

Structural Change Within Versus Across Firms: Evidence from the United States

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Comments Welcome!

Abstract

We document the role of intangible capital in manufacturing firms’ substantial contribution to non-manufacturing employment growth from 1977-2019. Exploiting data on firms’ “auxiliary” establishments, we develop a novel measure of proprietary in-house knowledge and show that it is associated with increased growth and industry switching. We rationalize this reallocation in a model where firms combine physical and knowledge inputs as complements, and where producing the latter in-house confers a sector-neutral productivity advantage facilitating within-firm structural transformation. Consistent with the model, manufacturing firms with auxiliary employment pivot towards services in response to a plausibly exogenous decline in their physical input prices.

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1 Introduction

One of the most striking features of the US economy over the last five decades is its transition away from manufacturing and towards services. Indeed, between 1977 and 2019 the share of employment in manufacturing fell from more than a quarter to less than a tenth. Researchers in both international trade and macroeconomics offer valuable insights into this transformation. In trade, which generally focuses on the manufacturing sector, this drop is linked to import competition, most recently from China (Autor et al., 2013; Pierce and Schott, 2016). In macro, the *relative* growth of non-manufacturing versus manufacturing employment is explained in terms of unbalanced productivity growth (Baumol, 1967; Ngai and Pissarides, 2007), rising incomes and non-homothetic demand (Comin et al., 2018), or both (Matsuyama, 2019).

In this paper, we take a firm-level view of structural change that captures essential elements of both perspectives, while highlighting a role for the firm boundary in developing proprietary knowledge. Our approach is motivated by a detailed decomposition of US employment growth over the last four decades, which reveals that a small set of continuing manufacturing (M) firms accounts for a substantial share of the US shift towards services. Non-manufacturing (NM) employment growth among these firms, as for the United States as a whole, is concentrated in Business Services, particularly high-skill, technologically-advanced Management and Professional, Scientific, and Technical Services (PSTS) that are used as inputs across a wide range of sectors, and which relate to their past M activities. We show descriptively that firms with greater in-house production of input services grow faster and pivot more towards new industries than other firms. We rationalize this reallocation in a model in which service workers are complementary to physical inputs, and in-house provision of these services confers a sector-neutral productivity advantage. In the model, reductions in the price of physical inputs thus induce increases in both the levels and shares of service inputs. Consistent with this framework, we find that US manufacturers with in-house service establishments exhibit greater non-manufacturing employment and sales growth in response to a plausibly exogenous reductions in their physical input costs.

In the first part of the paper, we provide a comprehensive, firm-level summary of the US transition towards services by constructing a 40-year panel of the universe of firms and the detailed industries in which their establishments operate. In line with our interest in studying how firms accumulate knowledge, we provide this summary for the conventional as well as a broader concept of a firm that allows for the possibility that firm knowledge may continue after a firm exits as long as some of its plants survive, for example due to merger and acquisition activity. Using these two definitions, we find that manufacturing firms account for 16 to 32 percent of the rise in aggregate US non-manufacturing employment between 1977 and 2019.

Manufacturing firms' NM growth does not simply reflect aggregate trends, and is instead concentrated in related service sectors. Manufacturers increase their Wholesale and Retail activities considerably, while non-manufacturers' growth is much stronger in Health Care. We also show that both manufacturers and non-manufacturers grow the most in Business Services, but non-manufacturers grow across all its subsectors, whereas manufacturers' growth is concentrated in just three: Computer Systems Design, Research and Development (R&D), and Architectural and Engineering Ser-

vices. These subsectors relate to manufacturing, both because they constitute key inputs (e.g., R&D), and because they rely on particular physical outputs (e.g., Computer Systems Design services uses computers). Indeed, we find that manufacturing firms increasingly pivot towards these related services over the period. For example, continuing firms with Computer Systems Design establishments at the end of our sample period exhibit an average decline in their manufacturing employment share from 40 to 15 percent from 1977 to 2016. These transitions suggest a mix of *functional* and *sectoral* structural change within firms, i.e., greater provision of input services to produce the same final goods (*functional*), and transition from sales of goods to sales of services (*sectoral*). They also raise a crucial question: how and why does a small set of manufacturers successfully transition to services, while most exit?

We posit that proprietary knowledge provides firms with a competitive advantage that relates to their successful transition to services.¹ To assess this hypothesis, we develop a novel measure of proprietary firm knowledge using data on auxiliary establishments. Auxiliaries, such as R&D labs and warehouses, are service establishments that primarily serve other establishments of their firm, and are therefore plausible creators and receptacles of firm knowledge. Auxiliaries are present in input service sectors, and consistent with the premise that they focus on in-house provision of these services using high-skill labor, we find that they are smaller but pay higher wages relative to comparable establishments in the same sector that sell to external customers. In line with our hypothesis that these plants facilitate functional and sectoral structural change, we find that firm growth and reallocation across sectors increase with auxiliary employment shares, even after controlling for differences in firm size, age, and industry composition.

In the second part of the paper, we rationalize the relationship between within-firm structural change and firms’ in-house provision of Professional, Scientific, and Technical Services in a model of heterogeneous, multi-product firms similar in spirit to Melitz (2003) and Bernard et al. (2010). In our setup, firms pay an upfront entry cost to obtain a differentiated brand and observe their productivity for each sector. Given fixed overhead costs, firms choose to participate in the subset of sectors in which they are sufficiently productive. Firms also decide whether to incur an additional fixed cost (paid in knowledge workers) to produce knowledge services in-house, or to procure them via outsourcing to a third party. When produced in-house, the knowledge generated is proprietary and gives firms a competitive advantage by lowering costs in all sectors. By contrast, when this knowledge is acquired at arm’s length, it diffuses freely to all firms. In equilibrium, firms with better sector-specific productivity draws choose to produce knowledge services in-house, boosting productivity in all industries.

Our framework features two key distinctions from past work. First, firms produce by combining two types of inputs – manufacturing and knowledge – which we assume are complementary. As a result, firms increase the level and share of knowledge inputs in response to a fall in their manufactured

¹For example, Target’s CIO describes shifting away from outsourced to in-house provision of services to avoid “...a third-party provider sending [an advantage through shorter lead times] to Retailer B down the road.” Target had been outsourcing significant parts of its application development and back-end systems to India and domestic companies including Infosys and IBM. As he told the Wall Street Journal, “We got to a stage where almost half the team is in third parties. It’s unhealthy. By keeping the intellectual property generated by the inhouse software engineers, the company can preserve competitive advantage.”

input costs. Second, firms that produce this knowledge in-house gain a sector-neutral productivity advantage. Although the model is static, one interpretation of firms' in-house knowledge investment is that it represents a stock of intangible capital that is non-rival within the firm and does not fully depreciate in response to changes in final-good demand or input prices.

The model shows how shocks to firms' output and input prices can induce within-firm structural change. An increase in competition in a firm's output markets represents a negative demand shock for firms' manufactured output, and thus decreases their manufacturing sales and their use of both manufactured and knowledge inputs. For firms with in-house knowledge workers, the output shock will thus decrease not only M, but also NM employment. By contrast, an increase in competition in a firm's physical inputs lowers input prices and thus the cost of production. Since knowledge and manufactured inputs are complements, firms will increase both the level and share of knowledge inputs, though only the subset of firms with in-house knowledge workers increase their NM employment. As these firms also have a relatively higher sector-neutral productivity, firms with in-house knowledge workers prior to the shock are also more likely to expand into new sectors that also use these non-rival inputs.

In the final part of the paper, we provide empirical support for our framework by examining US manufacturers' responses to plausibly exogenous variation in firms' output and input prices driven by China's global integration from 1997 to 2007. On the one hand, greater import competition in firms' output markets represents a conventional, negative demand shock for their manufactured goods. On the other hand, greater import competition in firms' physical inputs reduces their manufacturing costs. We construct measures of firms' output and input exposure using changes in China's market shares in Europe in firms' initial output products and material inputs. We focus on reduced-form specifications in which we regress changes in firm sales and employment by sector directly on these instruments, and on their interactions with indicators for the possession of auxiliaries.

Our results confirm prior findings of large, negative effects of Chinese import competition in a firm's output markets on its employment and sales. These results are evident regardless of firms' auxiliary status and are strongly increasing in firm size. Not surprisingly, the output shock has a larger impact on firms' manufacturing activities. In fact, it only affects NM employment at firms with auxiliaries, and has no statistically significant relationship with NM sales. This asymmetry supports the premise that firms with in-house knowledge workers use workers in their NM establishments to support their M sales.

Results for the input shock are quite different. We see no statistically significant impact on firms' total or M employment. However, in line with our assumed complementarity between manufactured and knowledge inputs, we find a strong, positive relationship between the input shock and NM employment for firms with auxiliaries: a 10 percentage point increase in China's market share in the EU in a 500 employee firm's inputs raises its NM employment by 19 percent. Unlike for the output shock, we also find that the input shock increases firms' NM sales, suggesting that functional structural change may induce sectoral structural change as firms that produce services in-house to support their M products begin selling these services to other firms. This result highlights a role for firm boundaries in aggregate structural change, and in developing and preserving knowledge that

cannot readily be sold in the marketplace.

As a specific example, the estimates imply that a firm with auxiliaries and 500 employees that faced the average output (0.18) and input (0.12) exposure in Computer Storage Device manufacturing (334112) would decrease its M employment by 23 log points from the output shock, with almost no offsetting effect from the input shock. Although, the input shock implies a 23 log point increase in its NM employment, this is halved by the implied NM employment reduction of 10 log points from the output shock. In total, the estimates imply a 9 log point reduction in the firm’s employment, though it pivots considerably towards NM activities. A firm in Motor Vehicle Body Manufacturing, however, fares quite differently since the output shock is close to zero (0.005), while the input shock is sizable (0.056). The estimates imply that a comparable representative firm in this sector would not change its M employment but would increase its NM employment by 10 log points. In both sectors, firms pivot considerably from M to NM activities, but only if they have in-house knowledge establishments.

Our paper is related to several strands of research. A large macro literature attributes structural transformation to changes in final-good expenditure shares across sectors as a result of rising incomes and non-homothetic preferences (Boppart, 2014; Comin et al., 2018; Matsuyama, 2000), or unbalanced productivity growth (Baumol, 1967; Ngai and Pissarides, 2007; Herrendorf et al., 2013; Kehoe et al., 2018).² Our paper is closest to work focused on the rise of skilled services (Buera and Kaboski, 2012; Buera et al., 2015). Relative to that research, we show that these services are primarily inputs that are complementary with manufacturing. The shift towards these inputs may still be due to non-homothetic demand if richer consumers increasingly value technology-intensive goods (e.g., talking refrigerators), and lessens concerns about aggregate stagflation (Baumol, 1967), since these service inputs are used across a wide range of sectors that will all benefit from any productivity growth in them (Oulton, 2001). We further show that the United States tilts towards these services, not only for internal reasons, but also in concert with increased low-wage production opportunities abroad. Prior work documents the distinct effects that an open versus closed economy can have in promoting these changes (Matsuyama, 2009, 2019), and on why complementarity between manufacturing and services can explain the global aggregate decline in M employment (Cravino and Sotelo, 2019).³ Our contribution is to exploit data on this transformation within firms to provide identified, reduced-form evidence on this complementarity, and to demonstrate the importance of within-firm knowledge in mediating these changes.⁴

We also contribute to a long literature on the boundary of the firm. That work has largely focused on how firms use integration to reduce transaction costs (Williamson, 1981) or change ex-ante investment decisions when contracts are incomplete (Grossman and Hart, 1986; Hart and Moore, 1990). Antràs and Helpman (2004) develop a model in which heterogeneous firms produce by combining headquarter and manufactured inputs under incomplete contracts, but assume that headquarter services are necessarily integrated and focus on the decision to integrate or outsource manufactured

²See Herrendorf et al. (2014) for an extensive review.

³See Alessandria et al. (2021) for a recent review of these papers.

⁴While these transitions are most easily observed within firms, similar movement towards complementary, comparative advantage activities across firms is evident in the emergence of factoryless-goods producers and their contribution towards US innovation Bernard and Fort (2015); Kamal (2020).

inputs. Our focus on firms’ decision to produce knowledge in-house is closest to [Teece \(1982\)](#), who posits that multi-product firms can be rationalized by “organizational knowledge,” and [Demsetz \(1988\)](#) who argues that “knowledge is costly to produce, maintain, and use” (p. 157). More recently, [Boehm et al. \(2022\)](#) show that common input knowledge facilitates expansion into new products, [Atalay et al. \(2014\)](#) argue that the transfer of intangibles across plants is an important motive for integration, [Ding \(2020\)](#) provides evidence that knowledge inputs are shared within multi-industry firms, and [Mengus and Michalski \(2022\)](#) report that certain service workers augment in-house knowledge. Our contribution is to expand the analysis to non-manufacturing, construct a new measure of firms’ in-house knowledge, and show that firms with this in-house knowledge both grow and pivot more in response to shocks. The evidence supports the premise that the boundary of the firm plays an important role in developing knowledge and excluding rivals from it.

Our work also connects with the international trade literature that studies the effects of low-wage imports. Increased competition from low-wage countries prompts firms to shut down their most-exposed plants ([Bernard et al., 2006](#)), focus on their core products ([Bernard et al., 2011](#)), and upgrade their quality and technology ([Khandelwal, 2010](#); [Bloom et al., 2016](#)). Recent work documents large US M employment declines in industries in which Chinese imports surged ([Pierce and Schott, 2016](#); [Acemoglu et al., 2016](#)), and the local labor markets that specialized in those industries ([Autor et al., 2013](#)). Closest to our evidence on rising NM employment is work that shows low-wage offshoring opportunities lead firms to increase employment in technology occupations ([Bernard et al., 2021](#)), and that UK firms in industries with larger tariff reductions shifted into services ([Breinlich et al., 2018](#)).⁵ On the US side, [Bloom et al. \(2019\)](#) argue that high-wage commuting zones exposed to China grew their NM employment as plants switched their industries, though this is at odds with firm-level analyses that show declining employment, sales, and R&D at exposed public US firms ([Hombert and Matray, 2018](#); [Autor et al., 2020](#)).⁶ Our contribution is to provide a comprehensive assessment of all US manufacturers’ responses across the full range of their activities, to show that the same import shock represents not only a negative demand shock, but also a positive input shock that raises NM employment, and to document a differential response for firms with auxiliaries prior to the shock.

Finally, we relate to a growing literature on rising concentration, markups, and new fixed-cost technologies. Recent work credits declining prices in Information and Communication Technologies (ICT) with increased spatial concentration of high-wage, tradable services ([Eckert, 2019](#); [Eckert et al., 2019](#)), disproportionate expansion by large firms across space ([Hsieh and Rossi-Hansberg, 2019](#)), increased production fragmentation [Fort \(2017\)](#), and rising industry concentration ([Bessen, 2017](#); [Ganapati, 2016](#); [Lashkari et al., 2021](#)). [Argente et al. \(2021\)](#) argue that “scalable expertise” constitutes a fixed-cost investment that renders large firms more responsive to shocks. Relative to these studies,

⁵Existing work on the effects of US firms’ offshoring finds conflicting results. While [Antràs et al. \(2017\)](#) provide structural and reduced-form evidence that US firms’ offshoring to China led to significant productivity gains that increased the use of domestic manufactured inputs, [Boehm et al. \(2020\)](#) show that US MNEs decrease their manufacturing employment considerably from 1993 to 2011, and provide structural estimates that suggest offshoring displaces US manufacturing employment.

⁶Though [Bloom et al. \(2019\)](#) report a high correlation between plants’ industry switching and import competition from China, we show in Appendix Figure [A2](#) that the actual employment associated with these switches is small. [Magyar \(2017\)](#) also examines US firms’ employment responses, but presents results (in Table 8) that suggest increased Chinese import competition increased firms’ M employment while it decreased their NM employment.

we show that in-house knowledge, measured explicitly using firms’ auxiliary establishments, is a specific fixed-cost investment in knowledge that not only facilitates firms’ growth, but also enables them to transition across industries. Since this knowledge is complementary with manufacturing but housed in separate establishments, standard productivity estimation may overstate firm productivity and thus markups for these large firms. Prior work on manufacturers shows that co-production within firms is not random (Bernard et al., 2010), and that strategic interactions across goods bias productivity estimates (Hottman et al., 2016). Our evidence on auxiliaries suggests that in-house knowledge is another source of bias that may explain the dramatic, rising markups documented in only the largest firms (de Loecker et al., 2020; Foster et al., 2022), and related to the growing importance of intangible capital documented in Haskel and Westlake (2017).

The remainder of the paper proceeds as follows. Section 2 discusses the data construction. Section 3 presents five stylized facts about structural transformation within and between firms, and studies the role of in-house knowledge plants in these transitions. Section 4 develops a theoretical framework to rationalize these stylized facts. Section 5 uses the China shock as an exogenous source of variation to provide empirical evidence in support of the key mechanism in the model. Section 6 concludes.

