1.7*	-1.0	-1.0
	(0.3)	(0.9)	(0.7)	(0.9)
All controls	✓	✓	✓	✓
$Avg(Y)$	4.2	12.6	20.9	27.0
N	299123	284307	299123	284307

Notes: This table corresponds to subsection 7. The sample is the near-universe of US manufacturing establishments that continued to exist from 1991 to 2007. Since I focus on extensive margin in this table, columns 1 and 3 further restrict the sample to those that were not importers in 1991, and columns 2 and 4 further restrict the sample to those that were not exporters in 1991. The dependent variables in each column is an indicator of becoming an importer or exporter by 2007. Estimates are from the establishment-level 2SLS regressions based on equation (6). The regressors $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ (defined in (1), (2), and (3)) are instrumented by $\Delta IPO_{j(i)}$, $\Delta IPO^U_{j(i)}$, and $\Delta IPO^D_{j(i)}$ (defined in (4) and (5)). Establishment-level controls and fixed effects include 1991 employment, age, state, and import & export status. Industry-level controls include the 1991 share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, 1976-1991 changes in log average wages, and 1976-1991 changes in industry share in US employment. 10 manufacturing dummies are the categorization of SIC 4-digit industries into 10 groups. Sanderson–Windmeijer F-Statistics for all three regressors are reported. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 24: Margins of Adjustments (Establishments in Single-Manufacturing-Industry Firms)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.603***	0.009***	0.416**	0.040	0.019**	0.752**
	(0.463)	(0.003)	(0.190)	(0.091)	(0.008)	(0.369)
ΔIP^U	-0.932**	-0.001	-0.527***	0.016	0.004	0.551*
	(0.382)	(0.002)	(0.114)	(0.130)	(0.006)	(0.329)
ΔIP^D	2.728***	0.001	0.717***	0.795***	0.016**	0.784*
	(0.574)	(0.002)	(0.156)	(0.207)	(0.008)	(0.421)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	47.421	.032	3.799	1.784	.155	8.425
N	511212	268783	268783	268783	268783	268783

Notes: The only difference from Table 3 is that now the sample is restricted to establishments that, in 1991, were in a firm that had no more than one SIC 4-digit manufacturing industry in 1991. Other than that, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. In column 1, Sanderson–Windmeijer F-Statistics for $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ are 89.1, 354.8, and 1883.6, respectively. In columns 2 to 6, they are 109.4, 377.7, and 1544.9. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 25: Employment Structure at Establishment-Level (Establishments in Single-Manufacturing-Industry Firms)

Outcome	Emp growth	Mfg emp growth	Emp growth among continuers	Mfg emp growth among continuers
	(1)	(2)	(3)	(4)
ΔIP	-0.037***	-0.036***	-0.008**	-0.012**
	(0.009)	(0.010)	(0.003)	(0.005)
ΔIP^U	0.017**	0.027***	-0.003	0.019***
	(0.008)	(0.008)	(0.005)	(0.006)
ΔIP^D	-0.052***	-0.067***	0.008*	-0.032***
	(0.012)	(0.012)	(0.004)	(0.007)
All controls	✓	✓	✓	✓
$Avg(Y)$	-.917	-1.004	.061	-.106
N	511212	511212	268783	268783

Notes: The only difference from Table 4 is that now the sample is restricted to establishments that, in 1991, were in a firm that had no more than one SIC 4-digit manufacturing industry in 1991. Other than that, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 4. In columns 1 and 2, Sanderson–Windmeijer F-Statistics for $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ are 89.1, 354.8, and 1883.6, respectively. In columns 3 and 4, they are 109.4, 377.7, and 1544.9. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 26: Margins of Adjustments (Establishments that Never Switched Industries)

Outcome	Exit	Be an importer	Be an exporter
	(1)	(2)	(5)
ΔIP	1.991***	0.010***	0.018**
	(0.560)	(0.004)	(0.008)
ΔIP^U	-0.921**	-0.001	0.003
	(0.399)	(0.002)	(0.006)
ΔIP^D	3.535***	0.003	0.018**
	(0.615)	(0.002)	(0.008)
All controls	✓	✓	✓
$Avg(Y)$	50.93	.039	.155
N	496539	243644	243644

Notes: The only difference from Table 3 is that now the sample is restricted to establishments that never switched SIC 4-digit industries between 1991 and 2007. Other than that, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. In column 1, Sanderson–Windmeijer F-Statistics for $\Delta IP_{j(i)}$, $\Delta IP^U_{j(i)}$, and $\Delta IP^D_{j(i)}$ are 85.4, 366.8, and 1891.9, respectively. In columns 2 and 3, they are 104.7, 388.5, and 1483.1. Standard errors are clustered on 3-digit SIC industries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 27: Results after Dropping Industries That Faced a Larger Import Demand Shock from High-Income Countries

Outcome	Exit	Be an importer	Switch to rtl, whsl	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.8***	1.0**	0.4*	0.0	1.9**	0.8**
	(0.5)	(0.4)	(0.2)	(0.1)	(0.9)	(0.4)
ΔIP^U	-0.5*	-0.0	-0.6***	-0.0	0.5	0.6*
	(0.3)	(0.2)	(0.2)	(0.1)	(0.7)	(0.3)
ΔIP^D	2.4***	0.2	0.8***	0.8***	1.8**	0.9*
	(0.5)	(0.3)	(0.2)	(0.2)	(0.9)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	47.5	4.1	3.9	1.7	17.0	9.0
N	531661	278962	278962	278962	278962	278962

Notes: The only difference from the columns 1 to 6 of Table 3 is that the establishments whose 1991 industry were steel, flat glass, cement, electronic computer, apparel, footwear, or textiles have been removed. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 28: Baseline Results (Probit)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	0.046***	0.097***	0.044**	-0.001	0.085**	0.045**
	(0.013)	(0.031)	(0.022)	(0.015)	(0.039)	(0.021)
ΔIP^U	-0.021**	-0.016	-0.066***	-0.010	0.022	0.035**
	(0.010)	(0.023)	(0.019)	(0.018)	(0.030)	(0.017)
ΔIP^D	0.079***	0.052*	0.091***	0.135***	0.062+	0.042*
	(0.015)	(0.029)	(0.023)	(0.022)	(0.040)	(0.025)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	1.8	4.1	11.8	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that I use instrumented probit instead of instrumented linear probability model. I also drop the employment control for column 2 to prevent the failure to calculate the liklihood. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 29: Baseline Results (Clustering at SIC 4-digit)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.8***	1.0***	0.4**	0.1	1.8**	0.8**
	(0.5)	(0.4)	(0.2)	(0.1)	(0.8)	(0.3)
ΔIP^U	-0.8**	-0.2	-0.6***	0.0	0.5	0.6*
	(0.4)	(0.2)	(0.1)	(0.1)	(0.5)	(0.3)
ΔIP^D	3.1***	0.2	0.8***	0.9***	1.5**	0.9**
	(0.5)	(0.2)	(0.2)	(0.2)	(0.8)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that I cluster standard errors at SIC 4-digit, not SIC 3-digit level. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 30: Baseline Results (Clustering at SIC 2-digit)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.8***	1.0***	0.4***	0.1	1.8***	0.8***
	(0.4)	(0.3)	(0.1)	(0.1)	(0.4)	(0.2)
ΔIP^U	-0.8**	-0.2	-0.6***	0.0	0.5	0.6*
	(0.3)	(0.2)	(0.1)	(0.2)	0.8	(0.3)
ΔIP^D	3.1***	0.2	0.8***	0.9***	1.5**	0.9***
	(0.8)	(0.3)	(0.3)	(0.3)	(0.6)	(0.3)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that I cluster standard errors at SIC 2-digit, not SIC 3-digit level. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 31: Baseline Results (Diagonal Entries of IO Table are Included for Upstream and Downstream Exposures)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.1	1.0**	0.2	-0.2**	1.4*	0.6
	(0.7)	(0.4)	(0.2)	(0.1)	(0.8)	(0.4)
$\Delta IP^U_{\text{NoDiagonal}}$	-1.2**	-0.2	-0.7***	-0.1	0.4	0.5
	(0.5)	(0.2)	(0.2)	(0.1)	(0.7)	(0.3)
$\Delta IP^D_{\text{NoDiagonal}}$	3.5***	0.2	1.0***	1.0***	1.6	0.9
	(0.7)	(0.3)	(0.2)	(0.3)	(1.0)	(0.5)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that, when I construct the upstream and downstream exposures, I do not include the diagonal entries in the input-output table. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 32: Baseline Results with SIC 2-digit Fixed Effects

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIP	1.8***	1.0***	0.4*	0.1	1.9***	0.8**
	(0.5)	(0.4)	(0.2)	(0.1)	(0.7)	(0.4)
ΔIP^U	-1.0***	-0.5**	-0.6***	-0.0	-0.3	0.3
	(0.3)	(0.2)	(0.1)	(0.2)	(0.5)	(0.3)
ΔIP^D	2.9***	-0.1	0.7***	0.8**	1.0*	0.7*
	(0.7)	(0.2)	(0.2)	(0.4)	(0.5)	(0.4)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that I include SIC 2-digit fixed effects instead of the 10 manufacturing industry dummies. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 33: Baseline Results (Net Imports as the Measure of Exposure)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IP_{NetImports}$	2.6***	1.2***	0.8***	0.3	2.7**	0.7
	(0.7)	(0.4)	(0.3)	(0.2)	(1.3)	(0.5)
$\Delta IP^U_{NetImports}$	0.4	0.2	0.1	0.1	2.8**	1.5***
	(0.7)	(0.3)	(0.2)	(0.2)	(1.1)	(0.5)
$\Delta IP^D_{NetImports}$	1.6	-0.9*	0.2	0.8***	-3.2**	-0.3
	(1.0)	(0.5)	(0.5)	(0.3)	(1.3)	(0.7)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

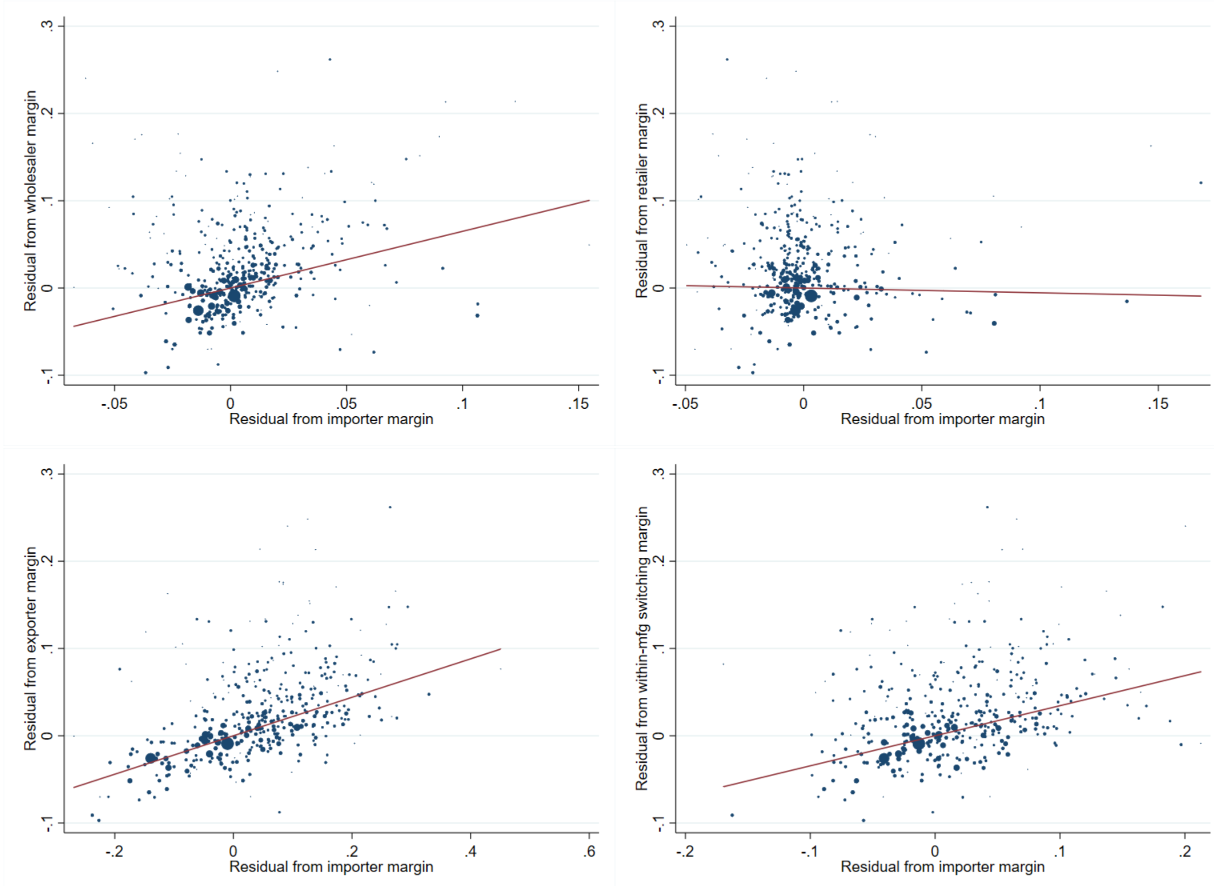
Notes: The only difference from the columns 1 to 6 of Table 3 is that I use net imports, instead of import penetration, as the measure of exposure. Note that this exercise is not a robustness check. As stated in Autor et al. (2014) and the main body of this paper, using net imports has a few problems, and likely captures different mechanisms. Other than different concept of exposures, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 34: Baseline Results (Import Penetration from All Low-Income Countries)

Outcome	Exit	Be an importer	Switch to retail, wholesale	Switch to cml. service	Be an exporter	Switch in Mfg
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IP_{\text{All low-income}}$	2.0***	1.2***	0.5**	0.1	2.0**	0.9**
	(0.6)	(0.4)	(0.2)	(0.1)	(0.8)	(0.4)
$\Delta IP^{U}_{\text{All low-income}}$	-0.7*	-0.1	-0.5***	0.0	0.6	0.7**
	(0.4)	(0.2)	(0.1)	(0.2)	(0.6)	(0.3)
$\Delta IP^{D}_{\text{All low-income}}$	3.7***	0.4	0.8***	1.1***	2.1**	1.3**
	(0.8)	(0.3)	(0.2)	(0.3)	(1.0)	(0.5)
All controls	✓	✓	✓	✓	✓	✓
$Avg(Y)$	48.6	4.1	4.1	1.8	17	9.3
N	583994	299921	299921	299921	299921	299921

Notes: The only difference from the columns 1 to 6 of Table 3 is that the measure of trade exposure now uses the import penetration from all low-income countries, not just from China. Other than that, the sample, the dependent variables, estimation equation, regressors and instruments, establishment-level controls, fixed effects, industry-level controls, and the level of clustering are the same as baseline result in Table 3. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3: Correlating Residuals Across Outcome Variables



Notes: I take the sample of continuing manufacturing establishments from 1991 to 2007, collapse them to SIC 4-digit industry level, regress each of the outcome variables in columns 2, 3, 5, 6 in Table 3 on the direct shock ΔIP_j(defined in (1)) with the instrument ΔIPO_j (defined in (4)), and obtain the residual from each regression. Then, I plot the relationship between the residuals from different regressions. The top left figure compares the margin of becoming an importer with the margin of becoming a wholesaler. The top right figure compares the margin of becoming an importer with the margin of becoming a retailer. The bottom left figure compares the margin of becoming an importer with the margin of becoming an exporter. The bottom right figure compares the margin of becoming an importer with the margin of switching industries within manufacturing.

Part II

Import Competition and Firms' Internal Networks: An Establishment-level Analysis (with Jay Hyun and Vladimir Smirnyagin)

Abstract

Using a dataset on U.S. establishments and their firm affiliations, we document a cross-sectoral propagation of import competition from China ("China shock") through firms' internal networks. The employment of an establishment in one industry is negatively affected by the China shock hitting other industries in which establishments within the same firm operate. This indirect propagation mechanism works toward both manufacturing and non-manufacturing establishments. Our finding holds after controlling for sectoral or regional shocks affecting the establishment's own industry or location. We demonstrate the macroeconomic significance of this finding by showing that the indirect propagation mechanism is preserved at the sector level. Therefore, we hypothesize that the great economic, social, and political impact of China shock found in the literature could be even greater once we incorporate the propagation mechanism.

9 Introduction

How does a shock to one sector propagate to another sector? How do multi-sector firms respond when one of their sectors is exposed to a shock? What caused the U.S. manufacturing employment decline? Why did the import competition from China have such a large impact on the U.S. economy? We answer these central questions in macro, financial, trade, and organizational economics by documenting the *within-firm* cross-sector propagation of the import competition shock from China.

Consider a firm which owns multiple establishments that operate in different industries. Since the exposure to import competition from China varies across industries, establishments in one industry could be affected by Chinese import competition more strongly than establishments that operate in other industries. For example, consider a case in which only one of the firm's establishments is directly exposed to import competition.

What impact will the China shock have on other establishments within the same firm? On the one hand, it could make other establishments larger because, to smooth out the shock's impact, the firm could reallocate workers from the affected establishment to those not directly affected. On the other hand, the shock could make other establishments smaller because a shock to a subset of the firm's establishments might dampen general production at the firm-level (for example, due to within-firm complementarities in production, or through tightening of financial conditions). Moreover, it can also be the case that establishments are not interdependent with each other without spillover effects.

To tackle these questions, we study within-firm networks by drawing on the National Establishment Time Series (NETS) data, which has a near-universal coverage of U.S. establishments during the time period 1991-2007. Critically for our analysis, each establishment's identifier in NETS data is associated with a headquarter identifier, which allows us to identify the set of establishments constituting each firm.[1]

Our direct sectoral shock measures the growth of import penetration from China to the U.S. between 1991 to 2007 ("China shock"). Following the literature, we interpret the China shock to be a result of China's internal supply shocks rather than U.S. demand shocks, since Chinese economic growth (and growth in exports in particular) has been spurred by China's internal reforms. Nonetheless, to remove the demand-driven part of the rising competition from China, we follow Autor, Dorn, Hanson, and Song (2014) and use the growth in import penetration from China to other high income countries as our instrument.[2]

In line with our research question, we construct our main independent variable—an indirect shock at

[1] Establishment identifier is not reused when establishment exits or goes inactive.

[2] The large existing literature on the China shock has shown that establishment-level employment and survival probability is negatively affected by the direct exposure to Chinese import competition (Asquith et al., 2019; Park, 2020). The direct sectoral China shock is also negatively associated with firms' R&D activities in the U.S. (Autor et al., 2016) and workers' longterm earnings Autor, Dorn, Hanson, and Song (2014). However, literature has not yet studied the impact of the China shock propagating through within-firm networks for any of these outcome variables.

the establishment-level—as a (weighted) average exposure to China shock of other establishments *within* the same firm.[3] We then study the impact of both direct and indirect China shocks on the establishment's employment. We find that the employment of an establishment in one industry is negatively affected when China shock hits other establishments in the same firm. Remarkably, the employment of both manufacturing and non-manufacturing establishments are affected by this indirect propagation mechanism. Our finding holds even after controlling for sectoral and regional shocks affecting the establishment's own industry or location.

We perform a number of robustness exercises and confirm our main findings. To list some of them, we consider a Placebo test by constructing a random within-firm sectoral network. We show that such a counterfactual Placebo network does not generate the within-firm sectoral spillovers that we find in our main analysis. We also show that our results are not driven by outliers, differences in manufacturing shares across firms, or the choice of weighted versus unweighted regressions.

We further show that the sectoral spillover is entirely driven by the extensive margin of employment adjustment through establishment exit, while the intensive margin of continuing establishment is not responsive to the indirect shock. This is in line with Asquith et al. (2019), who document that the China shock affects U.S. employment mainly through the establishment exit. We contribute to the literature by further showing that establishment closures in one industry also occur due to the increased competition with China in other industries in which the firm operates.

We also attempt to understand the mechanisms behind the within-firm propagation of the trade shock. In particular, we consider three possibilities. The first one is based on the work of Holmes and Stevens (2014) who argue that large plants respond stronger to the China shock because such establishments are likely to be mass-product oriented, and, thus, face a tougher competition from China. We find limited support to this view: while we do find that establishments within larger firms respond stronger to the increasing competition with China in some specifications, in general this effect is not statistically significant.

Following the lead of Giroud and Mueller (2019), we explore the role of financial frictions. To this end, we use a business credit score provided by NETS to proxy firm-level financial conditions. We also merge NETS with Compustat and adapt leverage[4] as an alternative measure of financial constraints for a set of publicly-traded firms. While it seems plausible that financial conditions could play a role in propagation of the within-firm China shock, we find no conclusive support for that view.

Finally, we evaluate the role of economies of scope—which several recent papers found important for firms' ability to respond and adjust to shocks (Ding 2020; Argente et al. 2020)— in within-firm propagation

[3] As we show below, the instrument is defined analogously.

[4] Leverage is defined as a ratio of short- and long-term liabilities to total assets.

of the China shock. In fact, we find that the indirect propagation is stronger in firms that have a larger number of industries.

Can China shock generate a significant sector-wide employment response by way of operating through within-firm networks? In general, the reallocation of displaced workers to firms that operate in the same sector can result in a quantitatively muted sector-level effect. To this end, we aggregate the establishment-level direct and indirect exposure measures to the sector level and document the macroeconomic significance of our findings by showing that the indirect propagation mechanism is preserved at the sector level.

Our work is related to several strands in the literature. First, we contribute to the large literature which studies the spillover effects that operate through firm networks. In particular, the literature has explored how shocks propagate through *multi-region* firms' internal networks using *region-level* and *country-level shocks* (see, for example, Giroud and Mueller (2019) and Hyun and Kim (2020a) for domestic cross-region propagation and Cravino and Levchenko (2017), Berman et al. (2015), Almunia et al. (2018), Boehm, Flaaen, and Pandalai-Nayar (2019) for international propagation).[5] This paper studies the propagation of *sector-level* shocks through the *multi-sector* firms' internal networks. On top of that, one of our contributions is to show that the propagation is not limited to plants that operate within the same industry (e.g., Giroud and Mueller (2019) find that housing shock propagates only to nontradable sector establishments); instead, it reaches establishments in both tradable and non-tradable industries.

Second, we contribute to the influential literature on multi-product firms in macroeconomics (e.g., Lach and Tsiddon 1992), international trade (e.g., Bernard, Redding, and Schott 2011; Bernard, Redding, and Schott 2010; Eckel and Neary 2010), and organizational theory (e.g., Teece 1982). Our analysis is related to this literature since we focus on multi-sector firms. Our focus on multi-sector firms and cross-sectoral propagation is distinct from Giroud and Mueller (2019) whose focus is multi-region firms and cross-regional propagation.[6]

Third, we contribute to the growing body of research on the U.S. manufacturing employment decline (summarized in Fort, Pierce, and Schott (2018b) and Abraham and Kearney (2018)). This strand of the literature identifies automation and import competition as key factors that account for this secular pattern. Our paper offers a new channel through which increasing import competition with China can negatively affect U.S. manufacturing sector. Since Giroud and Mueller (2019) study the impact of housing price bust on non-tradable sector employment rather than manufacturing employment, our paper is more closely aligned to the

[5] More broadly, we contribute to the literature on the propagation of shocks through networks. Such networks include input-output networks (Acemoglu et al. (2016b); Acemoglu et al. 2016a), within-region-cross-industry propagation (Helm, 2020), financial contagion (Cabrales et al., 2017), and social networks (Bailey et al., 2018).