2 Data

We construct a new dataset that tracks establishments over a forty-year period from 1977 to 2016. We make three contributions in the data construction. First, we improve upon the Census firmid definitions both by fixing clearly spurious breaks and by developing a method to account for merger and acquisition activity in decomposing employment changes across continuers versus net births. Second, we employ the longitudinally consistent industry codes from Fort and Klimek (2018) to address significant changes in the US industry classification schemes over the period. Finally, we exploit four different data sources to identify auxiliary establishments consistently throughout the period and analyze their behavior. To our knowledge, ours is the first study of auxiliaries over such a long period. Together these three data contributions allow us to offer the first quantification of structural transformation within and across firms, and to provide evidence on the role of intangible knowledge in shaping this process of structural transformation.⁷

2.1 Main Dataset Construction

The frame for our analysis is the US Census Bureau’s Longitudinal Business Database (LBD), initially assembled by Jarmin and Miranda (2002) and recently updated by Chow et al. (2021) to track the employment, pay, and industry of all private, non-farm US establishments from 1977 to 2019 annually. An establishment is a single physical location where business transactions take place and for which payroll and employment are recorded. The LBD contains a longitudinally consistent establishment identifier (*lbdnum*), a firm identifier (*firmid*) that captures all of the establishments under common ownership or control in a given year, and an LBD-specific firm identifier that corrects for recycled *firmids* in this long time series (*lbdfid*). In some of our regression analyses below, we exploit

⁷Prior work using auxiliary data includes Davis and Henderson (2008) and Aarland et al. (2007).

information on the county – i.e., FIPS code – in which plants reside to include location fixed effects.

We augment the LBD data with additional information from Economic Censuses (ECs) of Auxiliaries (AUX), Construction (CCN), Finance, Insurance, and Real Estate (CFI), Manufactures (CMF), Mining (CMI), Retail Trade (CRT), Services (CSR), Transportation, Communications, and Utilities (CUT), and Wholesale Trade (CWH). The EC data are collected in years ending in “2” and “7”, henceforth referred to as “Census” years, and provide establishment-level measures of sales for all sectors.

We also use CMF trailer data on manufacturers’ input purchases and product-level sales by industry to construct shares of manufacturing firms’ sales and input purchases by industry, which enable us to identify firms’ differential exposure to changes in Chinese import competition for their outputs and inputs. These trailer data are only available for a subset of manufacturing establishments that includes all large, multi-unit firms with industry-specific thresholds for the number of employees, as well as a random sample of smaller firms.⁸

2.2 New Firm Definitions

A primary goal of this paper is to assess the extent to which firms develop knowledge that may facilitate growth and pivoting across industries. This goal is complicated by the fact that Census’ *lbdid*’s are not longitudinally consistent. By Census convention, *lbdids* break whenever firms transition between single-unit (SU) and multi-unit (MU) status. The Census firm identifier may also change spuriously during reorganizations and merger and acquisition (M&A) activity. In this section we provide a brief summary of how we address these limitations, deferring a more complete discussion to Appendix A.1.

We correct spurious SU-to-MU breaks by developing a ‘fixed’ Census firm identifier based on a simple algorithm that links firms’ establishments across transitions between SU and MU status.⁹ We use this corrected firm identifier, referred to here as a “Census firm” or as *lbdid_{lc}* to denote its extended longitudinal consistency, to assign establishments to firms each year. We then use these “Census firms” to compute lower bounds on firms’ contribution to US structural change in Sections 3.1 and 3.2, to measure firms’ reallocation to other sectors (referred to as “pivoting”) in Section 3.4, and in all of our regressions.

We also develop a broader definition of the firm that accounts for merger and acquisition activity. Inspired by Haltiwanger et al. (2013) and referred to as “HJM”, this approach captures the idea that (at least some) knowledge may be preserved when plants move across firms, even if these transitions lead to firm entry or exit. Specifically, we classify a HJM firm as a continuer from year t to t' if at least one of its establishments exists in t' and t . Likewise, it is a death if all of its establishments exit before t' , and it is a birth if all of its establishments are born after t . This definition thus addresses

⁸The Census of Manufactures includes all manufacturing establishments in the United States. For very small establishments, data are based only on administrative records. All establishments that belong to multi-unit firms with at least 250 employees are sent the long census form, which includes questions about input purchases and sales by detailed product categories. A random sample of smaller establishments are also sent the long form. Remaining establishments are sent the short form, which does not include the questions on detailed inputs or outputs. For these firms, we calculate output and input exposure using their establishment industry code, imputing input purchases from input-output tables.

⁹We use Census’ *lbdid* in these corrections so that recycled *firmid*’s are not present in our analysis.

spurious breaks in firmids over time, and also treats a continuation of some part of the firm as a continuation of the firm. As HJM firms are broader than Census firms, they tend to assign greater activity to continuers.¹⁰ We use this definition to provide an upper bound on the amount of NM employment growth accounted for continuing M firms in Section 3.4.

2.3 Consistent Industry Classification

We measure the evolution of the US economy across industries by assigning each establishment to a single, six-digit North American Industry Classification System (NAICS) code. The governing principle under NAICS is to classify establishments based on the activities performed at the establishment, so it is particularly well-suited for studying changes in what firms and their employees actually do. As in all establishment-based Census data, all workers in an establishment are classified under the same industry.

To track activity as consistently as possible over time, we employ the new LBD’s *bds_vcnaics* variable, which contains the most recent vintage NAICS code for all establishments over the entire time period, along with additional information in accompanying industry files, as detailed in Fort and Klimek (2018).¹¹ An establishment may change its industry code over time, as its primary activity changes. We allow for these changes, but rely most heavily on codes assigned in EC years, since these contain the most accurate information. We use these establishment-level codes to identify the mix of industries in which multiple-establishment firms operate.

2.4 Auxiliary Panel

A significant contribution of this paper is to construct and analyze a long time series of auxiliary establishments. Auxiliaries are establishments that primarily serve other establishments of their firm, rather than sell goods or services to other firms, e.g., an R&D lab or a warehouse. Analyzing auxiliaries over our 1977 to 2019 sample period is particularly challenging because, under the Standard Industry Classification (SIC) system used until 1997, they were classified under the industry they served rather than the activities they performed. For example, if an R&D lab conducted research for a manufacturing plant, it was assigned the manufacturing industry SIC code of that manufacturing plant.

To identify auxiliary establishments and their activities consistently across our sample period, we combine information from three sources: (1) the FK_NAICS “aux files” included in the LBD and available during the SIC years; (2) the CBPBR files starting in 2002; and (3) the Censuses of Auxiliaries (AUX), Services (CSR) and Utilities (CUT). We find that there are 92 six-digit NAICS

¹⁰Haltiwanger et al. (2013) calculate firm age based on the maximum age of all its establishments in year t . Establishments are only classified as belonging to firms that die if all the establishments of the firm die, and only classified as firm births if all the establishments are new. This definition is robust to M&A activity and to spurious, longitudinal breaks in the Census firmid variable. The number of continuing “Census firms” across t and t' must be the same in both years, while the number of continuing HJM firms can differ in the two years.

¹¹NAICS replaced the former Standard Industrial Classification System (SIC) codes in 1997. Even within SIC and NAICS years, there are multiple vintages of these codes that change over time. We follow the suggestions in Fort and Klimek (2018) to avoid using codes that have too much noise to provide meaningful information. See Online Appendix A.2 for details.

industries that may contain auxiliary establishments. These industries are in Trucking and Warehousing (NAICS 48-49), Information (NAICS 51), Professional, Scientific, and Technical (NAICS 54), Administration Services (NAICS 56), and Repair Services (NAICS 81). We provide further details on auxiliary data construction in Online Appendix A.3, as well as technical documentation available within the Census RDC network.

3 An Anatomy of US Structural Change from 1977 to 2016

In this section, we characterize the US transition from manufacturing to services along a number of novel dimensions. First, we report upper and lower bounds for the amount of non-manufacturing (NM) employment and payroll growth that occurs within M firms. Second, we show that while Business Services dominate NM growth among both M and NM firms, manufacturing firms’ NM growth is concentrated in a subset of Business Service industries, whereas non-manufacturers grow across a broad range. Third, we demonstrate that continuing M firms’ reallocation towards business service inputs suggests redeployment of their manufacturing knowledge to related service activities. Finally, we link firm growth and pivoting to a novel measure of in-house knowledge production that we develop for all firms.

3.1 Manufacturing Firms Growth in Non-Manufacturing

We assess manufacturing firms’ contribution to US structural change via their share of NM employment and payroll growth from 1977 to 2019. Table 1 provides upper and lower bounds for employment growth based on the two firm definitions introduced in Section 2.2. For each type of firm, we distinguish between intensive and extensive margins, i.e., continuers versus net births and deaths.

Panel A of Table 1 reports the lower bounds using the conservative “Census firm” definition.¹² Panel B of Table 1 presents upper bounds using HJM firms. In this case, a firm is classified as a ‘continuer’ in 1977 or in 2019 if it owns any plants in that year that exist in both 1977 and 2019. In other words, a firm’s continuer status depends not upon the history of its firm identifier, but upon the history of the establishments it owns in that year. This more liberal definition of a continuer accounts for potential survival of firm knowledge through establishments as they move across firms over time.

In both panels, we distinguish between M and NM firms using two time-invariant classifications. In panel A, a Census firm is M if it ever owns an M establishment from the begin to end years. In panel B, an HJM firm is M if it contains an establishment that was ever part of a Census M firm over the entire period. As above, this broader HJM classification is designed to capture potential transfers of knowledge across plants as they wind their way through firms with manufacturing activity.¹³

¹²We define a Census firm using the the LBD firm identifier, *lbdfid1c*, but with corrections to spurious breaks that occur in SU-MU transitions.

¹³As an example, if an R&D lab is part of a manufacturing firm at some point, we flag that establishment as having belonged to an M firm. If that R&D lab is later acquired by a different firm, our HJM firm definition would classify the acquiring firm as an M firm, even if it does not have an M plant itself. By contrast, the Census definition only classifies a firm as an M firm if the firm itself owns an M plant.

The first row in each panel of Table 1 shows M firms’ contribution to M and NM employment growth over the period. The left columns in each panel show that M employment falls by 5.7 million workers, and M firms account for the total decline by definition. We decompose M firms’ total contribution by continuing firms versus net birth and deaths. While the Census definition (upper panel) indicates that continuing M firms only account for 20 percent of the total decline, the HJM definition (bottom panel) attributes 62 percent of the decline to continuers. This discrepancy highlights the fact that some portion of exiting manufacturing firms persists, presumably contributing positively to surviving and new Census firms.

Focusing on NM employment changes in the right columns of Table 1, we find that M firms account for substantial shares – 16 to 32 percent – of overall NM employment growth. Under the Census firm definition (Panel A), M firms approximately double their NM employment from 12.6 to 23.9 million workers. Perhaps unsurprisingly, NM firms exhibit even larger level growth, from 35.4 to 95.9 million workers. Nevertheless, the increase in NM employment at M firms accounts for almost one-fifth (16 percent) of the aggregate increase in NM employment. Among HJM firms (Panel B), M firms increase their NM employment from 17.4 to 40.2 million, while NM firms increase from 30.6 to 79.6 million workers. Despite this considerable growth at NM firms, M firms account for 32 percent of the aggregate increase in NM employment under the HJM definition.

Both panels of Table 1 reveal a striking difference in the margins by which M and NM firms contribute to US structural change. M firms’ growth in NM employment is overwhelmingly driven by continuing firms. These continuers comprise less than one percent of total firms in 2019 under either definition, yet account for 15 percent (Census definition) to 26 percent (HJM definition) of aggregate NM employment growth. By contrast, among NM firms, the bulk of NM employment growth occurs as a result of net birth-death, with continuing NM firms contributing only 18 to 16 percent of the aggregate increase.

Prior work has documented a disproportionate role for US multinational firms in the decline of US M employment (Boehm et al., 2020). While we explicitly consider the role of falling manufactured input costs due to Chinese imports in promoting within-firm structural change in Section 5, the mechanism we emphasize still requires US firms’ manufacturing employment shares to fall. If instead US firms are simply replacing their US M employment with foreign M employment, the patterns we depict here would represent solely a shift in the location of activities, and not a shift outside of the firm boundary. To assess this alternative story, we use public data from the Bureau of Economic Analysis to calculate manufacturing employment in US MNEs’ foreign affiliates. Online Appendix Figure D4 shows that manufacturing employment at foreign affiliates holds steady and does not offset the fall in US M workers. The broad patterns we depict here using firms’ US M employment thus apply to their global activities as well.

M firms’ contribution to US structural change is even larger in payroll terms. Analogous decompositions for payroll reported in Appendix Table A1 show that M firms contribute 25 to 40 percent of NM payroll growth over the same period, with continuing M firms accounting for 17 to 31 percent. By contrast, NM continuers account for just 16 percent of payroll growth under *both* firm definitions. Taken together, these results yield our first structural change fact:

Fact 1: Continuing manufacturing firms account for a substantial and disproportionate share (16 to 32 percent) of aggregate non-manufacturing employment growth, and 26 to 40 percent of non-manufacturing payroll growth.

Table 1: Employment Growth in M and NM from 1977 to 2019, by Firm Type and Margin

Panel A:		“Census Firms” (Lower Bound)						
	Manufacturing Emp				Non-Manufacturing Emp			
	1977	2019	Change	Share of Change	1977	2019	Change	Share of Change
M Firms	17.7	12.1	-5.7	1.00	12.6	23.9	11.3	0.16
Continuers	5.6	4.5	-1.1	0.20	5.3	15.9	10.6	0.15
Net Birth/Death	12.1	7.5	-4.6	0.80	7.3	7.9	0.7	0.01
NM Firms					35.4	95.9	60.5	0.84
Continuers					5.6	18.2	12.6	0.18
Net Birth/Death					29.8	77.7	47.9	0.67
Total	17.7	12.1	-5.7	1.00	48.0	119.8	71.7	1.00

Panel B:		“HJM Firms” (Upper Bound)						
	Manufacturing Emp				Non-Manufacturing Emp			
	1977	2019	Change	Share of Change	1977	2019	Change	Share of Change
M Firms	17.7	12.1	-5.7	1.00	17.4	40.2	22.8	0.32
Continuers	10.8	7.2	-3.5	0.62	13.8	32.5	18.7	0.26
Net Birth/Death	7.0	4.8	-2.1	0.38	3.7	7.7	4.0	0.06
NM Firms					30.6	79.6	48.9	0.68
Continuers					7.1	18.5	11.4	0.16
Net Birth/Death					23.5	61.1	37.5	0.52
Total	17.7	12.1	-5.7	1.00	48.0	119.8	71.7	1.00

Source: LBD and authors’ calculations. Table presents manufacturing (M) and non-manufacturing (NM) employment levels in 1977 and 2019, the change in these levels, and the share of the change accounted for by M firms, NM firms, and continuers versus net birth/deaths within these firm types. M employment is the sum of employment at all US manufacturing plants. NM employment is the sum of employment at all US establishments classified outside manufacturing. Census M firms (top panel) are those that ever have an M plant between 1977 and 2019. HJM M firms (bottom panel) are those that ever have an establishment that was ever in a firm with an M plant in the same year. Continuing Census firms are those for which the Census *lbd fid* exists in both years. HJM continuing firms are those with an establishment in 2019 that was active in 1977. Employment is in millions. There are 27.5 thousand continuing Census M firms, 46 thousand continuing HJM M firms, and 5.42 million firms in 2019.

3.2 Structural Transformation Towards Services

We now examine the NM sectors and industries that drive US structural change, show that they are primarily used as inputs across a wide range of sectors, and compare M versus NM firms' growth across these categories.

Business Services (NAICS 5) Figure 1 reports US employment (top panel) and payroll (bottom panel) by broad NAICS sector and firm type from 1977 to 2019. The first figure in each panel depicts total employment and payroll, while the second and third and figures differentiate between growth in M versus NM firms, respectively. We use Census firms and, as in Section 3.1, classify a Census firm as M if it possess at least one manufacturing plant in at least one year of the sample period.

The starkest trend in Figure 1, depicted in blue, is the dramatic rise in Business Services (NAICS 5). This sector grows from 20 to 28 percent of total employment, and 22 to 40 percent of total payroll. The next two figures in each panel of Figure 1 decompose the contributions of M and NM firms to aggregate growth. By definition, M firms' account for all of the decline in M employment, which falls 32 percent between 1977 and 2016, from 17.7 to 12.1 million. At the same time, M firms increase their NM employment over the period, but their NM growth is strongly concentrated in Business Services and Wholesale/Retail. By contrast, NM firms' growth is distributed more evenly across sectors, with Health Care (NAICS 62) and Accommodation and Food Services (NAICS 72) also growing strongly.