[6] Ding (2020) studies only a small fraction of multi-product firms. Our sample is more than 12 times larger than that of Ding (2020), who restricts his study to multi-industry firms that have at least one industry directly exports. His sample, therefore, contains very large businesses on average. In contrast, our result for unweighted and weighted regression shows that our channel applies to both small and large establishments.

literature on manufacturing employment declines. This is an important distinction because the manner in which non-tradable establishments are linked to other establishments can be very different from the manner in which tradable establishments are linked to other establishments due to potential migration, agglomeration, and input-output linkages within a firm.

Fourth, our work contributes to the literature on the "China shock." The China shock had an immense economic, social, and political impact on the U.S. and other developed countries. Previous work has documented the large role this shock played in the sharp decline in manufacturing employment (Autor, Dorn, and Hanson (2013), Pierce and Schott, 2016a, Asquith et al., 2019, Bloom et al., 2019), earnings of affected workers (Autor et al. (2014)), and firms' R&D and investment (Autor et al., 2016, Pierce and Schott, 2018). The literature has also evaluated the impact of the rising competition from China on various business-level adjustments (Park, 2020), political polarization and Trump's election (Autor et al., 2020), Brexit (Colantone and Stanig, 2018), childhood poverty and single motherhood (Autor, Dorn, and Hanson, 2019a)—to name just a few. Our work is unique in that we combine the concept of within-firm networks with methodologies from this literature.

The rest of this paper is organized as follows. Section 10 lays out our empirical strategy. Section 11 describes the dataset. Section 12 presents our main establishment-level results. In Section 13, we show that the effect of the increased import competition from China propagating through within-firm networks is preserved at the sector level. Section 14 concludes.

10 Empirical Strategy

In this section, we describe how China shock is measured and why it is our central analysis variables. Subsequently, we discuss our main empirical specification.

10.1 Measuring Import Competition with China

We measure each establishment's direct exposure to China shock by its industry-level increase in import penetration from 1991 to 2007[7] as constructed by Acemoglu et al. (2016b) (hereafter AADHP). AADHP construct a measure of import competition from China for 392 manufacturing industries at the SIC 4-digit

[7]In Appendix 14, we also consider stacking two subperiods, 1991-1999 and 1999-2007, as in Acemoglu et al. (2016b) and Asquith et al. (2019).

level. Industry-level change in import penetration from China into the U.S. is calculated as

$$\tilde{\Delta} IP_{j,91-07} = \frac{\Delta M^{UC}_{j,91-07}}{Y_{j,91} + M_{j,91} - E_{j,91}}, \tag{16}$$

where $\Delta M^{UC}_{j,91-07}$ represents the change in real imports from China to the U.S. between 1991 and 2007 in industry j, and $Y_{j,91} + M_{j,91} - E_{j,91}$ is the real domestic absorption of industry j in year 1991, which equals the sum of industry shipments $Y_{j,91}$ and industry imports $M_{j,91}$ less industry exports $E_{j,91}$.

A group of establishments that operate in some industry j share the same direct exposure to China shock. Therefore, if an establishment b owned by firm f has an industry code j, then the establishment's direct exposure to import competition from China equals the direct exposure of that industry j:

$$\tilde{\Delta} IP^{b,f}_{j,91-07} = \tilde{\Delta} IP_{j,91-07}. \tag{17}$$

In our analysis, we want to isolate the element of import competition that comes from Chinese supply shock. This is reasonable in the context of China because the increase in Chinese imports was to a large extent exogenous to the U.S. The Chinese productivity surge in the late 1980s and early 1990s came about mostly as a result of internal Chinese economic and political reforms. In other words, it was driven by the fact that reformists gained power through a power struggle within the Communist Party of China, that was exogenous to the U.S. demand shock.

That said, the origins of the increase in the import penetration may still partly lie in domestic U.S. demand shocks. To tackle this concern, we follow the lead of ADHS and AADHP, and instrument $\tilde{\Delta} IP_{jt}$ by the measure of import penetration from China to other high-income countries[8], defined as

$$\tilde{\Delta} IPO_{j,91-07} = \frac{\Delta M^{OC}_{j,91-07}}{Y_{j,88} + M_{j,88} - X_{j,88}}, \tag{18}$$

where $\Delta M^{OC}_{j,t}$ is the change in real imports from China to other high-income countries between 1991 and 2007 in industry j, and $Y_{j,88} + M_{j,88} - X_{j,88}$ is the real domestic absorption in year 1988. Applying the same logic as before, establishments that operate in the same industry j—regardless of the firm they belong to—share the same direct exposure to the China shock:

$$\tilde{\Delta} IPO^{b,f}_{j,91-07} = \tilde{\Delta} IPO_{j,91-07}. \tag{19}$$

[8]The list of other advanced economies includes Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

10.2 Indirect China Shock and Within-firm Sectoral Networks

Consider an establishment b in industry j owned by a firm f. Our objective is to investigate how establishment-level employment responds to import competition that hits other establishments in the same firm. Similar to Giroud and Mueller (2019) and Hyun and Kim (2020a), who study indirect local demand shock arising from within-firm regional networks, we construct the within-firm indirect China shock as follows:

$$\tilde{\Delta} IP^{f}_{j,91-07} \text{ (other)} = \sum_{j' \neq j} \omega^{f}_{j',-j,91} \times \tilde{\Delta} IP_{j',91-07}, \tag{20}$$

where $\omega^{f}_{j',-j,t} \equiv \frac{Emp^{f}_{j',t}}{\sum_{j'' \neq j} Emp^{f}_{j'',t}}$ is the initial employment shares weight assigned to industry $j' \neq j$. Note that firm's f employment in industry j is ignored when we construct this weight.[9] Thus, $\tilde{\Delta} IP^{f}_{j,91-07}$ (other) can be viewed as a weighted average China shock that a firms f faces through its establishments operating in industries other than j.

The instruments are similarly constructed. We instrument $\tilde{\Delta} IP^{f}_{j,91-07}$ (other) using $\tilde{\Delta} IPO^{f}_{j,91-07}$ (other) defined as follows:

$$\tilde{\Delta} IPO^{f}_{j,91-07} \text{ (other)} = \sum_{j' \neq j} \omega^{f}_{j',-j,91} \times \tilde{\Delta} IPO_{j',91-07}. \tag{21}$$

10.3 Dependent Variable

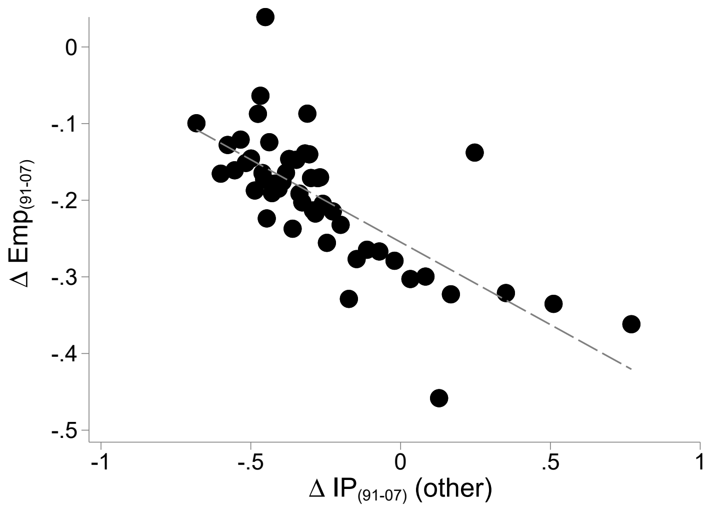
Our main dependent variable is establishment-level employment growth. We adapt the growth rate measure proposed by Davis, Haltiwanger, and Schuh (1998), which is standard in the literature on labor dynamics and is routinely used with establishment-level data. The employment growth of establishment b owned by a firm f between years 1991 and 2007 is defined as:

$$\tilde{\Delta} Emp^{b,f}_{91-07} = \frac{Emp^{b,f}_{07} - Emp^{b,f}_{91}}{\frac{1}{2}\left(Emp^{b,f}_{91} + Emp^{b,f}_{07}\right)}, \tag{22}$$

where $Emp^{b,f}_{t}$ stands for employment of establishment b owned by firm f at time t. This measure, which is a second-order approximation of the log difference growth rate around 0, provides a symmetric measure

[9] Some firms own both manufacturing and non-manufacturing establishments. When we construct $\tilde{\Delta} IP^{f}_{91-07}$, we assign $\tilde{\Delta} IP^{b,f}_{j,91-07} = 0$ to non-manufacturing establishments. Thus, if a firm's employment is concentrated in non-manufacturing industries, that firm is assigned a smaller (in absolute value) magnitude of the China shock. Our results are robust to alternative ways of shock construction, in which, for example, non-manufacturing establishments are treated to have a "missing" China shock.

Figure 4: Indirect China Shock and Employment Growth



Notes: Figure 4 is a bin scatter plot of establishment-level employment changes plotted against the indirect China shock, defined as in (20). Both variables have been standardized. The effect of the direct shock, as well as state and industry fixed effects have been factored out. The values of the indirect shock have been restricted to lie within ±1 standard deviations from the mean.

around 0 and is conveniently bounded between -2 and 2. These features reduce the impact of outliers with no arbitrary winsorization of extreme observations. Also, this measure allows for a unified treatment of establishment death and survival, where employment growth rates of 2 and -2 denote establishment entry and death, respectively.

Figure 4 visualizes a negative relationship between establishment-level employment growth and indirect China shock. Remarkably, the downward-sloping link between the two variables is preserved after the direct shock has been also included in the regression. We next evaluate the impact of the indirect China shock on establishment growth in a formal setup.

10.4 Empirical Specification

Our sample consists of multi-sector firms that own at least one manufacturing establishment. We include both manufacturing and non-manufacturing establishments in the baseline sample. We additionally confirm that our results hold in two subsamples, which are restricted to manufacturing and non-manufacturing establishments, respectively.

Our baseline empirical specification takes the following form:

$$\tilde{\Delta} Emp^{b,f}_{91-07} = \beta_0 + \beta_1 \tilde{\Delta} IP_{j,91-07} + \beta_2 \tilde{\Delta} IP^{f}_{j,91-07} \text{ (other)} + \beta_3' \mathbf{X}^{b,f}_{j,0} + \delta^{b,f}_{j} + e^{b,f}_{j,91-07}, \tag{23}$$

where $\mathbf{X}_{j,0}^{b,f}$ is a vector of establishment and firms-level controls, and $\delta_j^{b,f}$ is a set of various fixed effects.

While coefficient β_1 captures the direct impact of China shock on establishment-level employment growth, coefficient β_2, which is the key coefficient of interest, captures the impact of the indirect China shock that arises from the within-firm sectoral network.