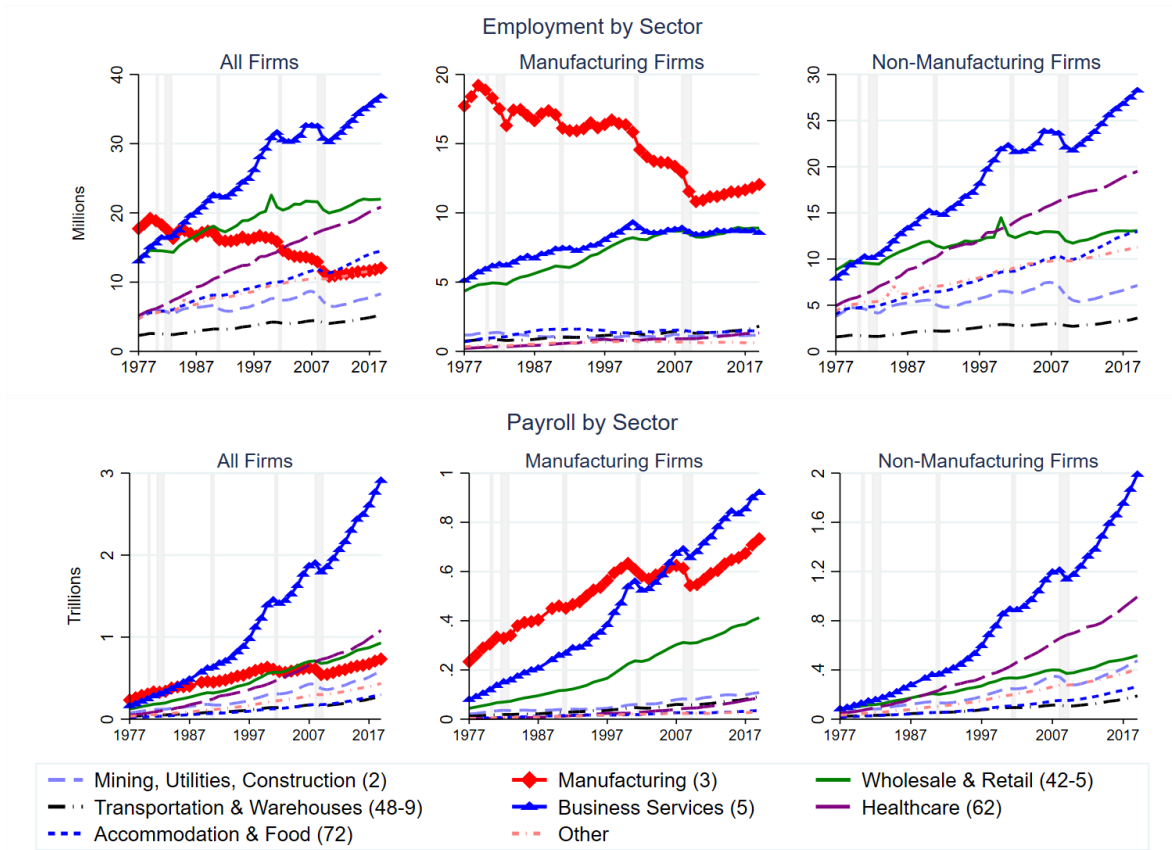
Professional, Scientific, and Technical Services (NAICS 54) To understand what drives the aggregate growth in Business Services, Figure 2 plots employment and payroll changes, in total and by firm type, across the six two-digit categories that comprise the sector: Information (NAICS 51), Finance, Insurance (NAICS 52), Real Estate (NAICS 53), Professional, Scientific, and Technical Services (NAICS 54, hereafter PSTS), Management Services (NAICS 55) and Administrative and Support Services (NAICS 56). Focusing on total employment and payroll growth, Administrative Services in purple and PSTS in green account for most of the employment growth.¹⁴ In payroll terms, PSTS dominate all other sectors, including Finance, growing from 3 to 7 percent of overall US employment and 4 to 11 percent of overall US payroll over the period.

We also examine M versus NM growth across two-digit sectors within Business Services. Most notably, the flattening in M firms' Business Services employment growth after 2000 is driven by declines in Information (51), Finance, Insurance (52), and Real Estate (53), while employment in PSTS and Management (54 and 55) both increase after the Great Recession. These sectors also demonstrate strong payroll growth, with Management growing disproportionately more for M versus NM firms.¹⁵

¹⁴See Dey et al. (2012) for evidence on the growing use of janitorial and staffing services by manufacturers. They estimate that these outsourced services, which would be contained in our NM firm measures, were equal to 9 percent of M employment in 2006.

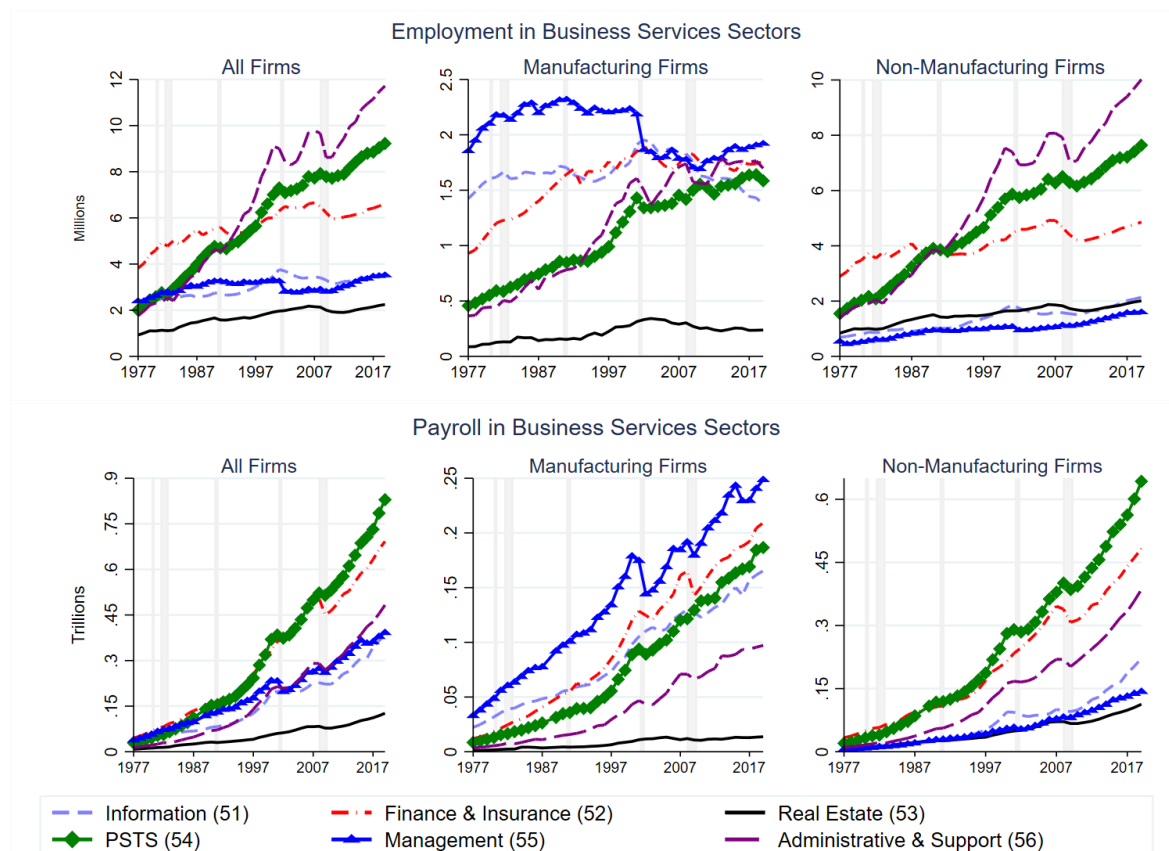
¹⁵Note that under NAICS, Management (551114) contains not only 'headquarter' establishments, but also any establishment that provides more than one support function for other establishments of the firm. For instance, an establishment that performs in-house R&D and accounting is classified under 551114.

Figure 1: US Employment and Payroll by Sector and Firm Type



Source: LBD and authors' calculations. Figure displays US employment (top panel) and payroll (bottom panel) by broad NAICS sector and firm type from 1977 to 2019. Other includes Educational (61), Arts, Entertainment and Recreation (71), Other (81) and Public Administration (92). Payroll data for 1988 are missing.

Figure 2: US Business Services Employment and Payroll by Sector



Source: LBD and authors' calculations. Figure displays US Business Services (NAICS 5) employment (top panel) and payroll (right panel) by two-digit NAICS sector and firm type from 1977 to 2019. Payroll data for 1988 are missing.

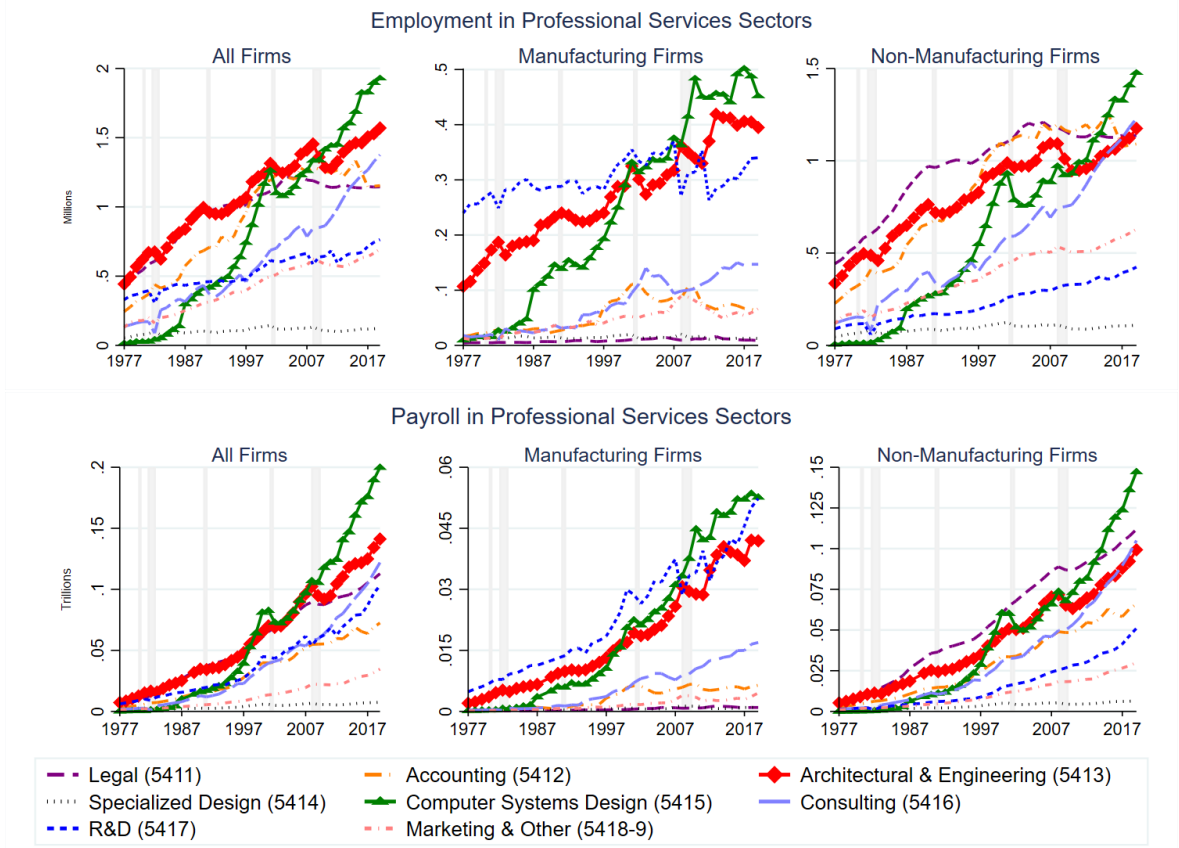
Computer Systems Design (NAICS 5415) Finally, we highlight the growth of industries within PSTS that provide knowledge services used as inputs in production. Figure 3 decomposes this sector's growth into its four-digit NAICS components: Legal Services (5411), Accounting (5412), Architectural and Engineering (5413), Specialized Design (5414), Computer Systems Design (5415), Management, Scientific, and Technical Consulting (5416), Research and Development (R&D - 5417), and Other, which combines Advertising (5418) and Other (5419) services.

As indicated in the figure, Computer Systems Design (5415), in solid green, exhibits the largest growth over the sample period, in both employment and payroll terms. Its employment increases to 1.9 million in 2019, or from 0.02 to 1.5 percent of overall US employment, while its share of overall US payroll increases from 0.03 to 2.8 percent.¹⁶

The right two figures in each panel of Figure 3 decompose PSTS growth by firm type. While NM firms exhibit significant employment growth in all sub-sectors except for Specialized Design Services (5414), M firms' growth is concentrated in just three of them: Architectural and Engineering Services

¹⁶Establishments providing these services are far more difficult to measure and analyze using SIC codes because under that industry classification system, vertically integrated establishments that primarily served other establishments of their firm were classified in the industry that they served. For example, an automobile manufacturing firm's R&D lab would be classified in automobile manufacturing. We are able to track these establishment during both the SIC and NAICS eras here using the Fort and Klimek (2018) NAICS codes discussed above.

Figure 3: PSTS Employment and Payroll by Sector and Firm Type



Source: LBD and authors' calculations. Figure displays US Professional, Scientific, and Technical Services (NAICS 54) employment (top panel) and payroll (bottom panel) by four-digit NAICS sector and firm type from 1977 to 2019. Payroll data for 1988 are missing.

(5413), Computer Systems Design (NAICS 5415), and R&D (5417). This differential growth is even starker in payroll terms, where M firms' growth is notably different from NM firms. These sectors are most relevant for manufacturing both because they constitute an important input (e.g., R&D), and because they are complementary with the physical good (e.g., computers and Computer Systems Design).

We summarize the empirical results from this subsection as our second structural change fact:

Fact 2: US aggregate employment is moving towards services and especially technology and skill-intensive Professional, Scientific, and Technical Services (PSTS).

3.3 Professional, Scientific, and Technical Services as Inputs

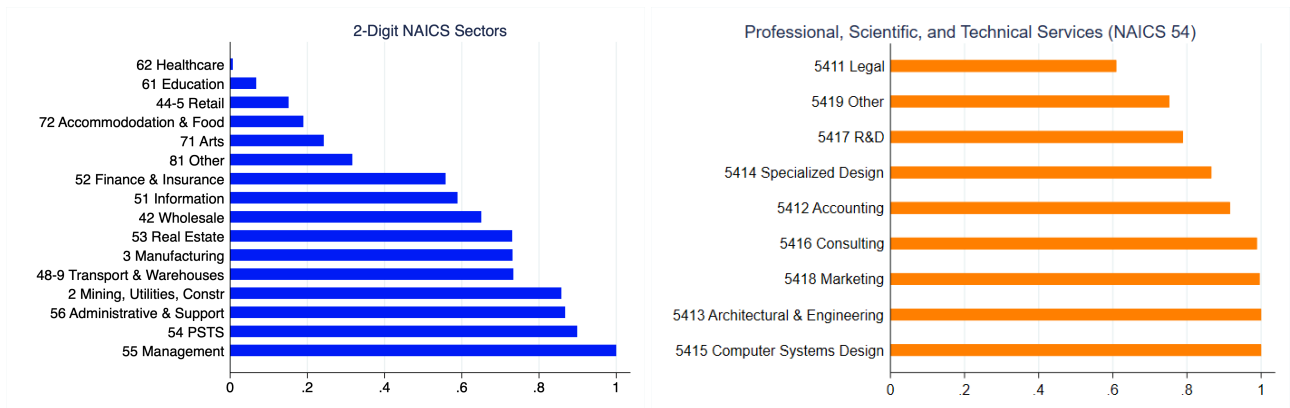
A distinctive feature of Business Services, and PSTS in particular, is that they are disproportionately used as inputs in production rather than for final household consumption. In Figure 4, we use data from the 1997 US supply-use input-output table to report the share of aggregate expenditures on each two-digit NAICS sector *not* consumed by final households.¹⁷ We use 1997 because it is halfway

¹⁷Besides final household consumption, remaining expenditures are expensed as intermediate inputs or as investment by businesses. We remove government expenditures when computing intermediate use shares since it is not clear how

through our sample period and the earliest NAICS-based year, but we find similar results for other years. We find that Wholesale (NAICS 42), Management Services (NAICS 55) and Professional, Scientific and Technical Services (NAICS 54) are predominantly consumed as inputs, while Healthcare (NAICS 62), Education (NAICS 61), and Retail (NAICS 44-45) are predominantly consumed by households. The growth of PSTS documented above is thus largely driven by intermediate input demand rather than changing shares across final consumption goods. By combining the aggregate growth depicted in Figures 2 and 3 with the input shares in Figure 4, we obtain our third fact about US structural change:

Fact 3: A substantial component of US structural change is reallocation towards service inputs rather than final goods. Input services account for 44 percent of NM employment growth and 54 percent of payroll growth.

Figure 4: Share of Expenditures Consumed as Inputs in 1997



Source: Bureau of Economic Analysis and authors' calculations. Figure displays the share of expenditures on goods and services from each sector consumed as intermediate inputs or as investment (i.e., not consumed by final households). Data are from the detailed 1997 US Supply-Use Table at producer prices.