The vector of controls $\mathbf{X}_{j,0}^{b,f}$ includes the logarithm of the initial establishment-level employment, the logarithm of the initial firm-level employment and sales, quadratic polynomial in firm age, and a manufacturing establishment dummy variable. In specifications wherein we only consider manufacturing establishments, we additionally include manufacturing industry controls, as in AADHP.[10]

The set of fixed effects $\delta_j^{b,f}$ includes county- and/or sector fixed effects. County fixed effects control for any common trends in establishment employment growth within each county. Thus, any general equilibrium adjustments at the county-level are absorbed by such fixed effects. Sector fixed effects control for any sectoral trends in establishment employment growth. We consider various levels of sector fixed effects up to the SIC 6-digit level. Provided that the China shock is defined at the SIC 4-digit industry, we do not include the direct China shock when we include sector fixed effects disaggregated beyond the SIC 4-digit level.

All regressions are weighted by initial establishment employment, although the results are similar in unweighted regressions (see Appendix 14). Throughout the analysis, standard errors are two-way clustered at the state and SIC 3-digit sectors, allowing for an arbitrary correlation in error terms among establishments in the same state and/or sector.

11 Data

11.1 National Establishment Time Series

Overview

We use the 1991-2007 National Establishment Time Series (NETS) for our analysis. The credit rating company Dun & Bradstreet first gathers data on each U.S. firm and establishment, and Walls & Associates subsequently scrutinizes and distributes it.

NETS is an annual time series of nearly the entire universe of U.S. establishments. We use its information on employment, SIC 8-digit industry, headquarter identifier, and location. Each establishment is assigned an establishment key, called a Data Universal Numbering System (DUNS) number. The DUNS number is robust to mergers and acquisitions, changes in industry and location. Moreover, it is not re-used when an

[10] These include an industry-level share of production workers, log average wages, capital over value added, computer as a share of investment, and high-tech equipment as a share of investment (all measured in 1991). Pretrend controls include 1976-1991 changes in log average wages and manufacturing share of the U.S. employment.

establishment exits.

Furthermore, NETS reports the DUNS number of the headquarter for each establishment, which is critically important for studies of the propagation of shocks through the within-firm network. When an establishment does not have a headquarter, its headquarter DUNS number matches its own DUNS number. A firm is defined to be the set of establishments that share the same headquarter DUNS number. In NETS, an establishment can serve as a headquarter itself, a subsidiary, or a branch.

NETS is also well-suited for our purposes because each establishment is assigned a separate industry code at the very fine SIC 8-digit level. Data from the U.S. government provides industry information only at SIC 4-digit level. Although the import competition is defined at SIC 4-digit, the presence of 8-digit industry classification information allows us to control for the fixed effect at a very granular level.

Moreover, NETS maintains the same set of SIC industry codes based on the 1987 version of SIC. This time-consistency allows us to conduct our dynamic analysis reliably. The U.S. official statistics, in contrast, switched from SIC to NAICS standards in 1997; since then, NAICS industry categories have changed repeatedly over time. Such changes raise certain empirical challenges (Pierce and Schott, 2016a; Fort and Klimek, 2018a), which we do not have to contend with.

NETS Quality

To maintain the quality of its data, Dun & Bradstreet conducts an extensive array of analyses. First, their analysts make phone calls to reliable sources, such as the firms' legal personnel, CFOs, and CIOs. Second, they make use of publicly available government registries, legal filings, yellow pages, news, annual reports, company websites, and so on. Third, the U.S. government requires companies to report their information based on their DUNS number for procurement purposes.

To establish the quality of NETS, several studies have compared it to U.S. administrative data sources. Neumark, Zhang, and Wall (2007) report that county-level employment in NETS and Quarterly Census of Employment and Wages (QCEW) has a correlation of 0.99. Barnatchez et al. (2017a) also find that the employment data in NETS is remarkably close to official statistics, with employment correlation at the state-industry-size cell level exceeding 0.9.

A recent paper by Crane and Decker (2019) raised concerns about NETS employment dynamics.[11] They argue that NETS employment appears to be sticky. Such stickiness may create a bias *against* finding a change in establishment-level employment as a response to a shock. The fact that we still find a significant

[11] Note that this and their previous work (Barnatchez et al., 2017a) acknowledge the accuracy of the *statics* of employment information in NETS.

establishment-level employment movement even under such a dynamic stickiness suggests that an actual impact can be even higher than what we find. Thus, our estimates are conservative and serve as a lower bound.

Moreover, our analysis is carried over a long time period, spanning the years 1991-2007. The literature has found that the correlation between NETS and official statistics significantly improves as the time horizon increases. Comparing industry-county-level employment changes between NETS and QCEW, Neumark, Zhang, and Wall (2007) find that while the yearly correlation between the two datasets is 0.53, the three-year correlation is 0.86. Our analysis focuses on a 16-year horizon, thereby further alleviating potential discrepancies between NETS and administrative data even more.[12]

11.2 Summary Statistics

Table 35: Summary Statistics

Establishment-level, 1991-2007						
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
$\tilde{\Delta}\text{Emp}_{(91-07)}$	290200	-1.417	0.991	-2	-2	0
$\tilde{\Delta}\text{IP}_{(91-07)}$	290200	0.153	0.620	0.000	0.000	0.310
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	290200	0.331	0.699	0.000	0.059	1.022
Emp 1991	290200	91.062	452.129	3	15	175
Firm-level, 1991-2007						
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Emp 1991	21957	1204.048	19193.632	15	102	1203
Sales 1991 (million)	21957	121.603	902.653	1.250	10.518	133.524
Firm Age 1991	21957	36.580	31.230	6	28	80
Num. of Sectors 1991	21957	3.563	4.835	2	2	6
Num. of Manu. Sectors 1991	21957	1.880	2.483	1	1	3
Num. of Non-Manu. Sectors 1991	21957	1.683	3.208	0	1	3
Num. of Establishments 1991	21957	13.223	84.875	2	3	15
Num. of Manu. Establishments 1991	21957	3.422	8.899	1	2	6
Num. of Non-Manu. Establishments 1991	21957	9.801	82.201	0	1	9

Notes: This table provides summary statistics of the final sample at the establishment and firm-level. The data comes from the National Establishment Time-series Database (NETS). $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth, $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock, and $\tilde{\Delta}\text{IP}_{(91-07)}$(other) is the indirect China shock through other industries within each firm. Detailed description of variables can be found in Section 10.

Table 35 provides summary statistics for our core sample, which consists of multi-sector firms that have at least one manufacturing establishment. A median firm operates in two sectors (at the SIC 4-digit level) and has three establishments, two of which are classified as manufacturing, and one of which is classified

[12] Rossi-Hansberg et al. (2018) and Asquith et al. (2019) also use this fact to argue in favor of the reliability of NETS over a long time horizon.

as non-manufacturing. However, the distribution of firms with respect to the number of sectors in which they operate in is right-skewed. A firm at the 90th percentile operates in six sectors, three of which are classified as manufacturing sector. Such a firm operates six establishments in the manufacturing sector, and nine establishments in the non-manufacturing sector. In terms of employment, 15 workers are employed by a typical establishment, and 102 workers are employed by a median firm. Firm- and establishment-size distributions are highly right-skewed: the 90th percentile is more than ten times larger than the median.

12 Sectoral Spillovers at the Establishment-level

12.1 Main Result

Table 36: Impact of Direct and Indirect China Shocks on Employment Growth:All Establishments, OLS

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.043***	-0.037***	-0.036***	-0.032***
	(0.013)	(0.013)	(0.011)	(0.011)
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)		-0.086***	-0.085***	-0.077***
		(0.020)	(0.019)	(0.017)
R^2	0.029	0.031	0.112	0.119
Controls	✓	✓	✓	✓
County FE	-	-	✓	✓
Sector FE	-	-	-	✓
Observations	290200	290200	290200	290200

Table 37: Impact of Direct and Indirect China Shocks on Employment Growth:All Establishments, IV

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.078***	-0.065***	-0.063***	-0.055***
	(0.022)	(0.020)	(0.018)	(0.014)
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)		-0.121***	-0.120***	-0.106***
		(0.024)	(0.023)	(0.017)
R^2	0.028	0.030	0.026	0.018
IV	✓	✓	✓	✓
First-stage F stat	56.8	28.6	34.9	30.4
Controls	✓	✓	✓	✓
County FE	-	-	✓	✓
Sector FE	-	-	-	✓
Observations	290200	290200	290200	290200

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22), $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock defined in (17), and $\tilde{\Delta}\text{IP}_{(91-07)}$(other) is the indirect China shock defined in 20. Controls include log of initial establishment- and firm-level employment, log of firm-level sales, firm age and age squared, and a manufacturing sector indicator. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit sector dummies. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

We begin by estimating Equation (23) using OLS on our baseline sample. Table 36 provides the results. Column (1) shows that an increase of import competition from China significantly reduces establishment-level employment in directly-affected industries. In Column (2), we add the within-firm indirect China Shock. As can be seen in the second row, an increase of the firm's average exposure to the China shock through its other sector establishments significantly reduces establishment-level employment. Importantly, this result is obtained after controlling for the establishment's direct exposure to the shock. We find that the direct and indirect effects are both economically and statistically significant at the 1% level. Moreover, the indirect effect is twice as large in magnitude as the direct effect, which highlights the importance of the within-firm sectoral networks in propagating the shock.

One potential concern in identifying the effect of the China shock on establishment-level employment is that a common regional shock can affect geographically clustered regions. This becomes a problem if particular industries tend to cluster in nearby regions. If this is the case, the effect of China shock we identify, especially the direct shock, might actually come from comparing two establishments located in different regions that are experiencing different regional shocks. To filter out such confounding effects, we saturate the model with county fixed effects in Column (3). These fixed effects absorb any common variation within a county across establishments that is attributable to a regional shock. We obtain similar results.

In Column (4), we add sector fixed effects constructed by combining ten manufacturing dummies borrowed from AADHP (for manufacturing establishments) and SIC 1-digit level sector dummies (for non-manufacturing establishments).[13] These fixed effects absorb the impact of any common trends in employment growth within each sector across establishments that may arise from more aggregated sectoral shocks. We find that the results are not affected.

Table 37 repeats the analysis in Table 36 by instrumenting $\tilde{\Delta} IP_{(91-07)}$ and $\tilde{\Delta} IP_{(91-07)}$ (other) with $\tilde{\Delta} IPO_{(91-07)}$ and $\tilde{\Delta} IPO_{(91-07)}$ (other), respectively. Consistent with the previous literature, we find a stronger impact of China shock on establishment-level employments both in terms of both direct and indirect shocks.

In Table 43 in the Appendix, we consider a specification with more disaggregated sector fixed effects that is defined up to SIC 6-digit level. These fixed effects absorb the establishment's direct exposure to Chinese import competition as well as other indirect effects operating through the input-output networks or general equilibrium adjustments (common across establishments within narrowly defined industries). We obtain robust results, which implies that the effect of indirect shocks on establishment-level employment is not driven by common disaggregate sectoral components that affect the establishment.

In Section 12.5, we present a number of additional robustness checks and confirm our main findings.

[13] Since the direct China shock itself is at the sector level (at SIC-4 digit level), including disaggregate sector fixed effects absorbs the variations in the data, which allows us to identify the effect of China shocks. Yet, in Table 43 in Appendix 14, we consider a specification with sector fixed effects up to SIC 6-digit level.

12.2 Spillover Effect Within and Outside Manufacturing Sector

Table 38: Impact of Direct and Indirect China Shocks on Employment Growth: Manufacturing Establishments

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.059***	-0.052***	-0.046***	-0.050***
	(0.019)	(0.017)	(0.016)	(0.015)
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)		-0.104***	-0.109***	-0.095***
		(0.029)	(0.025)	(0.022)
R^2	0.027	0.028	0.027	0.031
IV	✓	✓	✓	✓
First-stage F stat	58.3	30.3	35.6	33.7
Controls	✓	✓	✓	✓
County FE	-	-	✓	✓
Sector FE	-	-	-	✓
Observations	74784	74784	74784	74784

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22), $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock defined in (17), and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, and firm age and age squared. We also include industry-level controls and pretrend controls in AADHP: industry-level share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, (all in 1991), and 1976-1991 changes in log average wages and share of U.S. employment. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Our main result obtained in the previous subsection indicates that China shock spills over across sectors through within-firm sectoral networks. Does the shock propagate mainly within the manufacturing sector, or does it also affect establishments that operate in the non-manufacturing sector? So far, our analysis has been silent about potential differences in the impact of China shock on production sectors; in other words, the effect we have documented can mask substantial heterogeneity in responsiveness to Chinese import competition across sectors. To shed light on this issue, we split our baseline sample into two subsamples, (i) manufacturing establishments and (ii) non-manufacturing establishments, and we investigate whether our results hold in both cases.[14] We find remarkably comparable results in both cases: within-firm sectoral spillovers occur both from manufacturing establishments to non-manufacturing establishments, and they occur across plants that operate in different manufacturing sectors (at SIC 4-digit level).

[14] The shocks are constructed by using the baseline sample including all establishments owned by multi-sector firms that have at least one manufacturing establishment.

Spillovers within Manufacturing Establishments

In Table 38, we repeat the analysis from Table 37 by restricting our sample to manufacturing establishments. We find that a manufacturing plant reduces employment in response to the indirect China shock arising from establishments in other manufacturing industries within the firm as well as to the China shock affecting the establishment's industry directly. In particular, we find that the coefficient is -0.05 on the direct effect, and -0.10 on the indirect one, which is only marginally lower than in case of the baseline sample. Both effects are significant at the 1% level in the tighest specification considered (column 4 in Table 38).

We also find quantitatively similar effects when we saturate the model with narrow industry fixed effects, thereby controlling for the direct effect: Table 44 in Appendix 14 shows that our estimate of the indirect effect is -0.07, which is similar to that of the baseline.

Table 39: Regression with Disaggregate Sector Fixed Effects:Non-Manufacturing Establishments

	(1)	(2)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.081***	-0.059*
	(0.030)	(0.035)
R^2	0.005	0.004
IV	✓	✓
First-stage F stat	393.5	194.5
Contrls	✓	✓
County FE	✓	✓
Sector FE	SIC 4-digit	SIC 6-digit
Observations	214980	214877

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22) and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, and firm age and age squared. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Spillovers from Manufacturing to Non-Manufacturing Establishments

In Table 39, we consider a specification from Table 43 wherein we restrict the sample to non-manufacturing establishments. As before, we instrument $\tilde{\Delta}IP_{(91-07)}$ (other) using $\tilde{\Delta}IPO_{(91-07)}$ (other). Since direct China shock is defined only for manufacturing industries, we do not estimate the direct effect in this case; instead, we include sector fixed effects up to SIC 6-digit level as well as county fixed effects. As before, these disaggregate sector fixed effects absorb any industry-level shocks, including direct exposure to China shock and indirect effects that work through input-output networks or general equilibrium adjustments.

We find that the within-firm indirect China shock has an economically and statistically strong impact on employment in non-manufacturing establishments. Table 39 shows that the size of indirect effect is bound between -0.06 and -0.08, which is similar to the magnitude of the effect within the manufacturing sector. This indicates that a multi-sector firm's exposure to Chinese competition propagates nearly uniformly to both its manufacturing and non-manufacturing establishments through the within-firm network. Remarkably, this result is not driven by general equilibrium adjustments within regions (e.g., a within-region general equilibrium effect from manufacturing to non-manufacturing sectors) because we control for both county and sector fixed effects.

12.3 Extensive and Intensive Margins Decomposition

Table 40: Extensive versus Intensive Margin of Employment Adjustments:All Establishments

	(1) $\tilde{\Delta}\text{Emp}_{(91-07)}$	(2) $\tilde{\Delta}\text{Emp}^{\text{extensive}}_{(91-07)}$	(3) $\tilde{\Delta}\text{Emp}^{\text{intensive}}_{(91-07)}$	(4) $\tilde{\Delta}\text{Emp}_{(91-07)}$	(5) $\tilde{\Delta}\text{Emp}^{\text{extensive}}_{(91-07)}$	(6) $\tilde{\Delta}\text{Emp}^{\text{intensive}}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.055***	-0.061***	0.006			
	(0.014)	(0.021)	(0.009)			
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.106***	-0.123***	0.017	-0.086***	-0.103***	0.017
	(0.017)	(0.020)	(0.014)	(0.018)	(0.020)	(0.014)
R^2	0.018	0.036	0.058	0.009	0.022	0.045
IV	✓	✓	✓	✓	✓	✓
First-stage F stat	30.4	30.4	30.4	297.4	297.4	297.4
Controls	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	SIC 4-digit	SIC 4-digit	SIC 4-digit
Observations	290200	290200	290200	290199	290199	290199

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22), $\tilde{\Delta}\text{Emp}^{\text{extensive}}_{(91-07)}$ is the employment growth arising from establishment closures (extensive margin), and $\tilde{\Delta}\text{Emp}^{\text{intensive}}_{(91-07)}$ is the employment growth arising from continuing establishments (intensive margin). $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Our measure of the establishment-level employment adjustment (22) allows us to treat exiting and continuing establishments in a unified way, assigning the growth rate of -2 to exiting plants. This is a particularly attractive feature, provided that firms can adjust both along both the intensive (employment adjustments in continuing establishments) and the extensive (employment adjustments by establishment closures) margins. It is important to know whether employment adjustments occur through establishment exits or through contraction of continuing establishments.

Recent work by Asquith et al. (2019) documents that China shock affects U.S. employment mainly through the establishment exit. What is unclear is whether within-firm sectoral spillovers are driven by the extensive margin or the intensive margin (or both). We answer this question by decomposing the establishment-level employment growth into the two margins and re-estimating our main specification equation (23) for each margin separately.

Table 40 shows the result. In line with Asquith et al. (2019), we find that the direct shock mainly works through the extensive margin—i.e., establishment closures. Importantly, the indirect shock also works through the extensive margin. This implies that establishment death occurs not only in response to the direct increase of import competition from China; it is also due to increased competition with China in the other sectors in which the firm operates. Therefore, the economic, social, and political consequences of China shock emphasized by the existing literature could be even larger because of establishment closure induced by the within-firm shock propagation.

12.4 The Role of Economies of Scope, Size and Financial Conditions

In this section, we explore the role of several measurable dimensions of firm-level characteristics in the within-firm propagation of the China shock.

Firm Size

Column 1 of Table 41 shows that when we include an interaction of the indirect shock with firm size[15], the effect of increasing competition from China propagating through the within-firm network is increasing in the size of the firm.

Economies of Scope

A growing body of literature emphasizes the role of economies of scope in the ability of firms to respond and adjust to shocks (Argente et al., 2020; Ding et al., 2019). We measure economies of scope by the number of distinct manufacturing industries in which the firm operates.

Columns 2 through 4 in Table 41 report the results. As a benchmark, we define other manufacturing industries at a 6-digit level (column 2). Columns 3 and 4 consider economies of scope at a coarser (SIC 4-digit) and finer (SIC 8-digit) levels, respectively. In all cases, we find that employment growth responds

[15] Defined as a logarithm of firm-level employment in 1991.

more strongly to Chinese competition within firms that operate in a multitude of industries: the interaction term is negative and statistically significant at least at the 5% level. We, thus, complement (Argente et al., 2020) by documenting a stronger adjustment of plants to an *indirect* China shock within firms that have a larger scope.

Table 41: Interactions of the Spillover Shock with Initial Firm Characteristics

	Size Effects	Economies of Scope			Financial Conditions		All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$						
$\tilde{\Delta}\text{IP}_{(91-07)}$(other)	0.065	0.011	0.001	0.006	-0.030	-0.025	0.001
	(0.058)	(0.024)	(0.022)	(0.024)	(0.135)	(0.062)	(0.178)
$\tilde{\Delta}\text{IP}_{(91-07)}$(other) $\times$ ln(firm size)	-0.016*						0.008
	(0.009)						(0.015)
$\tilde{\Delta}\text{IP}_{(91-07)}$(other) $\times$ ln(mnf. scope)		-0.048***	-0.049**	-0.043**			-0.060**
		(0.018)	(0.020)	(0.017)			(0.029)
$\tilde{\Delta}\text{IP}_{(91-07)}$(other) $\times$ FC					0.000	-0.073	0.000
					(0.002)	(0.165)	(0.002)
ln(firm size)	0.029	0.028	0.028	0.027	0.028	0.054	0.028
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.055)	(0.035)
ln(mnf. scope)	-0.043**	-0.034*	-0.035	-0.032	-0.045**	-0.084***	-0.033
	(0.019)	(0.020)	(0.023)	(0.020)	(0.018)	(0.024)	(0.020)
FC	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.195	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.134)	(0.002)
R^2	0.013	0.013	0.013	0.013	0.012	0.009	0.013
IV	✓	✓	✓	✓	✓	✓	✓
First-stage F stat	161.1	160.1	165.3	166.6	167.2	495.7	135.8
Establishment Controls	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓
Sector FE	SIC 4-digit	SIC 4-digit	SIC 4-digit	SIC 4-digit	SIC 4-digit	SIC 4-digit	SIC 4-digit
Observations	267317	267317	267317	267317	267317	100392	267317

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the sector-level employment growth and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared. Economies of scope of each firm is measured by the number of distinct manufacturing industries defined at SIC 6-digit in which the firm operates (columns 1, 2 and 5-7). Columns 3 and 4 measure economies of scope at a coarser (SIC 4-digit) and finer (SIC 8-digit) level, respectively. Financial constraints are measured by "−PayDex Score" (columns 5 and 7) and firm-leverage (column 6), respectively. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Financial Conditions

We also evaluate the role of firm-level financial conditions in the response to heightened import competition from China. Giroud and Mueller (2019), for example, demonstrate that financial constraints are important for the within-firm propagation of demand shocks.

We consider two measures of financial conditions. The first one is a business credit score available in NETS data (column 5).[16] We additionally link NETS data with Compustat and use firm-level leverage as our second measure of financial conditions (column 6). We find no effect in the first and a negative effect in the second case, which is, nevertheless, statistically insignificant. Therefore, while it seems plausible that financial conditions could play a role in propagation of the within-firm China shock, we find no conclusive support for that view. This potentially can reflect the difference between our data and administrative records used by Giroud and Mueller (2019).

Finally, in column 7 we simultaneously include all interactions and find that only economies of scope remain significant. We conclude, therefore, that this characteristic of firms, examined in the recent literature, plays a key role in the within-firm propagation of sectoral shocks.

12.5 Robustness

In this section, we perform a number of robustness checks.

Placebo Test

What matters for the within-firm sectoral spillover is that establishments are connected to other sectors in which the firm is operating, and not to other sectors in general. To illustrate this, we perform a Placebo test by constructing a counterfactual random within-firm sectoral network, similar to what Giroud and Mueller (2019) and Hyun and Kim (2020a) propose. Specifically, for each establishment, we replace sectors of all other establishments to which the establishment is currently linked with randomly selected sectors. We then run our main regression and obtain the coefficients and standard errors. We repeat the process 500 times. As can be seen from Table 45 in Appendix 14, Placebo indirect shocks from other sectors have no significant effect on establishment-level employment.

[16] The variable is called "PayDex", which is a business credit score generated by Dun and Bradstreet (D&B). It is a numerical score ranging from 1 to 100, with higher score implying better payment history. We measure financial constraints by considering the negative of this index so that higher FC implies worse financial conditions.