3.4 Within-Firm Reallocation Towards Services

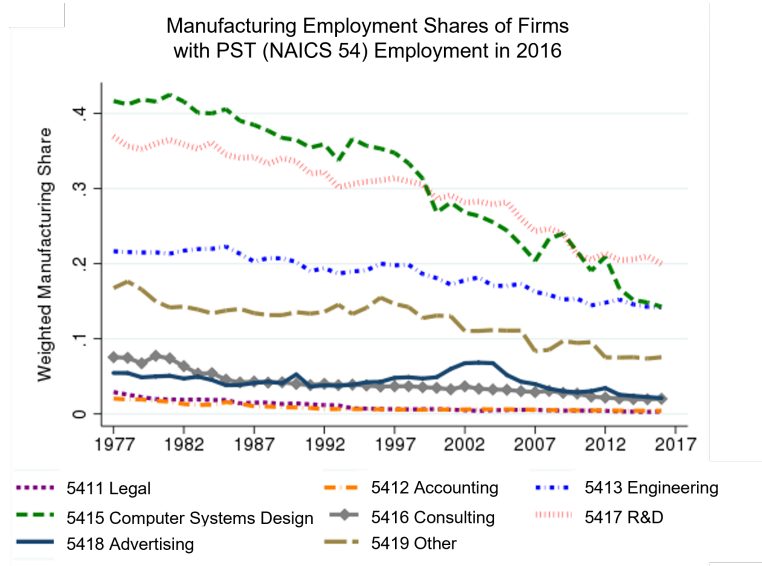
In this section we examine whether the pivoting from Manufacturing to PSTS depicted in Figure 3 takes place *within* firms by examining the evolution of manufacturing employment shares among firms that *end* the sample period with employment in one or more of the four-digit NAICS PSTS sub-sectors, e.g., R&D (NAICS 5417). Results are restricted to firms that continue from 1977 to 2016. For each year and four-digit sub-sector, we report the weighted average share of firms' manufacturing employment, by year, using 2016 employment in the corresponding four-digit sub-sector as weights.¹⁸

Figure 5 depicts two clear trends. First, manufacturing employment shares in 2016 are notably higher in the same three PSTS industries in which M firms grew their NM employment and payroll over the period: Architectural and Engineering (NAICS 5413), Computer Systems Design (NAICS 5415), the government allocates expenditures across intermediate versus final use.

¹⁸A given firm may contribute to the average in more than one line in Figure 5 if it has end-year employment in more than one Professional, Scientific, and Technical Services (PSTS) sector.

and R&D (NAICS 5417).¹⁹ On average, firms with employment in these three industries have 15 to 20 percent of their total employment in manufacturing. Second, these firms' manufacturing employment shares fall significantly over time. For example, firms with Computer Systems Design employment in 2016 saw their average manufacturing employment share more than halve over the period, falling from about 40 percent in 1977 to about 15 percent in 2016. By contrast, firms with Legal and Accounting Services employment in 2016 have almost no manufacturing employment throughout the period.

Figure 5: Firm Pivoting from Manufacturing into PSTS from 1977-2016



Source: LBD and authors' calculations. Sample is continuing firms with Professional, Scientific, and Technical Services (NAICS 54) employment in 2016. Figure displays the share of manufacturing in the employment of these firms in each year.

These patterns indicate that firms engaged in PSTS activities in 2016 pivoted from manufacturing into these services over time, either to embed higher levels of service inputs into their own physical products (*functional* structural change) or to produce these services for others (*sectoral* structural change).

Although Census disclosure rules preclude us from providing specific examples or showing the detailed transition paths along which these firms transform, we exploit publicly available data from Compustat to fill this gap. Specifically, we calculate a transition matrix for continuing Compustat firms from 1987 (the earliest year on a NAICS basis) to 2018, where the rows and columns correspond to firms' reported major NAICS sector in the beginning and end years. As shown in Online Appendix Table C8, M firms transition most into Data Processing (518) and Computer Systems Design (5415). Moreover, in line with the hypothesis that these firms redeploy their production expertise in related services, the pivoting firms were initially engaged in Computer and Electronics manufacturing (NAICS 334).²⁰

The patterns in Figure 5, along with concrete examples from Compustat, suggest that M firms

¹⁹We use 2016 employment here since these statistics were calculated in an earlier disclosure.

²⁰Specific examples of these pivoters from the publicly available Compustat data are IBM, National Cash Register Company, and Unisys.

pivot into NM sectors related to their past activities and provide our fourth fact on US structural change:

Fact 4: Manufacturing firms’ pivot towards a subset of growing NM input sectors that relate to their past manufacturing activities.

3.5 Auxiliary Establishments as Knowledge Plants

The transitions noted in the previous section suggest that knowledge from production in one sector (e.g., computers) may facilitate firms’ entry into others (e.g., computer systems design). In this section, we show that auxiliary establishments are plausible generators and repositories of such proprietary intangible capital.

3.5.1 Characteristics of Auxiliary Establishments

Auxiliaries are plants that primarily serve other establishments of their firm, such as an R&D lab or a warehouse. They are present in 92 six-digit NAICS industries in the following seven two-digit NAICS sectors: Transportation (48), Warehousing (49), Information (51), PSTS (54), Management (55), Administrative and Support (56), and Repair (81).²¹

We first assess how auxiliaries differ from non-auxiliaries in terms of employment, sales, and wages within the same detailed six-digit industry using the following regression specification:

$$y_{ift} = \beta_0 Aux_{ift} + X_{ift} + \epsilon_{ift}, \quad (1)$$

where Aux_{ift} is an indicator equal to one if establishment i at firm f in year t is an auxiliary. Baseline controls X_{ift} include a set of establishment age fixed effects (indicators for birth, 1 to 4 years, 5 to 9 years, 10 to 20 years and 20+ years), six-digit NAICS fixed effects, location (FIPS code) fixed effects, and year fixed effects. For outcomes y_{ift} , we consider the log of establishment employment, sales, and wage (payroll/employment). We limit the sample to six-digit NAICS industries that have auxiliary establishments. Since all establishments classified in NAICS 551114 are auxiliaries, we exclude NAICS 55 from this analysis.²²

Table 2 presents results from estimating equation (1) via OLS. Although columns 1 and 3 indicate that auxiliary establishments are 76 and 97 log points larger than non-auxiliaries in terms of employment and sales, these size premia are due to the fact that they belong to large firms. In fact, once we control for firm age, the log number of establishments in the firm, and the corresponding firm-level variable for each column, we find that auxiliaries are actually 7.8 and 15.8 percent smaller than non-auxiliaries in terms of employment and sales, respectively. Since the sales measure only captures sales to external customers, this result is in line with auxiliaries focusing on in-house service provision.

²¹Within these broad sectors, there is considerable variation in terms of the number of four- and six-digit NAICS sub-sectors in which they appear. Of note, auxiliaries are present in all four-digit sub-sectors of PSTS, though their importance varies considerably across them and over time.

²²It is unclear whether establishments in 551111 or 551112 are auxiliaries, and these sectors are too small to disclose.

Table 2: Auxiliary Establishment Premia

Dependent variable is the log of variable in column for establishment i , in industry j , and year t						
	$\ln(emp_{ijt})$		$\ln(sales_{ijt})$		$\ln(wage_{ijt})$	
	(1)	(2)	(3)	(4)	(5)	(6)
Aux_{ijt}	0.764*** (0.027)	-0.078*** (0.021)	0.970*** (0.025)	-0.158*** (0.021)	0.383*** (0.016)	0.064*** (0.011)
Adj. R-Squared	0.22	0.84	0.24	0.86	0.35	0.95
Observations (000s)	4,389	4,389	4,389	4,389	4,389	4,389
Firm Controls	No	Yes	No	Yes	No	Yes

Source: EC and author’s calculations. Table presents results from estimating equation (1) via OLS in each EC year from 1977 to 2012. Aux_{ijt} is an indicator for whether the establishment primarily serves other establishments in its firm. Sample limited to six-digit NAICS industries with auxiliary establishments. All regressions include six-digit NAICS, FIPs, and year fixed effects. Firm controls are firm age categories (births, 1-4, 5-9, 10-19, and 20+), the log number of establishments, and the firm-level counterpart of the dependent variable. Standard errors are clustered by firm.

Results in columns 5 and 6, however, indicate that auxiliaries pay higher wages compared to their peers in the same sub-sector, even when controlling for their firms’ characteristics. They are 38 log points higher in Column 5 and 6.4 points higher in Column 6. Together, the results in Table 2 are consistent with the premise that auxiliaries focus on providing services in-house using higher-skill workers than non-auxiliaries within the same industry.

3.6 Characteristics and Behavior of Firms with Auxiliaries

In this section, we examine the relative attributes and behavior of *firms* with auxiliaries. We find that they are larger and older than other firms, and that firm growth and pivoting are both increasing in firms’ share of auxiliary employment.

Firms with auxiliaries are rare, comprising less than one percent of firms over our sample period. On average, auxiliaries account for 17 percent of these firms’ employment, with Management (NAICS 55) auxiliaries, commonly known as “headquarters”, being the most prominent, on average representing 14 percent of employment.²³

To gauge how firms with auxiliaries differ from other firms, we estimate

$$y_{ft} = \beta_0 Aux_{ft} + \beta_1 EmpSh_{ft}(Aux) + \sum_{j \in N2} \gamma_j EmpSh_{ft}(j) + X_{ft} + \epsilon_{ft}, \quad (2)$$

where Aux_{ft} is an indicator equal to one if firm f in year t has any auxiliary establishments, and $EmpSh_{ft}(Aux)$ is the share of the firm’s employment in auxiliaries. We also include controls for $EmpSh_{ft}(j)$, which capture the firm’s employment shares outside auxiliaries across all two-digit NAICS sectors, to ensure that our auxiliary measure does not simply capture activity across potential

²³Online Appendix Table E10 presents the mean and standard deviation of auxiliary employment shares for all firms with auxiliaries.

auxiliary sectors more generally. X_{ft} includes fixed effects for the main four-digit NAICS of the firm (based on employment), and year. We consider the log of firm employment, the log of firm sales, the log number of establishments, and firm age as dependent variables. The sample consists of all firms in the Economic Censuses in 1977, 1987, 1997 and 2007.²⁴

Table 3: Auxiliary Firm Premia

Dependent variable is the log of variable in column for firm f in year t

	$\ln(emp_{ft})$		$\ln(sales_{ft})$		$\ln(estabs_{ft})$		Age_{ft}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aux_{ft}	3.481*** (0.008)	3.840*** (0.011)	3.690*** (0.009)	4.023*** (0.012)	2.186*** (0.006)	2.431*** (0.008)	5.310*** (0.029)	5.557*** (0.040)
$EmpSh_{ft}(Aux)$		-2.377*** (0.056)		-2.469*** (0.063)		-1.965*** (0.033)		-2.294*** (0.217)
Adj. R-Squared	0.20	0.20	0.30	0.30	0.35	0.36	0.24	0.24
Observations (Mill)	14.2	14.2	14.2	14.2	14.2	14.2	14.2	14.2
Non-Aux Emp Shares	No	Yes	No	Yes	No	Yes	No	Yes

Source: EC and author's calculations. Table presents results from estimating equation (2) via OLS, for EC years from 1977 to 2007. Aux_{ft} is an indicator for whether the firm has an auxiliary establishment. $EmpSh_{ft}(Aux)$ is the firm's share of employment in auxiliaries. For firms with an auxiliary, the mean and standard deviation of their auxiliary employment share are 0.17 and 0.19, respectively. All regressions include fixed effects for the firm's main four-digit NAICS (by employment) and year. Standard errors are clustered by firm. Non-Aux Emp Shares are the share of non-auxiliary employment by two-digit NAICS.

Table 3 presents the results from estimating equation (2) via OLS. We find that firms with auxiliaries are substantially larger, older, and have more establishments. All of these premia are decreasing in a firm's share of auxiliary employment. Since the average firm with an auxiliary has 17 percent of its employment in auxiliaries (Online Appendix Table E10), the average firm with an auxiliary is still about 348 log points larger in employment terms and 369 log points larger in sales.²⁵ The fact that the auxiliary firm premia are decreasing in auxiliary employment shares suggests that these establishments at least partially comprise a fixed cost, since the auxiliary employment does not seem to scale with firm size.

We next assess the extent to which auxiliary employment may provide a competitive advantage relative to other firms, and also facilitate transitions across industries. To do so, we estimate how firm growth and reallocation are associated with the presence and importance of auxiliaries using the same specification as in equation (2) but with the explanatory variable being the decadal changes in log employment and sales, or a measure of the industry overlap we refer to as "pivoting". The latter is defined as

²⁴We focus on these years so that the sample for these regressions matches the growth premia regressions in Table 4, both for consistency and to avoid disclosure challenges.

²⁵For employment, a firm with an auxiliary and the average auxiliary employment share is $3.840 + (-2.377 \cdot 0.173) = 343$ log points larger.

$$Pivot_{ft} = \left(1 - \sum_{j \in NAICS6} \min\{EmpSh_{ft}(j), EmpSh_{f,t+10}(j)\} \right). \quad (3)$$

This index is a number bounded between 0 and 1, with 1 indicating no overlap in industries (i.e. more change) from years t to $t + 10$, and 0 corresponding to identical proportionate employment (i.e., less change) across the decade. Given the significant size and age premia of firms with auxiliaries documented in Table 3, we also include the log of firm employment, firm age fixed effects, and the log of the number establishments at the firm in the vector of controls.

Results are reported in Table 4. While firms with auxiliaries do not seem to grow differentially on average, their growth rate is strongly increasing in their share of auxiliary employment. Firms with the average share of auxiliary employment (0.173) grow approximately 3.4 percentage points more relative to firms without auxiliaries ($-0.048 + (0.472 \times 0.173)$). This differential growth rate is even more pronounced for sales, where firms with the average auxiliary employment share grow about 4.2 percentage points more than firms without auxiliaries. Columns 5 and 6 of Table 4 document the relationship between auxiliary employment and pivoting. A firm with the average auxiliary employment share pivots by 1.28 ($-.013 + (0.149 \times 0.173)$) points more relative to firms without auxiliaries.²⁶

²⁶In Online Appendix Table E11, we interact the auxiliary dummy variable with the firms' auxiliary employment shares in each of the six sectors in which these establishments appear. The results indicate that the differential growth and pivoting documented here are driven by auxiliary employment in PSTS (NAICS 54), Management (NAICS 55), and Transportation and Warehousing NAICS (48-49). The industry descriptions for these sectors, and our results with respect to wages above, suggest that these are particularly high-skill or technology-intensive sectors.

Table 4: Auxiliaries and Firm Outcomes

Dependent variable is the 10-year change for firm f in year t of variable in column header

	$\Delta \ln(emp_{ft})$		$\Delta \ln(sales_{ft})$		$Pivot_{ft}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Aux_{ft}	0.00 (0.007)	-0.048*** (0.009)	-0.011 (0.009)	-0.086*** (0.010)	0.002 (0.003)	-0.013*** (0.003)
$EmpSh_{ft}(Aux)$		0.472*** (0.045)		0.738*** (0.059)		0.149*** (0.016)
Adj. R-Squared	0.09	0.09	0.06	0.06	0.11	0.11
Observations (Mill)	3.9	3.9	3.9	3.9	3.9	3.9
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes

Source: EC and author’s calculations. Table presents results from estimating equation (2) via OLS. $Pivot_{ft}$, from equation (3), is one minus the firm’s industry employment share overlap between years $t+10$ and t . Aux_{ft} is an indicator for whether the firm has an auxiliary establishment. $EmpSh_{ft}(Aux)$ is the firm’s share of employment in auxiliaries. For firms with an auxiliary, the mean and standard deviation of their auxiliary employment share are 0.17 and 0.19, respectively. Firm controls include the log of employment, age categories, the log number of establishments, the firm’s share of non-auxiliary employment across two-digit NAICS sectors, and fixed effects for both year and primary NAICS 4 industry. Standard errors clustered by firm. Sample consists of continuing firms in each decade from 1977 to 2007.

The data indicate that firms with auxiliaries grow faster and transition across industries more than other firms in the same industry, even after controlling for differences in firm size, age, number of establishments, and the distribution of firms’ employment across non-auxiliary establishments. These results are consistent with the idea that auxiliary employment within the firm confers a competitive advantage and is associated with greater transitions across industries.

We summarize the empirical findings in this section as our fifth fact about US structural change:

Fact 5: Auxiliary establishments have relatively high wages, and firms with auxiliaries are older, employ more workers, have more establishments and exhibit greater growth and pivoting as their share of auxiliary employment increases.

4 Theoretical Framework

We develop a model to rationalize the empirical patterns of US structural change presented above. In our model, firms produce by combining two types of inputs – manufacturing and knowledge – which are complementary. We view knowledge inputs as activities such as innovation and design that are crucial to product development and captured by employment in certain PSTS industries. Firms may produce PSTS in-house, which entails fixed-cost investments in intangible knowledge that are specific to the firm, but general across sectors. In doing so, firms develop excludable knowledge and hence have greater ability to pivot across sectors. If structural transformation occurs within firms,

this intangible knowledge is redeployed from one sector to another. In contrast, if reallocation occurs through firm entry and exit, it is destroyed.

The model features structural transformation within and across firms. We distinguish between “sectoral” structural change, in which the reallocation of economic activity towards services occurs across final consumption expenditure categories (e.g. from apparel to computers), in response for example to demand shocks, and “functional” structural change, in which this reallocation occurs when firms shift from using physical to knowledge inputs, in response for example to a decline in manufacturing input costs. Both sectoral and functional structural change are more likely to occur *within* firms with in-house knowledge.