Unweighted Regression

Instead of weighting each observation with the initial establishment-level employment, Appendix 14 reports the results of the unweighted regression. We find that the results barely change.

Controlling for the Firm-level Manufacturing Share

The responsiveness of the establishment-level employment to Chinese import competition can simply reflect the firm's manufacturing employment share. That is, an establishment might be experiencing lower employment growth not because its firm is highly exposed to Chinese import competition but because the firm's employment is more concentrated in the manufacturing sector. Since China shock is an industry shock, variation in the overall manufacturing share within firms is one of the key factors that generates a heterogeneous exposure to Chinese import competition. But it is still possible that the initial exposure to manufacturing industries relative to non-manufacturing ones may be a result of selection by firms.

In Appendix 14, we tackle this concern by directly controlling for the firm-level manufacturing employment share. We find our estimates to be robust to this alternative specification, implying that the results are not driven either by a firm' exposure to manufacturing industries or by selection considerations.

Stacking Subperiods 1991-1999 and 1999-2007

In Appendix 14, we allow for the possibility that the impact of direct and indirect shocks on establishment employment differed over time. To this end, we split the 16-year baseline period 1991-2007 into two subperiods (1991-1999 and 1999-2007), and subsequently stack them together by way of introducing an additional period fixed effect as in Acemoglu et al. (2016b) and Asquith et al. (2019). We find broadly similar results under this alternative specification.

Robustness to Outliers

We also show that our results are not driven by outliers. The first two columns in Table 51 in Appendix 14 exclude the top and bottom deciles of firms with respect to their employment in 1991. Note that when we drop the largest 10% of firms, the number of observations falls by more than 10% provided that large firms typically operate many establishments. Furthermore, in columns 3 and 4 we exclude the top and bottom

10% of establishments with respect to the size of the China shock hitting the firm they belong to. In all cases, we find the effect of the indirect shock to be large and statistically significant at 1%.

13 Sector-Level Spillovers

We have documented an economically and statistically strong impact of Chinese import competition on establishment-level employment that operates though the within-firm sectoral network. In this section, we take a step forward and investigate whether a firm-level spillover effect of the China shock survives aggregation to the sector level. That is, we study whether the sector-level employment responds to China shock hitting other sectors that are linked through within-firm networks.

13.1 Empirical Specification

We start by constructing a measure of a sector j's exposure to China shock that hits other industries and is propagated through the within-firm sectoral networks.[17] Formally, the measure is constructed as

$$\tilde{\Delta} IP_{j,91-07}\text{ (other)} = \sum_{j' \neq j} \lambda_{j',-j,91} \times \tilde{\Delta} IP_{j',91-07}, \tag{24}$$

where $\lambda_{j',-j,t}$ is a weight assigned to industry $j' \neq j$, and $\tilde{\Delta} IP_{j',91-07}$ is an import penetration measure for industry j defined in accordance with Equation (16). Thus, the construction of the sector-level shock is reminiscent of that of the firm-level "leave-one-out" shock (Equation 20), although the former has different weights.

We define sector j' weight $\lambda_{j',-j,t}$ as follows:

$$\lambda_{j',-j,t} \equiv \sum_{f} \frac{Emp^{f}_{j,t}}{\sum_{f'} Emp^{f'}_{j,t}} \times \omega^{f}_{j',-j,t}, \tag{25}$$

where the term $\omega^{f}_{j',-j,t}$ is identical to the same term in Equation (20):

$$\omega^{f}_{j',-j,t} \equiv \frac{Emp^{f}_{j',t}}{\sum_{j'' \neq j} Emp^{f}_{j'',t}}.$$

Therefore, the sector j' weight $\lambda_{j',-j,t}$ takes the firm-level employment share in sector j' for each firm f (term $\omega^{f}_{j',-j,t}$), and it subsequently averages these shares according to the relative employment size of firms

[17] Our approach is reminiscent of Giroud and Mueller (2019).

in sector j. Intuitively, we first construct the "importance" of sector j' for each firm, which is then averaged across firms with respect to their presence in sector j. Thus, $\lambda_{j',-j,t}$ measures the extent to which industry j is exposed to industry j' through within-firm sectoral networks created by multi-sector firms.

Guided by the same considerations as before, we instrument $\tilde{\Delta} IP_{j,91-07}$ (other) with the exposure of corresponding industries to the China shock in other high income countries:

$$\tilde{\Delta} IPO_{j,91-07} \text{ (other)} = \sum_{j' \neq j} \lambda_{j',-j,91} \times \tilde{\Delta} IPO_{j',91-07}. \tag{26}$$

We then estimate the following equation:

$$\tilde{\Delta} Emp_{j,91-07} = \beta_0 + \beta_1 \tilde{\Delta} IP_{j,91-07} + \beta_2 \tilde{\Delta} IP_{j,91-07} \text{ (other)} + Z'_{j,0}\beta_4 + \delta_j + e_{j,91-07}, \tag{27}$$

where $\tilde{\Delta} Emp_{j,91-07}$ is the growth in sector j employment between 1991 and 2007, $Z_{j,0}$ is a vector of industry-level controls, and δ_j is a set of various fixed effects. Our industry-level controls include the logarithm of initial industry-level employment and sales, constructed using NETS data, as well as those from AADHP. We consider two sets of fixed effects: a dummy variable that indicates whether the industry is classified as a manufacturing industry (i.e., SIC 2-digit $\in [20 - 39]$), and SIC 1-digit fixed effects.

13.2 Sector-Level Results

Table 42: Impact of Direct and Indirect China Shocks on Employment Growth:Sector-Level Regression

	(1) $\tilde{\Delta}\text{Emp}_{(91-07)}$	(2) $\tilde{\Delta}\text{Emp}_{(91-07)}$	(3) $\tilde{\Delta}\text{Emp}_{(91-07)}$	(4) $\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.058***	-0.067***	-0.088***	-0.091***
	(0.020)	(0.021)	(0.026)	(0.027)
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.041***	-0.030***	-0.043***	-0.026***
	(0.007)	(0.005)	(0.008)	(0.008)
R^2	0.440	0.549	0.363	0.288
IV	-	-	✓	✓
First-stage F stat	-	-	33.6	32.6
Industry Controls	✓	✓	✓	✓
Sector FE	-	✓	-	✓
Observations	555	555	555	555

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the sector-level employment growth, $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock defined in (16), and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Industry controls include log of initial industry-level employment and sales constructed using the NETS data, and an indicator indexing manufacturing sector. Sector fixed effects include both ten manufacturing sector dummies as in AADHP and SIC 1-digit level sector dummies. All regressions are weighted by initial sector-level employment. Standard errors are clustered at the SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 42 summarizes our findings. The first two columns report OLS estimates, while columns 3 and 4 report the results of IV estimation. In all specifications, we find that China shock has an economically and statistically significant effect on the sector-wide employment through both direct and indirect channels. The highly significant negative coefficients in front of the firm-level indirect exposure to the China shock indicate that an increase in the import competition that multi-sector firms face in other sectors negatively impacts employment growth in sectors that do not face a direct effect. The economic size of the effect suggests that the within-firm networks are quantitatively important for the propagation of shocks not only across establishments within the firm, but also across sectors of the aggregate economy.

14 Conclusion

We find that establishments owned by multi-sector firms reduce employment not only in response to their direct exposure to import competition from China, but also in response to import competition hitting the industries of other establishments in the same firm. This finding highlights the importance of firms' internal networks during the process of the propagation of sectoral shocks. Moreover, we document that such sectoral spillovers are not neutralized at the sector-level, implying that firms' internal networks play an important role in sector-wide employment adjustments. Thus, our findings point to a new channel through which the impact of trade can propagate across sectors and regions.

C. Additional Tables

C.1. Regressions with Disaggregate Sector Fixed Effects

Table 43: Regression with Disaggregate Sector Fixed Effects:All Establishments

	(1)	(2)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.086***	-0.071***
	(0.018)	(0.019)
R^2	0.009	0.008
IV	✓	✓
First-stage F stat	297.4	270.9
Contrls	✓	✓
County FE	✓	✓
Sector FE	SIC 4-digit	SIC 6-digit
Observations	290199	290028

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22) and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, and firm age and age squared. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 44: Regression with Disaggregate Sector Fixed Effects:Manufacturing Establishments

	(1)	(2)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.077***	-0.071***
	(0.017)	(0.016)
R^2	0.020	0.018
IV	✓	✓
First-stage F stat	186.2	191.2
Contrls	✓	✓
County FE	✓	✓
Sector FE	SIC 4-digit	SIC 6-digit
Observations	74784	74714

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22) and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, and firm age and age squared. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

C.2. Placebo Test

Table 45: Placebo Test: A Random Within-Firm Sectoral Network

	(1)	(2)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.057***	
	(0.015)	
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other, placebo)	0.003	0.002
	(0.052)	(0.050)
R^2	0.017	0.008
IV	✓	✓
First-stage F stat	31.9	651.9
Controls	✓	✓
County FE	✓	✓
Sector FE	✓	SIC 4-digit
Observations	289035	289034

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22), $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock defined in (17), and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other, placebo) is the Placebo indirect China shock constructed from random within-firm sectoral networks. All numbers in the table are the average of 500 random draws and the associated regressions. Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, and firm age and age squared. Sector fixed effects in Column (1) include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

C.3. Unweighted Regression

Table 46: Impact of Direct and Indirect China Shocks on Employment Growth:
All Establishments with Equal Weights

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.056***	-0.037***		
	(0.017)	(0.012)		
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.081***	-0.079***	-0.067***	-0.049***
	(0.014)	(0.012)	(0.012)	(0.014)
R^2	0.029	0.020	0.015	0.010
IV	✓	✓	✓	✓
First-stage F stat	44.6	38.5	202.6	67.5
Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Sector FE	-	✓	SIC 4-digit	SIC 6-digit
Observations	290200	290200	290199	290028

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22), $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock defined in (17), and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared, and an indicator indexing manufacturing establishments. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

C.4. Controlling for Firm-level Manufacturing Employment Share

Table 47: Impact of Direct and Indirect China Shocks on Employment Growth:
All Establishments-Control for Firm's Manufacturing Employment Share

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.064***	-0.056***		
	(0.018)	(0.015)		
$\tilde{\Delta}\text{IP}_{(91-07)}$ (other)	-0.104***	-0.089***	-0.078***	-0.065***
	(0.024)	(0.018)	(0.019)	(0.021)
Manufacturing $\text{Share}_{(91)}$	-0.109**	-0.110**	-0.064	-0.048
	(0.054)	(0.054)	(0.056)	(0.053)
R^2	0.027	0.019	0.010	0.008
IV	✓	✓	✓	✓
First-stage F stat	35.0	30.6	271.1	248.3
Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Sector FE	-	✓	SIC 4-digit	SIC 6-digit
Observations	290200	290200	290199	290028

Notes: $\tilde{\Delta}\text{Emp}_{(91-07)}$ is the establishment-level employment growth defined in (22), $\tilde{\Delta}\text{IP}_{(91-07)}$ is the direct China shock defined in (17), and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock defined in (20). Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared, and an indicator indexing manufacturing establishments. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

C.5. Stacking Subperiods 1991-1999 and 1999-2007

Table 48: Impact of Direct and Indirect China Shocks on Employment Growth: All Establishments, 1991-1999 & 1999-2007

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp
$\tilde{\Delta}$IP	-0.034***	-0.031***	-0.029***	-0.025**
	(0.012)	(0.011)	(0.010)	(0.010)
$\tilde{\Delta}$IP (other)		-0.046**	-0.044**	-0.025*
		(0.021)	(0.017)	(0.014)
R^2	0.018	0.018	0.015	0.019
IV	✓	✓	✓	✓
First-stage F stat	77.7	39.2	45.0	40.0
Controls	✓	✓	✓	✓
Period FE	✓	✓	✓	✓
County FE	-	-	✓	✓
Sector FE	-	-	-	✓
Observations	158691	158691	158691	158691

Notes: $\tilde{\Delta}$Emp is the establishment-level employment growth between either 91-99 or 99-07, $\tilde{\Delta}$IP is the direct China shock for corresponding subperiod, and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock for corresponding subperiod. Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared, and an indicator indexing manufacturing establishments. Period fixed effect is a dummy indicating subperiods. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 49: Impact of Direct and Indirect China Shocks on Employment Growth: Manufacturing Establishments, 1991-1999 & 1999-2007

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp
$\tilde{\Delta}$IP	-0.053***	-0.045***	-0.041***	-0.028***
	(0.014)	(0.012)	(0.012)	(0.010)
$\tilde{\Delta}$IP (other)		-0.085***	-0.083***	-0.073***
		(0.018)	(0.017)	(0.017)
R^2	0.018	0.019	0.016	0.016
IV	✓	✓	✓	✓
First-stage F stat	72.8	36.8	41.5	36.0
Controls	✓	✓	✓	✓
Period FE	✓	✓	✓	✓
County FE	-	-	✓	✓
Sector FE	-	-	-	✓
Observations	761929	761929	761929	761929

Notes: $\tilde{\Delta}$Emp is the establishment-level employment growth between either 91-99 or 99-07, $\tilde{\Delta}$IP is the direct China shock for corresponding subperiod, and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock for corresponding subperiod. We also include industry-level controls and pretrend controls in AADHP: industry-level the share of production workers, log average wage, capital over value added, computer as a share of investment, high-tech equipment as a share of investment, all in 1991, and 1976-1991 changes in log average wages and share of U.S. employment. Period fixed effect is a dummy indicating subperiods. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 50: Regression with Disaggregate Sector Fixed Effects:
Non-Manufacturing Establishments, 1991-1999 & 1999-2007

	(1)	(2)
	$\tilde{\Delta}$Emp	$\tilde{\Delta}$Emp
$\tilde{\Delta}$IP (other)	-0.068***	-0.030*
	(0.022)	(0.018)
R^2	0.010	0.009
IV	✓	✓
First-stage F stat	816.8	586.6
Controls	✓	✓
Period FE	✓	✓
County FE	✓	✓
Sector FE	SIC 4-digit	SIC 6-digit
Observations	603036	602987

Notes: $\tilde{\Delta}$Emp is the establishment-level employment growth between either 91-99 or 99-07 and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock for corresponding subperiod. Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared. Period fixed effect is a dummy indicating subperiods. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

C.6. Robustness of Establishment-Level Result to Outliers

Table 51: Robustness of Establishment-Level Result to Outliers:All Establishments

	Drop 10% outlier firms by size		Drop 10% outlier estab. by indirect shock	
	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$	$\tilde{\Delta}\text{Emp}_{(91-07)}$
$\tilde{\Delta}\text{IP}_{(91-07)}$	-0.064***	-0.056***	-0.061***	-0.062***
	(0.019)	(0.017)	(0.021)	(0.019)
$\tilde{\Delta}\text{IP}_{(91-07)}$(other)	-0.121***	-0.072***	-0.109***	-0.334***
	(0.021)	(0.014)	(0.020)	(0.045)
R^2	0.014	0.029	0.012	0.015
IV	✓	✓	✓	✓
Establishment Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	285201	81645	261130	264838

Notes: $\tilde{\Delta}$Emp is the establishment-level employment growth between 1991 and 2007, $\tilde{\Delta}$IP is the direct China shock for corresponding subperiod, and $\tilde{\Delta}\text{IP}_{(91-07)}$ (other) is the indirect China shock for corresponding subperiod. Controls include log of initial establishment-level employment, log of firm-level employment, log of firm-level sales, firm age and age squared, and an indicator indexing manufacturing establishments. Sector fixed effects include both ten manufacturing sector dummies in AADHP and SIC 1-digit level sector dummies. All regressions are weighted by initial establishment-level employment. Standard errors are double clustered at the state and SIC 3-digit sector level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge (2017). *When should you adjust standard errors for clustering?* Tech. rep. National Bureau of Economic Research.

Abraham, Katharine G and Melissa S Kearney (2018). *Explaining the decline in the US employment-to-population ratio: A review of the evidence*. Tech. rep. National Bureau of Economic Research.

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016a). "Networks and the macroeconomy: An empirical exploration". *NBER Macroeconomics Annual* 30.1, pp. 273–335.

Acemoglu, Daron, David Autor, David Dorn, Gordon Hanson, and Brendan Price (2016b). "Import competition and the great US employment sag of the 2000s". *Journal of Labor Economics* 34.S1, S141–S198.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012). "The network origins of aggregate fluctuations". *Econometrica* 80.5, pp. 1977–2016.

Akcigit, Ufuk and William R Kerr (2018). "Growth through heterogeneous innovations". *Journal of Political Economy* 126.4, pp. 1374–1443.

Alfaro, Laura, Davin Chor, Pol Antras, and Paola Conconi (2019). "Internalizing global value chains: A firm-level analysis". *Journal of Political Economy* 127.2, pp. 508–559.

Almunia, Miguel, Pol Antràs, David Lopez-Rodriguez, and Eduardo Morales (2018). "Venting Out: Exports during a Domestic Slump". Working Paper.

Amiti, Mary and Amit Khandelwal (2013). "Import competition and quality upgrading". *Review of Economics and Statistics* 95.2, pp. 476–490.

Amiti, Mary and Jozef Konings (2007). "Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia". *American Economic Review* 97.5, pp. 1611–1638.

Amiti, Mary, Stephen Redding, and David Weinstein (2019). "The impact of the 2018 tariffs on prices and welfare". *Journal of Economic Perspectives* 33.4, pp. 187–210.

Angrist, Joshua D and Jörn-Steffen Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Antras, Pol, Teresa Fort, and Felix Tintelnot (2017). "The margins of global sourcing: Theory and evidence from us firms". *American Economic Review* 107.9, pp. 2514–64.

Antras, Pol and Elhanan Helpman (2004). "Global sourcing". *Journal of Political Economy* 112.3, pp. 552–580.

Argente, David, Sara Moreira, Ezra Oberfield, and Venky Venkateswaran (2020). "Scalable Expertise".

Ashournia, Damoun, Jakob Roland Munch, and Daniel Nguyen (2014). "The impact of chinese import penetration on danish firms and workers".

Asquith, Brian, Sanjana Goswami, David Neumark, and Antonio Rodriguez-Lopez (2019). "Us job flows and the china shock". *Journal of International Economics* 118, pp. 123–137.

Autor, David, David Dorn, and Gordon Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". *American Economic Review* 103.6, pp. 2121–68.

— (2015). "Untangling trade and technology: Evidence from local labour markets". *The Economic Journal* 125.584, pp. 621–646.

— (2019a). "When work disappears: Manufacturing decline and the falling marriage market value of young men". *American Economic Review: Insights* 1.2, pp. 161–78.

Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi (2020). "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure". *American Economic Review*.

Autor, David, David Dorn, Gordon Hanson, Gary Pisano, and Pian Shu (2019b). "Foreign competition and domestic innovation: Evidence from US patents". *American Economic Review: Insights* 2.3, pp. 357–374.

Autor, David, David Dorn, Gordon Hanson, Gary Pisano, Pian Shu, et al. (2016). *Foreign competition and domestic innovation: Evidence from US patents*. National Bureau of Economic Research.

Autor, David, David Dorn, Gordon Hanson, and Jae Song (2014). "Trade adjustment: Worker-level evidence". *The Quarterly Journal of Economics* 129.4, pp. 1799–1860.

Autor, David, Lawrence Katz, and Alan Krueger (1998). "Computing inequality: have computers changed the labor market?" *The Quarterly Journal of Economics* 113.4, pp. 1169–1213.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong (2018). "Social connectedness: Measurement, determinants, and effects". *Journal of Economic Perspectives* 32.3, pp. 259–80.

Balsvik, Ragnhild, Sissel Jensen, and Kjell Salvanes (2015). "Made in China, sold in Norway: Local labor market effects of an import shock". *Journal of Public Economics* 127, pp. 137–144.

Bamieh, Omar, Matteo Fiorini, Bernard Hoekman, and Adam Jakubik (2020). "Services input intensity and US manufacturing employment responses to the China shock". *Review of Industrial Organization* 57.2, pp. 333–349.

Barnatchez, Keith, Leland D. Crane, and Ryan A. Decker (2017a). "An Assessment of the National Establishment Time Series (NETS) Database". Working Paper.

Barnatchez, Keith, Leland Dod Crane, and Ryan Decker (2017b). "An assessment of the national establishment time series (nets) database".

Becker, Randy, Wayne Gray, and Jordan Marvakov (2013). "NBER-CES manufacturing industry database: Technical notes". *NBER Working Paper* 5809.

Bellora, Cecilia and Lionel Fontagné (2019). "Shooting oneself in the foot? Trade war and global value chains".

Berman, Nicolas, Antoine Berthou, and Jérôme Héricourt (2015). "Export Dynamics and Sales at Home". *Journal of International Economics* 96.2, pp. 298–310.

Bernard, Andrew B, Teresa C Fort, Valerie Smeets, and Frederic Warzynski (2020). "Heterogeneous globalization: Offshoring and reorganization".

Bernard, Andrew, Emily Blanchard, Ilke Van Beveren, and Hylke Vandenbussche (2019). "Carry-along trade". *The Review of Economic Studies* 86.2, pp. 526–563.

Bernard, Andrew and Bradford Jensen (2007a). "Firm structure, multinationals, and manufacturing plant deaths". *The Review of Economics and Statistics* 89.2, pp. 193–204.

Bernard, Andrew, Bradford Jensen, Stephen Redding, and Peter Schott (2007b). "Firms in international trade". *Journal of Economic Perspectives* 21.3, pp. 105–130.

— (2018). "Global firms". *Journal of Economic Literature* 56.2, pp. 565–619.

Bernard, Andrew, Bradford Jensen, and Peter Schott (2006a). "Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of US manufacturing plants". *Journal of International Economics* 68.1, pp. 219–237.

— (2006b). "Trade costs, firms and productivity". *Journal of Monetary Economics* 53.5, pp. 917–937.

Bernard, Andrew, Stephen Redding, and Peter Schott (2010). "Multiple-product firms and product switching". *American Economic Review* 100.1, pp. 70–97.

— (2011). "Multiproduct firms and trade liberalization". *The Quarterly Journal of Economics* 126.3, pp. 1271–1318.

Bernard, Andrew, Valerie Smeets, and Frederic Warzynski (2017). "Rethinking deindustrialization". *Economic Policy* 32.89, pp. 5–38.

Bloom, Nicholas, Mirko Draca, and John Van Reenen (2016). "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity". *The Review of Economic Studies* 83.1, pp. 87–117.

Bloom, Nicholas, Kyle Handley, Andre Kurman, and Phillip Luck (2019). "The impact of chinese trade on us employment: The good, the bad, and the debatable". *Unpublished draft*.

Boehm, Christoph, Aaron Flaaen, and Nitya Pandalai-Nayar (2019). *Multinationals, offshoring and the decline of US manufacturing*. Tech. rep. National Bureau of Economic Research.

Branstetter, Lee G, Brian K Kovak, Jacqueline Mauro, and Ana Venancio (2019). *The China Shock and Employment in Portuguese Firms*. Tech. rep. National Bureau of Economic Research.