4.1 Preferences

We consider a world of N countries indexed by $n, i \in N$.²⁷ Consumer’s preferences in country n are defined over consumption indexes (C_{nj}) of a set of final demand sectors indexed by $j \in J$:

$$U_n = \left[\sum_{j \in J} (\eta_{nj}^U C_{nj})^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}}, \quad (4)$$

where ν is the elasticity of substitution across sectors; η_{nj}^U captures the representative consumer’s relative preferences across sectors; to streamline notation, we suppress the implicit dependence on time, but take it as understood that we allow all variables to vary over time.

The consumption index for each sector j in destination country n (C_{nj}) is defined over consumption (c_{nijf}) of horizontally-differentiated varieties supplied by firms $f \in F_{ij}$ from each origin country i :

$$C_{nj} = \left[\sum_{i \in N} \sum_{f \in F_{ij}} c_{nijf}^{\frac{\sigma_j-1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j-1}}, \quad (5)$$

where σ_j is the elasticity of substitution across varieties within sectors. Given this nested constant elasticity of substitution (CES) demand structure, sales for firm f from origin country i in destination country n and in sector j (x_{nijf}) are:

$$x_{nijf} = p_{nijf}^{1-\sigma_j} X_{nj} P_{nj}^{\sigma_j-1}, \quad (6)$$

where X_{nj} is expenditure on sector j in destination country n and P_{nj} is the price index for sector j in destination country n (dual to equation (5)). Total firm sales (x_{if}) are the sum of sales across all sectors within each destination country and across all destination countries served by the firm:

$$x_{if} = \sum_{n \in N_{if}} \sum_{j \in J_{nif}} x_{nijf} = \sum_{n \in N_{if}} \sum_{j \in J_{nif}} p_{nijf}^{1-\sigma_j} X_{nj} P_{nj}^{\sigma_j-1}, \quad (7)$$

²⁷Unless otherwise noted, we use n to indicate countries of consumption (destinations) and i to denote countries of production (origins).

where N_{if} is the set of destination countries served by firm f from origin country i and J_{nif} denotes the set of sectors in which firm f from origin country i serves destination country n .

4.2 Endowments

Each country i is endowed with an inelastic supply of workers \bar{L}_i . Workers make an endogenous choice between the two occupations of PSTS (superscript S) and production (superscript P). We assume that each worker draws an idiosyncratic productivity (z^O) for each occupation $O \in \{S, P\}$, which corresponds to the number of effective units of labor for that occupation. After observing these idiosyncratic productivity draws, each worker chooses the occupation that offers her the highest income ($v_i^O = z^O w_i^O$), taking into account both the number of effective units of labor (z^O) and the wage per effective unit of labor (w_i^O).

In particular, we assume that idiosyncratic productivity is drawn independently for each worker and occupation from the following Fréchet distribution: $G^O(z) = e^{-A_i^O z^{-\epsilon}}$, where the scale parameter (A_i^O) determines average productivity for the occupation, and the shape parameter (ϵ) controls the dispersion of idiosyncratic productivity draws. Under these assumptions, each occupation faces an upward-sloping supply function for workers with a constant elasticity determined by the shape parameter (ϵ), such that the share of workers that choose to work in occupation O is:

$$\lambda_i^O = \frac{A_i^O (w_i^O)^\epsilon}{\sum_{K \in \{P, S\}} A_i^K (w_i^K)^\epsilon}. \quad (8)$$

Expected income in each occupation, taking into account the idiosyncratic productivity draw, is:

$$\bar{v}_i = \eta \Phi_i^{\frac{1}{\epsilon}}, \quad \Phi_i \equiv \left[\sum_{K \in \{P, S\}} A_i^K (w_i^K)^\epsilon \right], \quad (9)$$

where $\eta \equiv \Gamma\left(\frac{\epsilon-1}{\epsilon}\right)$ and $\Gamma(\cdot)$ is the Gamma function.

Expected worker productivity (average efficiency units of labor) in each occupation is given by $\bar{h}_i^O = \eta (\Phi_i / w_i^O)$. Intuitively, to employ a larger share of workers, an occupation must offer a higher wage, in order to attract workers with lower idiosyncratic productivity. Therefore, average worker productivity is decreasing in the wage offered by an occupation, other things equal.

4.3 Final-Good Production

Our specification of production and entry builds on [Melitz \(2003\)](#) to incorporate multiple sectors and factors of production, with a complementarity between PSTS services and production activities. In order to enter, a final-good firm must incur an upfront entry cost of f_e units of PSTS workers. Incurring this sunk entry cost creates a horizontally-differentiated brand, which can be used to supply one variety in each sector j , and reveals the firm's productivities in each sector (φ_{fj}). If the firm chooses to serve a country n in sector j , it must incur an additional fixed market entry cost of F_{nj}^N units of PSTS workers for that country and sector. After incurring this market entry cost, the firm can supply its variety in sector j to country n at a constant unit cost that depends on its productivity

in that sector (φ_{fj}). Additionally, the firm faces iceberg variable trade costs, such that $\tau_{nij} \geq 1$ units of a variety must be shipped from origin country i in sector j in order for one unit to arrive in destination country n , where $\tau_{nij} > 1$ for $n \neq i$ and $\tau_{nnj} = 1$. Finally, if a firm decides to enter, it faces a constant probability of death (δ), which induces ongoing entry and exit of firms in the steady-state equilibrium of the model.

Unit costs for firm f in sector j in origin country i depend on the cost of performing PSTS (e.g. research, design, management) and production activities (e.g. assembling, machining, stamping). We assume that PSTS and production activities are combined with constant elasticity of substitution μ_j : which yields the following CES unit cost function

$$\frac{1}{\theta_f} \gamma_{ifj} = \frac{1}{\theta_f} \left[(q_{if}^S)^{1-\mu_j} + \left(\frac{(w_i^P)^{\beta_j} (Q_{ij})^{1-\beta_j}}{\varphi_{fj}} \right)^{1-\mu_j} \right]^{\frac{1}{1-\mu_j}}, \quad \begin{matrix} 0 < \mu_j < 1 \\ 0 < \beta_j < 1 \end{matrix}, \quad (10)$$

where $\theta_f \geq 1$ is a Hicks-neutral productivity shifter that depends on firm investments in intangible knowledge; q_{if}^S is the cost of PSTS; w_i^P is the wages of production workers; Q_{ij} is the cost of intermediate inputs in sector j in country i ; and β_j controls the intensity with which production in sector j involves the use of production workers relative to intermediate inputs.

We model intermediate inputs using roundabout production, in which each sector uses output from all sectors as intermediate inputs with the same elasticity of substitution between sectors as for final demand. The cost of intermediate inputs for each sector (Q_{ij}) takes the same form as the price index dual to the utility function (4):

$$Q_{ij} = \left[\sum_{k \in J} \left(\frac{P_{ik}}{\eta_{ijk}^P} \right)^{1-\nu} \right]^{\frac{1}{1-\nu}}, \quad (11)$$

where η_{ijk}^P controls the relative intensity with which each sector k is used as an input for sector j , which can differ from the relative preferences for each sector k in consumption ($\eta_{nk}^U \neq \eta_{ijk}^P$).

Two aspects of this production technology are noteworthy. First, we assume that PSTS and production activities are complements ($0 < \mu_j < 1$), which is in line with the assumption in the macroeconomics literature that services and goods are complements. Second, we assume that the same PSTS are used across sectors within firms, which implies that the cost of PSTS inputs is the same across all sectors within firms ($q_{ifj}^S = q_{if}^S$ for all j), although the relative shares of PSTS and production activities in unit costs vary across sectors with the firm's productivity in each sector (φ_{fj}). We now turn to examine the determination of this cost of PSTS (q_{if}^S).

4.4 Professional, Scientific, and Technical Services

Each final-good firm faces the choice between outsourcing PSTS to a standalone supplier or incurring a fixed cost of F^S units of PSTS workers to undertake them in-house. Each firm also chooses how much to invest in intangible knowledge to reduce unit costs. We assume that a firm can obtain

a stock of $\theta_f > 1$ of intangible knowledge by employing $\psi (\theta_f^\zeta - 1)$ PSTS workers in research.²⁸ The parameter ψ governs the productivity of these investments, while the parameter ζ controls the convexity of research costs with respect to these investments. We assume that investments in intangible knowledge are only excludable if PSTS are undertaken within the boundaries of the firm. Therefore, if a final-good firm incurs the fixed cost of vertically integrating PSTS, only it retains access to its intangible knowledge. In contrast, if the final-good firm outsources PSTS, its intangible knowledge diffuses freely to all firms in the economy.

Under these assumptions, the vertical integration and intangible investment decisions become closely connected. If a firm incurs the fixed cost of vertically integrating PSTS and invests in intangible knowledge, its exclusive access to this intangible knowledge raises its share of revenue within each sector. In contrast, if a firm outsources PSTS, any investment in intangible knowledge diffuses freely to all firms, and leaves the firm's share of revenue within each sector unchanged. Assuming that each firm is sufficiently small that its investments in intangible knowledge have a negligible effect on the sector price index and total sector expenditure, it follows that no firm that outsources PSTS has any incentive to undertake costly investments in intangible knowledge ($\theta_f = 1$). In contrast, firms that vertically integrate PSTS in general undertake positive investments in intangible knowledge ($\theta_f > 1$), as determined below.

We assume that PSTS are produced using PSTS service workers according to the following unit cost function:

$$q_{if}^S = w_i^S, \quad (12)$$

where q_{if}^S denotes the unit cost of PSTS for firm f in origin country i , and w_i^S is the wage of PSTS workers.

We assume that this production technology for PSTS is freely available to all firms. If PSTS are outsourced, they are produced by a standalone supplier using this technology under conditions of perfect competition. Therefore, zero profits implies that the price of PSTS equals unit cost, which is equal to the wage of PSTS workers (w_i^S). If PSTS are vertically integrated in-house, they are produced by the final-good firm using this same technology, which implies that unit cost is again equal to the wage of PSTS workers (w_i^S). Therefore, in either case, the final-good firm's unit cost function (10) can be re-written as follows:

$$\frac{1}{\theta_f} \gamma_{ifj} = \frac{1}{\theta_f} \left[(w_i^S)^{1-\mu_j} + \left(\frac{(w_i^P)^{\beta_j} (Q_{ij})^{1-\beta_j}}{\varphi_{fj}} \right)^{1-\mu_j} \right]^{\frac{1}{1-\mu_j}}. \quad (13)$$

Under our assumptions, there are only two differences between vertical integration and outsourcing. First, vertical integration requires incurring an additional fixed cost (F^S). Second, only final-good firms that vertically integrate PSTS have an incentive to invest in intangible knowledge ($\theta_f > 1$). In contrast, final-good firms that outsource PSTS make zero investments in intangible knowledge ($\theta_f = 1$).

²⁸This formulation of research costs ensures that a firm that makes no investment in intangible knowledge ($\theta_f = 1$) incurs zero costs, since $\psi (1^\zeta - 1) = 0$.

4.5 Firm Problem

We assume that final-good producers compete under conditions of monopolistic competition within each sector. Each firm chooses the number of countries to serve, the number of sectors in which to serve each country, whether to outsource PSTS or undertake them in-house, its investment in intangible knowledge, the price to charge for each variety, and inputs of PSTS, production workers, and intermediates to maximize its profits. Using the unit cost function (13), the firm problem can be written as follows:

$$\max_{\{\{p_{nifj}\}, N_{if}, J_{nif}, \mathbb{I}_{if}^S, \theta_f\}} \left\{ \sum_{n \in N_{if}} \sum_{j \in J_{nif}} p_{nifj} y_{nifj} (p_{nifj}) - \frac{1}{\theta_f} \gamma_{ifj} y_{nifj} (p_{nifj}) - \sum_{n \in N_{if}} \sum_{j \in J_{nif}} w_i^S F_{nj}^N - \mathbb{I}_{if}^S w_i^S F^S - w_i^S \psi (\theta_f^\zeta - 1) \right\}, \quad (14)$$

where $y_{nifj}(p_{nifj})$ is output of firm f from origin country i in each sector j and destination country n , which is a function of the price chosen for its variety (p_{nifj}), and \mathbb{I}_{if}^S is an indicator variable that equals one if firm f in origin country i chooses to undertake PSTS in-house and zero otherwise.

We characterize the solution to the firm's problem as follows. First, we solve for the equilibrium price for the firm's variety in each country and sector conditional on its choice of the sets of countries and sectors to serve, its decision whether to organize PSTS in-house, and its investment in intangible knowledge. Second, we determine a firm's usage of factor inputs conditional on its market entry, vertical integration and intangible investment decisions. Third, we characterize the firm's choice of the set of countries and sectors to serve conditional on its vertical integration, and intangible investment decisions. Fourth, we analyze the firm's vertical integration and intangible investment decisions.

4.6 Equilibrium Prices

Beginning with the equilibrium pricing rule, profit maximization under CES demand and monopolistic competition implies that the equilibrium price for each firm variety is a markup over marginal cost:

$$p_{nifj} = \frac{\sigma_j}{\sigma_j - 1} \tau_{nij} \frac{1}{\theta_f} \gamma_{ifj}, \quad (15)$$

where this markup depends on the constant elasticity of substitution (σ_j); and marginal costs include both the unit production cost (γ_{ifj}/θ_f) and the iceberg variable trade cost (τ_{nij}).²⁹

Using this equilibrium pricing rule in the revenue function (6), firm revenue in a given sector and market is a power function of firm unit costs:

$$x_{nifj} = \left(\frac{\sigma_j}{\sigma_j - 1} \tau_{nij} \frac{1}{\theta_f} \gamma_{ifj} \right)^{1-\sigma_j} X_{nj} P_{nj}^{\sigma_j-1}. \quad (16)$$

²⁹Although we have interpreted intangible knowledge investments as reducing unit costs, an isomorphic interpretation for equilibrium firm revenue is that they increase product quality.

4.7 Final-Good Costs

Turning now to the firm's optimal choice of factor inputs, we establish a number of predictions for which we provide empirical evidence in Section 5. Using cost minimization, the share of PSTS in the unit costs of final-good firm f in origin country i in sector j (ξ_{iffj}^S) depends on the prices of PSTS and production workers in that country (w_i^S, w_i^P), the cost of intermediate inputs in that sector and country (Q_{ij}), and firm productivity (φ_{fj}):

$$\xi_{iffj}^S = \frac{(w_i^S)^{1-\mu_j}}{(w_i^S)^{1-\mu_j} + \left(\frac{(w_i^P)^{\beta_j} (Q_{ij})^{1-\beta_j}}{\varphi_{fj}} \right)^{1-\mu_j}}. \quad (17)$$

We now establish some properties of this final-good cost share with respect to shocks to technology and international trade. Totally differentiating this cost share (17), the log change in the share of PSTS in firm costs can be linearly decomposed into log changes in factor prices and log changes in productivity:

$$d \ln \xi_{iffj}^S = (1 - \mu_j) (1 - \xi_{iffj}^S) \left[d \ln w_i^S - \beta_j d \ln w_i^P - (1 - \beta_j) d \ln Q_{ij} + d \ln \varphi_{fj} \right]. \quad (18)$$

Using our assumption that PSTS and production activities are complements ($0 < \mu_j < 1$), and holding constant factor prices ($d \ln w_i^S = 0$ and $d \ln w_i^P = 0$), equation (18) implies that both productivity growth ($d \ln \varphi_{fj} > 0$) and lower prices of intermediate inputs as a result of lower trade costs ($d \ln Q_{ij} < 0$) induce structural transformation in the form of a higher share of PSTS in unit costs ($d \ln \xi_{iffj}^S > 0$).³⁰ The mechanism underlying this structural transformation is the same as that in the macroeconomics literature on unbalanced productivity growth following Baumol (1967). Whereas this macroeconomics literature focuses on structural transformation between final-good sectors, our framework features both this sectoral structural transformation and functional structural transformation between intermediate activities (PSTS versus production activities), consistent with our stylized facts above.

We now connect this result for the share of PSTS in overall firm unit costs to the share of PSTS in labor costs and employment, which are directly observable in the data. We start with the share of PSTS in labor costs:

$$\vartheta_{iffj}^S = \frac{w_i^S L_{iffj}^S}{w_i^S L_{iffj}^S + w_i^P L_{iffj}^P}. \quad (19)$$

Totally differentiating this share of PSTS in labor costs, we have:

$$d \ln \vartheta_{iffj}^S = (1 - \vartheta_{iffj}^S) [d \ln w_i^S - d \ln w_i^P + d \ln L_{iffj}^S - d \ln L_{iffj}^P]. \quad (20)$$

Therefore, holding constant factor prices ($d \ln w_i^S = 0$ and $d \ln w_i^P = 0$), and noting $0 < \vartheta_{iffj}^S < 1$, a rise in the share of PSTS in labor costs ($d \ln \vartheta_{iffj}^S > 0$) goes together with a rise in PSTS employment

³⁰ Although we hold factor prices constant here, wages of PSTS (non-production) workers rise faster than those of production workers during our sample period, which increases the share of PSTS in unit costs under our assumption that PSTS and production activities are complements.

relative to production employment ($d \log L_{ifj}^S > d \log L_{ifj}^P$), and hence an increase in the share of PSTS in total employment.

To link these changes in labor cost and employment shares to the changes in unit cost shares examined above, we use the implication of the Cobb-Douglas production technology that expenditures on intermediate inputs are a constant multiple of the wage bill for production workers:

$$Q_{ij}M_{ifj} = \frac{1 - \beta_j}{\beta_j} w_i^P L_{ifj}^P, \quad (21)$$

where M_{ifj} is the quantity of intermediate inputs used by firm f from origin country i in sector j .

Using this linear relationship between intermediate input costs and production worker costs, we can rewrite the share of PSTS in overall unit costs in equation (17) as:

$$\xi_{ifj}^S = \frac{w_i^S L_{ifj}^S}{w_i^S L_{ifj}^S + w_i^P L_{ifj}^P + Q_{ij}M_{ifj}} = \frac{w_i^S L_{ifj}^S}{w_i^S L_{ifj}^S + \left[1 + \frac{1 - \beta_j}{\beta_j}\right] w_i^P L_{ifj}^P}. \quad (22)$$

Totally differentiating this relationship and using our earlier expressions for the total derivatives of unit costs (18) and labor costs (20), we find that the change in the share of PSTS in labor costs ($d \ln \vartheta_{ifj}^S$) is linearly related to the change in the share of PSTS in unit costs ($d \ln \xi_{ifj}^S$) as follows:

$$d \ln \vartheta_{ifj}^S = \left(\frac{1 - \vartheta_{ifj}^S}{1 - \xi_{ifj}^S} \right) d \ln \xi_{ifj}^S, \quad (23)$$

where the shares of unit costs (ξ_{ifj}^S) and labor costs (ϑ_{ifj}^S) both lie strictly in between zero and one for $0 < \mu_j < 1$, thereby ensuring that the term in parentheses in equation (23) is strictly positive.

Combining the total derivative of the share of PSTS in unit costs (18) with this linear relationship between unit cost and labor cost shares in equation (23), we can now characterize the effects of technology and trade shocks on the shares of PSTS in labor costs and employment. Under our assumption that PSTS and production activities are complements ($0 < \mu_j < 1$) and holding constant factor prices ($d \ln w_i^S = 0$ and $d \ln w_i^P = 0$), equations (18) and (23) imply that productivity growth ($d \ln \varphi_{fj} > 0$) and lower prices of intermediate inputs due to lower trade costs ($d \ln Q_{ij} < 0$) raise the share of PSTS in unit costs ($d \ln \xi_{ifj}^S > 0$) and hence the share of PSTS in labor costs ($d \ln \vartheta_{ifj}^S > 0$). From the relationship between the share of PSTS in labor costs and employment levels in equation (20), and holding constant factor prices ($d \ln w_i^S = 0$ and $d \ln w_i^P = 0$), this higher share of PSTS in labor costs also translates into a higher share of PSTS in employment.

Therefore, using only properties of the firm cost minimization problem, we obtain sharp empirical predictions for the effect of technology and input price shocks on structural transformation towards PSTS. In contrast to the macroeconomic literature on sectoral structural transformation, these predictions are for functional structural transformation between intermediate activities (PSTS versus production activities). For firms that produce PSTS in-house, this reallocation occur within firms. For firms that outsource PSTS, this reallocation occur between firms, namely between each final-good producer and its standalone suppliers.

4.8 Market Entry

We have thus completed our characterization of the final-good firm's equilibrium price and factor input choices. We now turn to its choice of countries and sectors to serve, conditional on its in-house knowledge production decisions. Using the firm's equilibrium pricing rule (15) in the definition of firm variable profits for a given sector and market, we obtain the standard result under CES demand and monopolistic competition that variable profits are a constant multiple of revenue in that sector and market:

$$\pi_{nifj} = \frac{1}{\sigma_j} x_{nifj}. \quad (24)$$

Given this solution for equilibrium variable profits, firm f from origin country i chooses to serve a given sector j and destination country n if these variable profits exceed their fixed market-entry costs (F_{nj}^N). The set of sectors J_{nif} served by the firm within a given destination country is thus simply the set of sectors for which these variable profits exceed the fixed entry costs:

$$J_{nif} = \left\{ j : \frac{1}{\sigma_j} x_{nifj} - w_i^S F_{nj}^N \geq 0 \right\}. \quad (25)$$

Similarly, the set of countries N_{if} served by the firm is simply the set of countries for which there is at least one sector for which these variable profits exceed the fixed market-entry costs:

$$N_{if} = \left\{ n : \max_j \left\{ \frac{1}{\sigma_j} x_{nifj} - w_i^S F_{nj}^N \right\} \geq 0 \right\}. \quad (26)$$

Conditional on the firm's vertical-integration decisions, its decision to enter a given sector and country is independent of its decision to enter any other sector and country, because marginal costs are constant. Substituting the equilibrium revenue function (16) into equation (25), the zero-profit condition to enter a given country and sector can be re-written as:

$$J_{nif} = \left\{ j : \frac{1}{\sigma_j} \left(\frac{\sigma_j}{\sigma_j - 1} \tau_{nij} \frac{1}{\theta_f} \gamma_{ifj} \right)^{1-\sigma_j} X_{nj} P_{nj}^{\sigma_j-1} - w_i^S F_{nj}^N \geq 0 \right\}. \quad (27)$$

This zero-profit condition shows that the model features conventional structural transformation between sectors in response to technology and trade shocks that affect final demand within each sector (through sectoral expenditure (X_{nj}) or the sectoral price index (P_{nj})). While the macroeconomics literature is typically silent as to whether this reallocation occurs through firm entry and exit versus shifts across activities within firms, our model features both of these margins. As shocks to technology and trade costs increase variable profits in some sectors and reduce them in others, the set of sectors chosen by entering firms will change (between-firm reallocation) and incumbent firms will choose to drop some sectors and add other sectors (within-firm reallocation).

From this zero-profit condition (27), a lower unit cost ($\frac{1}{\theta_f} \gamma_{ifj}$) increases a firm's variable profits and expands the set of countries and sectors that it finds it profitable to enter. As discussed in the previous section, firms that produce knowledge in-house have lower unit costs ($\theta_f > 1$) than firms that outsource these services. Therefore, by reducing unit costs and increasing variable profits, these

investments in intangibles increase the set of countries and sectors in which a firm operates.

4.9 Investments in Intangible Knowledge Capital

Finally, we turn to the final-good firm's vertical integration and intangible investment decisions. We already established that firms that outsource PSTS make no investments in intangibles. Therefore, we first solve for a firm's optimal investment in intangibles conditional on vertically integrating PSTS. Taking into account this optimal investment decision, we next determine whether the firm outsources or vertically integrates PSTS by comparing the firm's total profits under these two alternatives.

Using the equilibrium revenue function (16), the total profits of a firm across all countries and sectors can be written as follows:

$$\Pi_{if}(\varphi) = \sum_{n \in N_{if}} \sum_{j \in J_{nif}} \frac{1}{\sigma_j} \left(\frac{\sigma_j}{\sigma_j - 1} \tau_{nij} \frac{1}{\theta_f} \gamma_{ifj} \right)^{1-\sigma_j} X_{nj} P_{nj}^{\sigma_j-1} - \sum_{n \in N_{if}} \sum_{j \in J_{nif}} w_i^S F_{nj}^N - \mathbb{I}_{if}^S w_i^S F^S - w_i^S \psi \left(\theta_f^\zeta - 1 \right), \quad (28)$$

which depends on the firm's vector of productivity draws across sectors $\{\varphi_{fj}\}$ through its vector of unit costs across sectors $\{\gamma_{ifj}\}$.

Conditional on incurring the fixed cost of vertically integrating PSTS, the first-order condition for the firm's investment in intangibles yields the following optimal investment:

$$\sum_{n \in N_{if}} \sum_{j \in J_{nif}} \frac{\sigma_j - 1}{\sigma_j} \left(\frac{\sigma_j}{\sigma_j - 1} \tau_{nij} \gamma_{ifj} \right)^{1-\sigma_j} X_{nj} P_{nj}^{\sigma_j-1} (\theta_{if}^*)^{(\sigma_j-1)-\zeta} = \zeta \psi w_i^S, \quad (29)$$

which depends on the firm's vector of productivity draws across sectors $\{\varphi_{fj}\}$ through its vector of unit costs across sectors $\{\gamma_{ifj}\}$. As a firm that makes no investment in intangibles has a unit productivity ($\theta_f = 1$), only firms for which there is an interior solution in which $\theta_f^* > 1$ make positive investments in intangibles. For sufficiently convex research costs ($\zeta > (\sigma_j - 1)$), this optimal positive investment in intangibles is finite ($1 < \theta_f^* < \infty$).

From this solution for equilibrium investment in intangibles and the unit cost function (13), firms with higher sector-level productivity draws (the set of $\{\varphi_{fj}\}$) have lower unit costs, which increases total firm profits in equation (28) on both the intensive margin (higher profits within each sector and country) and the extensive margin (entry into more sectors and countries). These higher total profits in turn raise the return to intangible investments and thus their equilibrium level. This role for the extensive margin of the range of sectors and countries served in influencing equilibrium intangible investment implies that there is an interdependence between a firm's decisions to serve each sector and country and its level of intangible investment. On the one hand, serving an additional sector and country raises the return to intangible investment. On the other hand, an increased investment in intangibles raises the variable profits from entering each sector and country.

Given the solution for the firm's optimal investment in intangibles (θ_{if}^*) implicitly defined by equation (29), we have determined a firm's total profits from vertically integrating PSTS. A firm chooses to produce PSTS in-house if the total profits from doing so exceed those from outsourcing

them. As vertical integration requires an additional fixed cost F^S , only the most productive firms find it profitable. Through this selection mechanism, the model rationalizes our empirical findings above that firms that vertically integrate PSTS (as measured by auxiliary establishments in the data) are substantially larger. Furthermore, the sector-neutral productivity advantage from in-house knowledge capital ($\theta_f > 1$) means these firms have lower unit costs across all sectors, and hence are more likely to be able to pivot to other sectors in response to shocks.

4.10 General Equilibrium

The empirical predictions discussed above and examined below are derived from the firm's optimization problem for given sectoral expenditures (X_{nj}), sectoral price indices (P_{nj}), PSTS wages (w_i^S) and production worker wages (w_i^P). In this section, we briefly discuss closing the model to determine these variables in general equilibrium.

The general equilibrium of the model is referenced by the following variables: (i) the set of sectors served for each country ($J_{ni}(\varphi)$) and the set of countries served ($N_i(\varphi)$) as a function of a firm's productivity vector across sectors (φ); (ii) an indicator variable for whether a firm vertically integrates PSTS ($\mathbb{I}_i^S(\varphi)$) as a function of its productivity vector; (iii) investment in intangibles as a function of a firm's productivity vector ($\theta(\varphi)$); (iv) the wage for PSTS workers (w_i^S); (v) the wage for production workers (w_i^P); (vi) the employment shares for PSTS and production (λ_i^S, λ_i^P); (vii) the price index for each sector and country (P_{nj}); and (viii) aggregate expenditure for each country (X_n). All other endogenous variables can be determined as functions of these elements of the equilibrium vector.

General equilibrium is determined by the following equilibrium conditions: (i) a firm with each productivity vector makes non-negative profits from all sectors and countries that it enters; (ii) a firm with each productivity vector incurs the fixed cost to vertically integrate PSTS if this yields higher total profits than outsourcing PSTS and vice versa; (iii) investment in intangibles equals zero for productivities for which firm's outsource PSTS and is chosen to maximize profits for productivities for which firms vertically integrate; (iv) the labor market for PSTS workers clears; (v) the labor market for production workers clears; (vi) workers' choice of occupation maximizes their income; (vii) revenue in each sector and country equals expenditure on goods produced in that sector and country; (viii) free entry ensures that the expected value of entry is equal to the sunk entry cost.

4.11 Sectoral and Functional Structural Change Within and Between Firms

The model thus provides a framework for understanding the five facts about US structural change presented in Section 3. First, manufacturing firms can contribute to aggregate non-manufacturing employment growth as they shift among final-good sectors (sectoral structural transformation) and as they reallocate towards services inputs in response to reductions in production costs (functional structural transformation). Second, to the extent that reductions in production input costs drive functional structural change, aggregate employment moves towards skill-intensive Professional, Scientific, and Technical Services used as knowledge inputs within the firm. Third, as employment in this sector grows, it contributes to greater structural change towards service inputs versus outputs. Fourth, non-manufacturing firms can supply a different mix of services than manufacturing firms,

which arises because they have a different mix of final-good sectors in the model. Finally, firms with proprietary in-house knowledge capabilities, i.e., auxiliaries, have greater Hicks-neutral productivity θ_f , which makes them bigger, more likely to survive, more capable of pivoting across sectors.

In the next section, we exploit the China shock to provide identified evidence in support of our assumption that PSTS and manufactured inputs are complements. In addition, we use firms’ initial auxiliary status to assess the importance of in-house provision of PSTS in mediating firms’ responses to shocks.

5 Firm Structural Transformation and Intangible Knowledge

In this section, we provide empirical evidence in support of four predictions generated by the model. First, firms respond differently to shocks that affect the relative profitability of their final-good sectors (“output shocks”) versus shocks that alter the relative costs of their physical inputs (“input shocks”). Second, shocks that lower the cost of firms’ physical inputs induce within-firm structural transformation towards services due to the complementarity between knowledge and physical inputs. Third, firms with in-house knowledge workers are more responsive to output and input shocks, because optimal use of these workers is also affected by the shocks. Finally, firms with in-house knowledge will be more responsive to a positive input shock, as this intangible capital lowers their production costs in all sectors thereby facilitating their movement into other industries that use those inputs. Moreover, this effect will be particularly strong if in-house knowledge does not fully depreciate in response to shocks.

To assess these predictions, we follow a large empirical literature and use the “China shock” as a source of quasi-experimental variation. Our approach differs from past work on the China shock in three ways. First, we construct separate output and input shocks. Second, we compute exposure to these shocks at the firm level using detailed information on firms’ output and input product-mixes, which vary relative to peers within the same industry. Third, we investigate the role of firm knowledge capital in mediating firm-level responses by interacting the shocks with firms’ auxiliary status. We use auxiliary status at the beginning of the sample period to mitigate potential endogeneity associated with firms’ decisions to operate auxiliaries.

5.1 Measuring Shocks to Input and Output Prices

We exploit the substantial growth of Chinese exports during the middle of our 1977 to 2019 sample period to measure variation in competition in firms’ outputs and inputs. In terms of our model, we interpret increased output competition as a reduction in P_{nj} , which lowers residual demand for the firm’s products, and increased input competition as a reduction in Q_{ij} , which lowers the firm’s unit costs. To identify plausibly exogenous variation in these prices, we focus on Chinese imports in high-income European countries. Using data from Comtrade, we compute the 1997 to 2007 change in China’s EU import market shares across industries as our measure of increased competition.³¹ We

³¹As in [Antràs et al. \(2017\)](#), we focus on market-shares rather than levels, e.g., [Autor et al. \(2013\)](#), which differences out common shocks from the numerator and denominator of these market shares.

find that China’s market share gains in Europe across industries range from -0.07 to 0.62, with a mean of 0.09 and median of 0.09.

Our empirical strategy exploits the fact that increased Chinese competition may affect firms differently when it occurs in their input markets. To demonstrate the potential for the same underlying shock to affect outcomes through the output versus input channels, we calculate the implied ‘input’ shock for a representative firm in each industry using input expenditure weights across industries from the 1997 input-output (IO) tables from the BEA. The input shock is smaller on average, with a range of -0.003 to 0.164, a mean of 0.047, and a median of 0.05. Appendix Figure A1 plots these six-digit NAICS input and output shocks, which have a correlation coefficient of 0.47.

A novel contribution of our estimation is to utilize detailed data from the Product and Material Trailers of the Census of Manufacturers on the products firms produce and the material inputs they purchase. As a result, exposure to shocks varies across firms producing in the same industry, and the input exposure is not defined simply by a firm’s mix of output industries. We define firm f ’s output exposure as the sales-weighted average change in China’s EU market share across the six-digit NAICS manufacturing industries it sells in 1997, using the concordance from [Pierce and Schott \(2012\)](#) to aggregate the Harmonized System trade data to the NAICS level,

$$\Delta Output_f = \sum_{j \in \text{Manuf}} \frac{Sales_{fj}^{1997}}{Sales_f^{1997}} \Delta ChinaMarketShare_j^{EU}, \quad (30)$$

where $Sales_{fj}^{1997}$ is the firm’s sales in the six-digit manufacturing NAICS industry j in 1997 and $\Delta ChinaMarketShare_j^{EU}$ is the 1997 to 2007 change in China’s market share in the EU (relative to other non-US producers) in that six-digit NAICS industry. The denominator used to construct these weights, $Sales_f^{1997}$, is the firm’s total sales in both manufacturing and non-manufacturing, which allows for predominantly non-manufacturing firms to be naturally less affected by import competition.