Breinlich, Holger, Anson Soderbery, and Greg Wright (2018). "From selling goods to selling services: Firm responses to trade liberalization". *American Economic Journal: Economic Policy* 10.4, pp. 79–108.

Cabrales, Antonio, Piero Gottardi, and Fernando Vega-Redondo (2017). "Risk sharing and contagion in networks". *The Review of Financial Studies* 30.9, pp. 3086–3127.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang (2019). *Tariff passthrough at the border and at the store: evidence from US trade policy*. Tech. rep. National Bureau of Economic Research.

Che, Yi, Yi Lu, Justin Pierce, Peter Schott, and Zhigang Tao (2016). *Does trade liberalization with China influence US elections?* Tech. rep. National Bureau of Economic Research.

Colantone, Italo and Rosario Crinò (2014). "New imported inputs, new domestic products". *Journal of International Economics* 92.1, pp. 147–165.

Colantone, Italo, Rosario Crino, and Laura Ogliari (2019). "Globalization and mental distress". *Journal of International Economics* 119, pp. 181–207.

Colantone, Italo and Piero Stanig (2018). "Global competition and Brexit". *American Political Science Review* 112.2, pp. 201–218.

Crane, Leland Dod and Ryan Decker (2019). "Business Dynamics in the National Establishment Time Series (NETS)".

Cravino, Javier and Andrei A. Levchenko (2017). "Multinational Firms and International Business Cycle Transmission". *Quarterly Journal of Economics* 132.2, pp. 921–962.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum (2014). "The rise of the East and the Far East: German labor markets and trade integration". *Journal of the European Economic Association* 12.6, pp. 1643–1675.

Davis, Steven, John Haltiwanger, and Scott Schuh (1998). *Job creation and destruction*.

De Lyon, Josh and Joao Paulo Pessoa (2020). "Worker and Firm Responses to Trade Shocks: The UK-China Case".

Dhyne, Emmanuel, Ayumu Ken Kikkawa, Magne Mogstad, and Felix Tintelnot (2020). "Trade and domestic production networks". *forthcoming in Review of Economic Studies*.

Ding, Xiang (2020). "Industry Linkages from Joint Production". Working paper.

Ding, Xiang, Teresa Fort, Stephen Redding, and Peter Schott (2019). *Structural change within versus across firms: Evidence from the United States*. Tech. rep. Technical Report, Discussion Paper). Dartmouth College.

Dippel, Christian, Robert Gold, Stephan Heblich, and Rodrigo Pinto (2017). *Instrumental variables and causal mechanisms: Unpacking the effect of trade on workers and voters*. Tech. rep. National Bureau of Economic Research.

Dix-Carneiro, Rafael and Brian Kovak (2017). "Trade liberalization and regional dynamics". *American Economic Review* 107.10, pp. 2908–46.

Dix-Carneiro, Rafael, Rodrigo Soares, and Gabriel Ulyssea (2018). "Economic shocks and crime: Evidence from the brazilian trade liberalization". *American Economic Journal: Applied Economics* 10.4, pp. 158–95.

Doms, Mark, Timothy Dunne, and Kenneth Troske (1997). "Workers, wages, and technology". *The Quarterly Journal of Economics* 112.1, pp. 253–290.

Dunne, Timothy, Mark Roberts, and Larry Samuelson (1988). "Patterns of firm entry and exit in US manufacturing industries". *The RAND journal of Economics*, pp. 495–515.

Eckel, Carsten and J Peter Neary (2010). "Multi-product firms and flexible manufacturing in the global economy". *The Review of Economic Studies* 77.1, pp. 188–217.

Ekholm, Karolina, Andreas Moxnes, and Karen Helene Ulltveit-Moe (2012). "Manufacturing restructuring and the role of real exchange rate shocks". *Journal of International Economics* 86.1, pp. 101–117.

Faber, Marius, Andrés Sarto, and Marco Tabellini (2019). "The Impact of Technology and Trade on Migration: Evidence from the US". *Harvard Business School BGIE Unit Working Paper* 20-071.

Fajgelbaum, Pablo, Pinelopi Goldberg, Patrick Kennedy, and Amit Khandelwal (2020). "The return to protectionism". *The Quarterly Journal of Economics* 135.1, pp. 1–55.

Fajgelbaum, Pablo, Gene Grossman, and Elhanan Helpman (2015). "A Linder hypothesis for foreign direct investment". *The Review of Economic Studies* 82.1, pp. 83–121.

Felbermayr, Gabriel, Giammario Impullitti, and Julien Prat (2018). "Firm dynamics and residual inequality in open economies". *Journal of the European Economic Association* 16.5, pp. 1476–1539.

Fort, Teresa and Shawn Klimek (2018a). "The effects of industry classification changes on US employment composition". *Tuck School at Dartmouth*.

Fort, Teresa, Justin Pierce, and Peter Schott (2018b). "New perspectives on the decline of us manufacturing employment". *Journal of Economic Perspectives* 32.2, pp. 47–72.

Giroud, Xavier and Holger Mueller (2019). "Firms' internal networks and local economic shocks". *American Economic Review* 109.10, pp. 3617–49.

Halpern, László, Miklós Koren, and Adam Szeidl (2015). "Imported inputs and productivity". *American Economic Review* 105.12, pp. 3660–3703.

Helm, Ines (2020). "National Industry Trade Shocks, Local Labour Markets, and Agglomeration Spillovers". *The Review of Economic Studies* 87.3, pp. 1399–1431.

Hoffmann, Mathias and Lilia Ruslanova (2020). "Softening the Blow: U.S. State-Level Banking Deregulation and Sectoral Reallocation after the China Trade Shock".

Holmes, Thomas and John Stevens (2014). "An alternative theory of the plant size distribution, with geography and intra-and international trade". *Journal of Political Economy* 122.2, pp. 369–421.

Hombert, Johan and Adrien Matray (2018). "Can innovation help US manufacturing firms escape import competition from China?" *The Journal of Finance* 73.5, pp. 2003–2039.

Hsieh, Chang-Tai and Ralph Ossa (2016). "A global view of productivity growth in China". *Journal of International Economics* 102, pp. 209–224.

Hummels, David, Jun Ishii, and Kei-Mu Yi (2001). "The nature and growth of vertical specialization in world trade". *Journal of International Economics* 54.1, pp. 75–96.

Hyun, Jay and Ryan Kim (2020a). "Spillovers and Redistribution through Intra-Firm Networks: The Product Replacement Channel". Working paper.

Hyun, Jay, Ziho Park, and Vladimir Smirnyagin (2020b). "Import competition and internal firm network: Establishment-level analysis".

Jovanovic, Boyan (1982). "Selection and the Evolution of Industry". *Econometrica*, pp. 649–670.

Kamal, Fariha and Mary E Lovely (2017). "Import competition from and offshoring to low-income countries: Implications for employment and wages at US domestic manufacturers". *Journal of Asian Economics* 48, pp. 100–119.

Kasahara, Hiroyuki and Beverly Lapham (2013). "Productivity and the decision to import and export: Theory and evidence". *Journal of international Economics* 89.2, pp. 297–316.

Kasahara, Hiroyuki and Joel Rodrigue (2008). "Does the use of imported intermediates increase productivity? Plant-level evidence". *Journal of Development Economics* 87.1, pp. 106–118.

Khandelwal, Amit (2010). “The long and short (of) quality ladders”. *The Review of Economic Studies* 77.4, pp. 1450–1476.

Kolko, Jed and David Neumark (2008). “Changes in the location of employment and ownership: evidence from California”. *Journal of Regional Science* 48.4, pp. 717–744.

Kueng, Lorenz, Nicholas Li, and Mu-Jeung Yang (2016). *The impact of emerging market competition on innovation and business strategy.* Tech. rep. National Bureau of Economic Research.

Lach, Saul and Daniel Tsiddon (1992). “The behavior of prices and inflation: An empirical analysis of disaggregat price data”. *Journal of political economy* 100.2, pp. 349–389.

Long, John and Charles Plosser (1983). “Real business cycles”. *Journal of Political Economy* 91.1, pp. 39–69.

Magyari, Ildiko (2017). “Firm reorganization, chinese imports, and us manufacturing employment”.

Malgouyres, Clément (2017). “The impact of Chinese import competition on the local structure of employment and wages: Evidence from France”. *Journal of Regional Science* 57.3, pp. 411–441.

McManus, Clay and Georg Schaur (2016). “The effects of import competition on worker health”. *Journal of International Economics* 102, pp. 160–172.

Medina, Pamela (2017). “Import competition, quality upgrading and exporting: Evidence from the peruvian apparel industry”. *University of Toronto mimeo.*

Melitz, Marc (2003). “The impact of trade on intra-industry reallocations and aggregate industry productivity”. *Econometrica* 71.6, pp. 1695–1725.

Melitz, Marc and Daniel Trefler (2012). “Gains from trade when firms matter”. *Journal of Economic Perspectives* 26.2, pp. 91–118.

Mion, Giordano and Linke Zhu (2013). “Import competition from and offshoring to China: A curse or blessing for firms?” *Journal of International Economics* 89.1, pp. 202–215.

Naughton, Barry (2006). *The Chinese economy: Transitions and growth.* MIT press.

Neumark, David, Junfu Zhang, and Brandon Wall (2007). *Employment dynamics and business relocation: New evidence from the National Establishment Time Series.* Emerald Group Publishing Limited.

Orr, Scott (2020). “Within-Firm Productivity Dispersion: Estimates and Implications”.

Park, Ziho (2020). “Trade Adjustment: Establishment-Level Evidence”. Working paper.

Pavcnik, Nina (2002). “Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants”. *The Review of Economic Studies* 69.1, pp. 245–276.

Pierce, Justin R. and Peter K. Schott (2016a). “The Surprisingly Swift Decline of US Manufacturing Employment”. *American Economic Review* 106.7, pp. 1632–1662.

Pierce, Justin and Peter Schott (2016b). “The surprisingly swift decline of US manufacturing employment”. *American Economic Review* 106.7, pp. 1632–62.

— (2018). “Investment responses to trade liberalization: Evidence from US industries and establishments”. *Journal of International Economics* 115, pp. 203–222.

— (2020). “Trade liberalization and mortality: evidence from US counties”. *American Economic Review: Insights* 2.1, pp. 47–64.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Nicholas Trachter (2018). “Diverging trends in national and local concentration”.

Sanderson, Eleanor and Frank Windmeijer (2016). “A weak instrument F-test in linear IV models with multiple endogenous variables”. *Journal of Econometrics* 190.2, pp. 212–221.

Teece, David J (1982). “Towards an economic theory of the multiproduct firm”. *Journal of Economic Behavior & Organization* 3.1, pp. 39–63.

Timoshenko, Olga (2015). “Product switching in a model of learning”. *Journal of International Economics* 95.2, pp. 233–249.

Topalova, Petia and Amit Khandelwal (2011). "Trade liberalization and firm productivity: The case of India". *Review of Economics and Statistics* 93.3, pp. 995–1009.

Trefler, Daniel (2004). "The long and short of the Canada-US free trade agreement". *American Economic Review* 94.4, pp. 870–895.

Utar, Hale (2018). "Workers beneath the floodgates: Low-wage import competition and workers' adjustment". *Review of Economics and Statistics* 100.4, pp. 631–647.

Wang, Zhi, Shang-Jin Wei, Xinding Yu, and Kunfu Zhu (2018). *Re-examining the effects of trading with china on local labor markets: A supply chain perspective.* Tech. rep. National Bureau of Economic Research.

Waugh, Michael (2019). *The consumption response to trade shocks: Evidence from the US-China trade war.* Tech. rep. National Bureau of Economic Research.