Similarly, we define firm f ’s input exposure as the expenditure-weighted average change in China’s EU market share across the six-digit goods it purchases as inputs in 1997:

$$\Delta Input_f = \sum_{j \in \text{Manuf}} \frac{Expenditures_{fj}^{1997}}{Expenditures_f^{1997}} \Delta ChinaMarketShare_j^{EU}, \quad (31)$$

where $Expenditures_{fj}^{1997}$ is the firm’s purchases of inputs in the six-digit NAICS manufacturing industry j , and the denominator $Expenditures_f^{1997}$ is a measure of the firm’s total variable costs, which allows firms that are either predominantly non-manufacturing or manufacturing but more labor intensive to be naturally less affected by import competition shocks in manufacturing input markets. For firms with missing material expenditures, we calculate input usage across their output products using the implied ‘input’ exposure constructed from the IO tables, as described above. In the firm-level data, the average output and input exposures are 0.14 and 0.06, respectively, with a correlation coefficient of 0.17.³²

³²This correlation drops to 0.05 after residualizing on control variables used in the main regression specification. Prior research on the impact of China on US outcomes uses the aggregate IO table approach ([Pierce and Schott, 2016](#); [Acemoglu et al., 2016](#)), or assumes that a firm’s imports of all goods outside its main three-digit industry represent

We follow a reduced-form approach in which we regress the outcome variables directly on these instruments. In Appendix Table A4 we show that the instruments are strongly correlated with the change in Chinese import penetration in the United States, with correlations of 0.52 and 0.66 for outputs and inputs, respectively. We provide first-stage estimates in Online Appendix Table G15.

5.2 Empirical Specification

To estimate the effect of increased output and input market competition on the level and composition of firms' employment and sales, we regress changes in firm-level outcomes on the instruments:

$$\begin{aligned}\Delta Outcome_f = & \beta_O \Delta Output_f + \beta_{OA} \Delta Output_f \times Aux_f^{1997} + \beta_{OE} \Delta Output_f \times \ln(Emp_f^{1997}) \\ & + \beta_I \Delta Input_f + \beta_{IA} \Delta Input_f \times Aux_f^{1997} + \beta_{IE} \Delta Input_f \times \ln(Emp_f^{1997}) \\ & + \beta_A Aux_f^{1997} + \beta_E \ln(Emp_f^{1997}) + \beta_X X_f^{1997} + \epsilon_f,\end{aligned}\quad (32)$$

where $\Delta Outcome_f$ denotes the firm's 1997 to 2007 growth rate in employment or sales.

We focus on a balanced panel of firms with manufacturing establishments in 1997. These firms account for 61 percent of US manufacturing employment in 1997, and 26 of the aggregate decline. While the sample consists of continuing firms, firms may shut down all their manufacturing plants over the period, or expand into non-manufacturing. In fact, the sample accounts for 10 percent of US NM employment in 1997, and 20 percent of aggregate NM growth over the period. To capture these changes, we compute growth rates following Davis et al. (1996), where entry or exit into M or NM is measured as 2 and -2, respectively:

$$\Delta Outcome_f \equiv (Outcome_f^{2007} - Outcome_f^{1997}) / ((Outcome_f^{2007} + Outcome_f^{1997}) / 2). \quad (33)$$

We interact firms' output and input exposures ($\Delta Output_f$ and $\Delta Input_f$) with their auxiliary status in 1997 (Aux_f^{1997}) to assess our hypothesis that in-house knowledge plants affect firms' ability to grow in complementary service sectors in response to manufactured input-cost reductions. Since firms with auxiliaries are considerably larger, we also interact the log of firm employment in 1997, $\ln(Emp_f^{1997})$, with both shocks to ensure that our auxiliary-by-shock interactions do not simply reflect a differential impact of the shock on large versus small firms.

In all our specifications we also include a vector of controls for firm attributes in 1997, X_f^{1997} , that consists of age quintiles, the log number of establishments, and fixed effects for the firm's main four-digit NAICS industry (by employment). The industry fixed effects remove substantial across-industry variation in outcomes documented in the literature (Autor et al., 2013; Pierce and Schott, 2016), but also address potential concerns about industry-level demand and technology trends that might drive correlated changes in Chinese market share change in Europe and US manufacturers' shift into services. We also control for the sums of shares used to construct the output and input shocks: (i) the share of manufacturing in the firm's total sales, and (ii) the share of manufacturing inputs in

inputs (Mion and Zhu, 2013). Additional details on our variable construction are in the Online Appendix F.

the firm’s total variable expenditures. These “incomplete sum of shares” address the possibility that output and input shocks might capture manufacturing intensity rather than exposure to increased competition (Borusyak et al., 2021).³³ We two-way cluster the standard errors by the firm’s main output and input industries.³⁴

The coefficients $\{\beta_O, \beta_I\}$ in equation (32) identify the impact of Chinese input and output exposure among comparable firms, i.e., those in the same four-digit NAICS industry and of similar age, size, and number of establishments. The interaction coefficients $\{\beta_{OA}, \beta_{OE}, \beta_{IA}, \beta_{IE}\}$ capture the extent to which the impact of this exposure differs by firms’ auxiliary status and size.

5.3 Results

We present our main estimation results for firm sales and employment growth from 1997 to 2007 in Table 5. Panel A reports employment results, while Panel B contains the sales results. Since our focus is on how different firms respond to shocks, we report unweighted regressions, but include interactions between the shocks and firm size in the second column for each outcome variable. Columns 1 and 2 report estimates for firms’ total activity (both manufacturing and non-manufacturing); Columns 3 and 4 present estimates for manufacturing activity; and Columns 5 and 6 give estimates for non-manufacturing activity.

Consistent with most prior work, Panel A displays large, negative, and statistically significant effects of the output shock on firms’ total, M, and NM employment.³⁵ Although the first columns for both total and M employment suggest that this impact is statistically significant only for firms with auxiliaries, the second columns for each of these variables reveal that the effect of the output shock is strongly increasing in firm size, as rationalized by Holmes and Stevens (2014). The estimates in Column 2 imply that a 10 percentage point increase in China’s EU market share in the outputs of a firm with 500 employees decreases its total employment by 3.9 percent if it does not have auxiliaries, and 8.2 percent if it does. These large declines are predominantly driven by manufacturing employment. The estimates in Columns 5 and 6 indicate that the same output shock would reduce a firm’s non-manufacturing employment by 5.6 percent, independently of its size, but only if it had auxiliaries prior to the shock. The fact that the output shock only affects non-manufacturing employment for firms with in-house knowledge plants is precisely in line with the premise that those plants provide inputs into firms’ manufacturing sales.

³³Though not shown in equation (32), we interact these sum-of-share controls with Aux_f^{1997} to ensure that any differential effects we estimate for firms with auxiliaries are not similarly biased. When we include the interaction between the shocks and firm size, we also interact firm size with these sum-of-share controls.

³⁴The latest research on shift-share analyses emphasizes the importance of adjusting the standard errors to address the mismatch between the levels at which the shocks are observed versus applied, as in Adão et al. (2019) or Borusyak et al. (2021). Our application differs from the settings studied in those papers, because we construct and utilize multiple shift-share shocks with differing Bartik weights. By two-way clustering at the firm’s main output and input industry levels, we match the level of aggregation of the shocks themselves, following Bertrand et al. (2004). We thank Kirill Borusyak for this suggestion. In Online Appendix Section G.5, we also present results from Monte Carlo simulations that suggest the two-way clustering we implement suitably addresses potential correlations across firms through output or input mixes.

³⁵These results seem at odds with Bloom et al. (2019) who argue that the China shock led plants to switch from M to NM sectors. An important distinction here is that our analysis is at the firm level, whereas that paper analyzes local labor markets.

Table 5: Effects of Output and Input Shocks on Firm Sales and Employment

Dependent variable is the DHS growth rate from 1997 to 2007 of firm-level outcome indicated in column header						
Panel A: Employment	Total Emp		Manuf Emp		Non-Manuf Emp	
	(1)	(2)	(3)	(4)	(5)	(6)
Output Shock	-0.046 (0.092)	0.324* (0.196)	-0.064 (0.113)	0.465* (0.271)	0.068 (0.066)	0.132 (0.211)
Output Shock $\times Aux_f^{1997}$	-0.703*** (0.208)	-0.433** (0.210)	-1.110*** (0.262)	-0.709** (0.312)	-0.636** (0.248)	-0.579** (0.256)
Output Shock $\times \ln(Emp_f^{1997})$		-0.115** (0.049)		-0.164** (0.067)		-0.018 (0.059)
Input Shock	-0.024 (0.200)	-0.067 (0.450)	-0.149 (0.192)	-0.238 (0.440)	0.094 (0.158)	-0.224 (0.543)
Input Shock $\times Aux_f^{1997}$	0.465 (0.565)	0.457 (0.533)	0.149 (0.497)	0.135 (0.510)	1.725*** (0.646)	1.537*** (0.551)
Input Shock $\times \ln(Emp_f^{1997})$		0.018 (0.130)		0.034 (0.138)		0.091 (0.140)
R ²	0.115	0.116	0.082	0.084	0.058	0.059

Panel B: Sales	Total Sales		Manuf Sales		Non-Manuf Sales	
	(1)	(2)	(3)	(4)	(5)	(6)
Output Shock	-0.036 (0.127)	0.615** (0.237)	-0.046 (0.154)	0.875*** (0.318)	0.105 (0.067)	0.075 (0.195)
Output Shock $\times Aux_f^{1997}$	-0.690*** (0.232)	-0.192 (0.210)	-1.307*** (0.306)	-0.591* (0.338)	-0.234 (0.369)	-0.250 (0.391)
Output Shock $\times \ln(Emp_f^{1997})$		-0.201*** (0.060)		-0.283*** (0.077)		0.009 (0.054)
Input Shock	-0.127 (0.162)	-0.163 (0.569)	-0.214 (0.203)	-0.322 (0.662)	0.140 (0.162)	0.229 (0.438)
Input Shock $\times Aux_f^{1997}$	0.014 (0.579)	0.031 (0.481)	-0.129 (0.516)	-0.128 (0.502)	1.569** (0.641)	1.619*** (0.598)
Input Shock $\times \ln(Emp_f^{1997})$		0.020 (0.169)		0.045 (0.194)		-0.026 (0.111)
R ²	0.075	0.077	0.067	0.069	0.067	0.067
Observations	73,500	73,500	73,500	73,500	73,500	73,500

Source: Comtrade, Bureau of Economic Analysis, EC and author's calculations. Table presents results from estimating equation (32) via OLS. Aux_f^{1997} is an indicator for whether the firm has one or more auxiliary establishments in 1997. Davis-Haltiwanger-Schuh (DHS) growth rate is $DHS_f = (x_f^{2007} - x_f^{1997}) / ((x_f^{2007} + x_f^{1997}) / 2)$. All regressions include firm-level controls for age, the log number of establishments, the share of sales in manufacturing and its interaction with Aux_f^{1997} , the share of materials in manufacturing costs and its interaction with Aux_f^{1997} , and four-digit NAICS fixed effects. Columns 2, 4, and 6 include the manufacturing sales and cost shares interacted with $\ln(Emp_f^{1997})$. Standard errors are two-way clustered by firm's primary output and input NAICS.

Results for the input shock are quite different. There is no statistically significant impact on firms' total or M employment. However, in line with our assumed complementarity between manufactured and knowledge inputs, we find a positive and significant relationship between the input shock and NM employment. Indeed, a 10 percentage point increase in China's market share in a firm's inputs raises its NM employment by 19 percent for firms with 500 workers. As this effect is only present for firms with auxiliaries, it supports our hypothesis that in-house knowledge plants play a key role in firms' ability to pivot across complementary sectors.

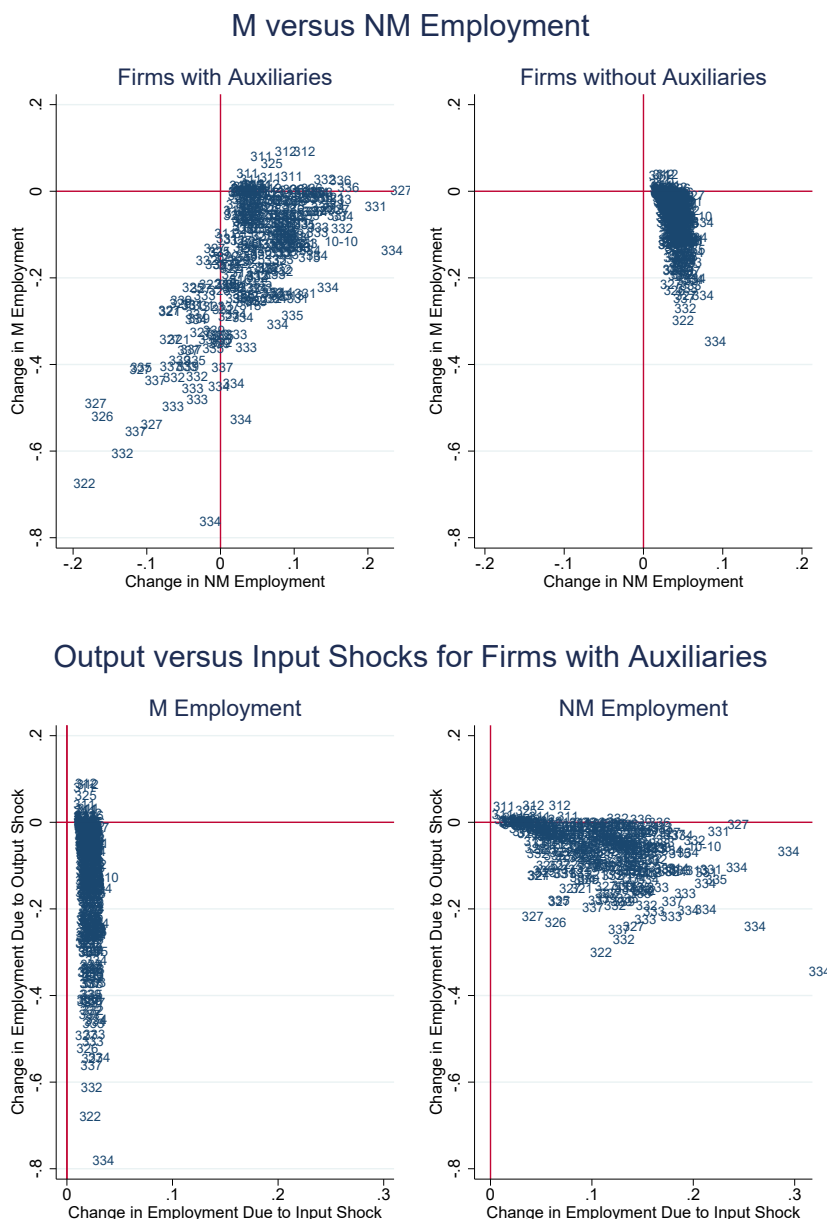
We illustrate the effects of the China shock on within-firm pivoting by calculating the implied changes in manufacturing versus non-manufacturing employment using actual changes in Chinese market shares across industries. We calculate these effects for firms with 500 workers, using the actual output shocks for each six-digit industry, along with the implied input shocks for a representative firm in that industry based on the IO table expenditures weights, as depicted in Appendix Figure A1. The top panel of Figure 6 plots the predicted net effects in log changes on M versus NM employment. The left-hand side figure uses the estimates for firms with auxiliaries, while the right corresponds to firms without them. Our estimates imply firm-level manufacturing employment declines in the vast majority of industries in response to the China shock. By contrast, the predicted changes in NM employment are positive in most industries. Consistent with the model, these NM employment responses are magnified for firms with auxiliaries. While the shocks in some industries led to net NM employment declines for firms, the majority of industry shocks imply NM gains. The net effects of these output and input shocks thus lead firms to pivot from M to NM employment, and particularly so if they had in-house knowledge workers prior to the shock.

The bottom panel of Figure 6 depicts the predicted employment effects separately by output versus input shock, on M employment (left panel) and NM employment (right panel). Here we focus on a representative firm in each industry with 500 workers and auxiliary employment prior to the shock (i.e., we decompose the net employment impacts shown in the top-left panel into separate impacts of the output versus the input shock). The left panel shows that the output shock predicts large M employment declines in almost every industry, whereas the input shock predicts zero or small increases in M employment. Consistent with our assumed complementarity between manufactured inputs and knowledge workers, the right panel demonstrates large and positive predicted effects of the input shocks on NM employment. While the output shocks continue to predict NM employment declines for firms in most industries, these are generally at least half the size of the predicted effects on M employment.

To fix ideas, the estimates imply that a firm in Computer Storage Device manufacturing (NAICS 334112) with 500 employees and the average input (0.12) and output (0.18) exposure would decrease its M employment by 23 log points from the output shock, with almost no offsetting effect from the input shock. By contrast, the input shock implies a 23 log point increase in its NM employment, which is more than double the implied NM reduction of 10 log points from the output shock. In total, the estimates imply a 9 log point reduction in the firm's employment, though it pivots considerably towards NM activities. A firm in Motor Vehicle Body Manufacturing, however, fares quite differently since the output shock is close to zero (0.005), while the input shock is sizable (0.056), likely due to

China's strong growth in metals manufacturing. The estimates imply that a representative firm in this sector with 500 workers would have no M employment declines, but increase its NM employment by 10 log points. The implied net effects of the shocks in this industry on total employment is in fact positive, at 2.4 log points.

Figure 6: Predicted Log Changes in Employment



Source: Comtrade, Bureau of Economic Analysis, EC and author's calculations. Figure depicts the predicted log changes in manufacturing (M) and non-manufacturing (NM) employment responses of a representative firm in a six-digit NAICS industry with 500 employees to the observed output and input shocks in that industry, using three-digit NAICS labels for expositional ease. Top panel presents net effects of the input and output shocks. Bottom panel presents the gross effects of the input and output shocks on M (left panel) and NM (right panel) employment for firms with auxiliaries.

We present similar estimates for sales growth in Panel B of Table 5. The output shock has a large,

negative, and statistically significant impact on firms' total and M sales that is strongly decreasing in firm size. The most notable distinction from the employment results in Panel A is that firms' NM sales do not decrease in response to the output shock. The fact that the output shock reduces NM employment for firms with auxiliaries but has no statistically significant impact on NM sales is consistent with firms using NM workers to produce in-house knowledge to support their manufacturing output. As with employment, the input shock has no statistically significant impact on firms' total or M sales, but does raise their NM sales: a 10 percentage point increase in Chinese import competition in firms' inputs raises the NM sales of firms with auxiliaries by 17 log points. This result suggests that functional structural change may itself lead to sectoral structural change, as firms that produce services in-house eventually sell them to other firms.

In Table 6, we examine the impact of output and input shocks on specific service sectors within NM. We find that the input shock leads to growth in employment and sales in Professional, Scientific and Technical Services (NAICS 54-55), Mining, Utilities and Construction (NAICS 21-23), and Transportation and Warehousing (NAICS 48-49).³⁶ By contrast it has no statistically significant effect in Health, Education, or other Business Services outside of PSTS. These results are in line with the aggregate patterns depicted in Figure 1. On the other hand, while M firms exhibit strong growth in Wholesale and Retail, we do not find a statistically significant impact of the input or output shocks on their employment or sales in these sectors.

Overall, the results in Table 6 suggest that US M firms tilt towards high-skill, technology-intensive sectors that are inputs into manufacturing in response to the China input shock. These responses are consistent with functional structural change, in which cheaper manufactured inputs lead firms to reorient towards complementary knowledge inputs. The fact that firm sales also grow in these sectors, however, suggests that this functional structural change may also lead to sectoral functional change, as firms begin to sell those inputs to other firms.³⁷

Although many of the model predictions relate to changes in firm employment shares, we focus on growth rates here to ensure that our results are not driven solely by declines in firms' manufacturing activities. We show that we find similar results for manufacturing employment shares in Appendix Table A5, and that the output shock increases firm pivoting for firms with auxiliaries. Since our primary objective is to assess within-firm transformation, the results in this section are based on a balanced panel of continuing firms. In Online Appendix Table A6, however, we show that the output shock induces firm exit, whereas the input shock reduces it for smaller firms or those with auxiliaries. Finally, we consider the role of offshoring in these firm-level adjustments by examining how firm imports respond to the shock and by estimating our specifications for the subset of non-importers. In contrast, to the idea that the output shock induced offshoring, results in Appendix Table A5 indicate that firm imports *decline* in response to Chinese import competition in the firm's outputs. The input shock, however, lead to increased importing, though only for firms with auxiliaries. Offshoring does

³⁶We include NAICS 55 in the results for PSTS in Table 6 because establishments that perform two or more PSTS for their firm are classified in 551114.

³⁷Consider the example from publicly available information of Amazon's creation of cloud computing services to host its website traffic. Over time, and in an effort to capitalize on excess capacity it required during the Christmas shopping period, Amazon began selling those services to other firms.

Table 6: Effects of Output and Input Shocks on Firm Sales and Employment

Dependent variable is the DHS growth rate from 1997 to 2007 of firm-level outcome indicated in column header							
Panel A: Employment	PSTS (54-55)	WR (42-45)	TrWh (48-49)	MUC (2)	Other BS (51-53, 56)	AAF (71-72)	Other (6,8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output Shock	0.244** (0.108)	-0.037 (0.114)	0.006 (0.048)	0.011 (0.048)	0.052 (0.065)	-0.044 (0.047)	0.066 (0.060)
Output Shock $\times Aux_f^{1997}$	-0.603** (0.257)	-0.087 (0.265)	-0.297 (0.221)	-0.860*** (0.265)	0.270 (0.207)	-0.028 (0.084)	0.221** (0.110)
Output Shock $\times \ln(Emp_f^{1997})$	-0.081** (0.033)	0.033 (0.032)	0.009 (0.014)	-0.001 (0.016)	-0.008 (0.019)	0.013 (0.014)	-0.013 (0.017)
Input Shock	-0.178 (0.224)	-0.572* (0.333)	0.000 (0.140)	-0.147 (0.265)	0.053 (0.191)	-0.112 (0.106)	-0.243 (0.159)
Input Shock $\times Aux_f^{1997}$	1.324*** (0.384)	0.391 (0.416)	0.830*** (0.286)	2.545*** (0.806)	-0.329 (0.268)	0.198* (0.118)	-0.389** (0.157)
Input Shock $\times \ln(Emp_f^{1997})$	0.048 (0.066)	0.153* (0.090)	-0.013 (0.040)	0.059 (0.085)	-0.005 (0.054)	0.027 (0.027)	0.077 (0.047)
R ²	0.098	0.045	0.040	0.124	0.031	0.044	0.031
Observations	73,500	73,500	73,500	73,500	73,500	73,500	73,500
Panel B: Sales	PSTS (54-55)	WR (42-45)	TrWh (48-49)	MUC (2)	Other BS (51-53, 56)	AAF (71-72)	Other (6, 8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Output Shock	0.064 (0.095)	0.050 (0.124)	-0.008 (0.039)	0.019 (0.041)	0.045 (0.064)	-0.041 (0.045)	0.056 (0.052)
Output Shock $\times Aux_f^{1997}$	-0.108 (0.318)	-0.138 (0.238)	-0.167 (0.156)	-0.788*** (0.281)	0.261 (0.212)	-0.049 (0.093)	0.077 (0.104)
Output Shock $\times \ln(Emp_f^{1997})$	-0.018 (0.028)	0.011 (0.033)	0.010 (0.012)	-0.006 (0.012)	-0.003 (0.018)	0.013 (0.013)	-0.008 (0.014)
Input Shock	-0.405** (0.170)	-0.251 (0.341)	-0.229** (0.114)	0.271 (0.210)	-0.018 (0.179)	-0.109 (0.103)	-0.118 (0.118)
Input Shock $\times Aux_f^{1997}$	0.780** (0.334)	0.229 (0.405)	0.892*** (0.231)	2.143** (0.959)	-0.100 (0.238)	0.155 (0.126)	-0.136 (0.170)
Input Shock $\times \ln(Emp_f^{1997})$	0.118** (0.055)	0.065 (0.091)	0.052 (0.035)	-0.050 (0.064)	0.010 (0.049)	0.028 (0.027)	0.042 (0.036)
R ²	0.042	0.044	0.051	0.270	0.031	0.038	0.028
Observations	73,500	73,500	73,500	73,500	73,500	73,500	73,500

Source: Comtrade, Bureau of Economic Analysis, EC and author's calculations. Table presents results from estimating equation (32) via OLS. PSTS is Professional, Scientific and Technical Services (NAICS 54) plus Management (NAICS 55); WR is Wholesale and Retail (NAICS 42-5); TrWh is Transportation and Warehousing (NAICS 48-9); MUC is Mining, Utilities, and Construction (NAICS 2); Other BS is other Business Services (NAICS 51-3,56); AAF is Arts, Accommodation and Food Services (NAICS 71-2); Other is Education, Health, and Repair (NAICS 6,8). Aux_f^{1997} is an indicator for whether the firm has one or more auxiliary establishments in 1997. Davis-Haltiwanger-Schuh (DHS) growth rate is $DHS_f = (x_f^{2007} - x_f^{1997}) / ((x_f^{2007} + x_f^{1997}) / 2)$. All regressions include firm-level controls for age, the log number of establishments, the share of sales in manufacturing, the share of materials in manufacturing costs, these shares interacted with Aux_f^{1997} and $\ln(Emp_f^{1997})$, and four-digit NAICS fixed effects. Standard errors are two-way clustered by firm's primary output and input NAICS.

not seem to be the only channel through which firms adjust, however, as the main results in Table 5 continue to hold when we limit our sample to non-importing firms between 1997 and 2007. This suggests that Chinese import competition lowered prices for all firms, even if they were not direct importers.

6 Conclusion

We provide new theory and evidence highlighting a role for firms in the United States’ structural transformation towards services over the last four decades. To do so, we construct a comprehensive dataset that tracks US firms and the full range of their establishments’ activities. These data yield three key insights about structural transformation. First, while most existing research emphasizes changes in final consumption, we find that a substantial proportion of reallocation occurs towards business services that are largely used as inputs. Second, we show that a major component of this reallocation occurs within surviving manufacturing firms, as they pivot away from production and towards related, high-skill input services. Third, we develop a new measure of in-house investments in intangible knowledge, based on input-service establishments that primarily serve their firm (e.g., an R&D lab), and show that it is correlated with higher growth and pivoting to new industries.

We rationalize these features of the data in a model in which production entails manufacturing and knowledge services, which are complementary. In addition, firms that perform these knowledge services in-house (versus purchasing them at arm’s length) develop proprietary intangible capital that is excludable from other firms, and which leads to differential responses to exogenous changes in their input and output market prices. Using China’s integration in the global economy as a natural experiment, we provide empirical evidence in support of these predictions. While greater import competition in output markets leads to the conventional contraction of firm employment, increased import competition in firms’ input markets induces structural transformation within firms from production to knowledge services. Moreover, we find that firms with in-house knowledge workers, as measured by auxiliary establishments, are more responsive to these output and input market shocks.

Our empirical findings and theoretical framework convey a number of micro and macro implications. First, in existing research on structural transformation through unbalanced productivity growth, reallocation of final consumption expenditure and employment across sectors is captured through the change in a common technology parameter across all firms. In contrast, when structural transformation occurs within firms, the magnitude of the resulting employment reallocation across sectors depends on endogenous within-industry reallocation across production establishments and within-firm reallocation between production and knowledge services. Second, the extent to which economic growth involves creative destruction depends on whether structural transformation occurs within versus between firms. To the extent that intangible knowledge is firm-specific but general across sectors, intangible knowledge can be preserved within firm boundaries, but is created and destroyed when firms enter and exit, respectively.

Our results also reignite past work that emphasizes the role of firm boundaries in the production of knowledge. By following firms’ transitions over time and demonstrating the importance of in-house

input provision in response to shocks, we provide new support for the premise that firms play a key role in developing knowledge and using it to adapt to changing economic circumstances. We hope this evidence will spur future work investigating what knowledge really is, how it is developed, and how it influences firm behavior. Given the transition we document in the United States towards ‘knowledge-related’ industries, work in these areas is likely to be increasingly valuable.

References

- Aarland, Kristin, James C. Davis, J Vernon Henderson, and Yukako Ono**, “Spatial Organization in Firms: The Decision to Split Production and Administration,” *The RAND Journal of Economics*, 2007, 38 (2), 480–494.
- Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price**, “Import Competition and the Great US Employment Sag of the 2000s,” *Journal of Labor Economics*, 2016, 34 (S1), S141–S198.
- Adão, Rodrigo, Michal Kolesár, and Eduardo Morales**, “Shift-Share Designs: Theory and Inference,” *Quarterly Journal of Economics*, 2019, 134 (4), 1949–2010.
- Alessandria, George A., Robert C. Johnson, and Kei-Mu Yi**, “Perspectives on Trade and Structural Transformation,” Working Paper 28720, NBER 2021.
- Antràs, Pol and Elhanan Helpman**, “Global Sourcing,” *Journal of Political Economy*, 2004, 112 (3), 552–80.
- Antràs, Pol, Teresa C. Fort, and Felix Tintelnot**, “The Margins of Global Sourcing: Theory and Evidence from U.S. Firms,” *American Economic Review*, 2017, 107 (9), 2514–64.
- Argente, David, Sara Moreira, Sara Oberfield, and Venky Venkateswaran**, “Scalable Expertise,” 2021. Princeton University, mimeograph.
- Atalay, Enghin, Ali Hortacsu, and Chad Syverson**, “Vertical Integration and Input Flows,” *American Economic Review*, 2014, 104 (4), 1120–48.
- Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu**, “Foreign Competition and Domestic Innovation: Evidence from US Patents,” *American Economic Review: Insights*, 2020, 2 (3), 357–374.
- Autor, David H., David Dorn, and Gordon H. Hanson**, “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 2013, 103 (6), 2121–68.
- Baumol, William J.**, “Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis,” *American Economic Review*, 1967, 57, 415–26.
- Bernard, Andrew B. and Teresa Fort**, “Factoryless Goods Producing Firms,” *American Economic Review*, 2015. forthcoming.
- , **J. Bradford Jensen, and Peter K. Schott**, “Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of U.S. Manufacturing Plants,” *Journal of International Economics*, 2006, 68, 219–237.
- , —, **Stephen Redding, and Peter Schott**, “Multi-Product Firms and Trade Liberalization,” *Quarterly Journal of Economics*, 2011, 126 (3), 1271–1318.
- , **Stephen J. Redding, and Peter K. Schott**, “Multi-product Firms and Product Switching,” *American Economic Review*, 2010, 100 (1), 70–97.
- , **Teresa C. Fort, Valerie Smeets, and Frederic Warzynski**, “Heterogeneous Globalization: Offshoring and Reorganization,” Working Paper 26854, NBER 2021.

- Bertrand, Marianne, Esther Dufo, and Sendhil Mullainathan**, “How Much Should We Trust Differences-in-Differences Estimators?,” *Quarterly Journal of Economics*, 2004, 119 (1), 249–275.
- Bessen, James**, “Information technology and industry concentration,” *Boston University School of Law Law & Economics Paper Series*, 2017, 17-41.
- Bloom, Nicholas, Kyle Handley, Andre Kurmann, and Philip Luck**, “The Impact of Chinese Trade on U.S. Employment: The Good, The Bad, and The Debatable,” 2019. Stanford University, mimeo.
- , **Mirko Draca, and John Van Reenen**, “Trade Induced Technical Change: The Impact of Chinese Imports on Innovation, Diffusion, and Productivity,” *Review of Economic Studies*, 2016, 83, 87–117.
- Boehm, Christoph E., Aaron Flaaen, and Nitya Pandalai-Nayar**, “Multinationals, Offshoring, and the Decline of U.S. Manufacturing,” *Journal of International Economics*, nov 2020, 127, 103391.
- Boehm, Johannes, Swati Dhingra, and John Morrow**, “The Comparative Advantage of Firms,” *Journal of Political Economy*, 2022, *forthcoming*.
- Boppart, Timo**, “Structural Change and the Kaldor Facts in a Growth Model with Relative Price Effects and Non-Gorman Preferences,” *Econometrica*, 2014, 82 (6), 2167–2196.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel**, “Quasi-Experimental Shift-Share Research Designs,” *Review of Economic Studies*, 2021, *forthcoming*.
- Breinlich, Holger, Anson Soderbery, and Greg C. Wright**, “From Selling Goods to Selling Services: Firm Responses to Trade Liberalization,” *American Economic Journal: Economic Policy*, 2018, 10 (4).
- Buera, Francisco J and Joseph P Kaboski**, “The rise of the service economy,” *American Economic Review*, 2012, 102 (6), 2540–69.
- , —, and **Richard Rogerson**, “Skill Biased Structural Change,” Working Paper 21165, National Bureau of Economic Research May 2015.
- Chow, Melissa, Teresa Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T. Kirk White**, “Redesigning the Longitudinal Business Database,” Working Paper 21-08, CES 2021.
- Comin, Diego, Danial Lashkari, and Marti Mestieri**, “Structural Change with Long-run Income and Price Effects,” 2018. Northwestern, mimeograph.
- Cravino, Javier and Sebastian Sotelo**, “Trade-Induced Structural Change and the Skill Premium,” *AEJ: Macroeconomics*, 2019, 11 (3), 289–326.
- Davis, James C. and J Vernon Henderson**, “The Agglomeration of Headquarters,” *Regional Science and Urban Economics*, 2008, 35 (5), 445–460.
- Davis, Steven J., John Haltiwanger, and Scott Schuh**, *Job Creation and Destruction*, Cambridge MA: MIT Press, 1996.
- de Loecker, Jan, Jan Eeckhout, and Gabriel Unger**, “The Rise of Market Power and the Macroeconomic Implications,” *The Quarterly Journal of Economics*, jan 2020, 135 (2), 561–644.

- Demsetz, Harold**, “The Theory of the Firm Revisted,” *Journal of Law, Economics, & Organization*, 1988, 4 (1), 141–161.
- Dey, Matthew, Susan H. Houseman, and Anne E. Polivka**, “Manufacturers’ Outsourcing to Staffing Services,” *ILR Review*, 2012.
- Ding, Xiang**, “Industry Linkages from Joint Production,” *Mimeo*, 2020.
- Eckert, Fabian**, “Growing apart: Tradable services and the fragmentation of the us economy,” 2019. UCSD.
- , **Sharat Ganapati, and Conor Walsh**, “Skilled Tradable Services: The Transformation of U.S. High-Skill Labor Markets,” 2019. UCSD.
- Fort, Teresa C.**, “Technology and Production Fragmentation: Domestic versus Foreign Sourcing,” *Review of Economic Studies*, 2017, 84 (2), 650–687.
- Fort, Teresa C and Shawn Klimek**, “The Effects of Industry Classification Changes on US Employment Composition,” CES Working Paper 18-28, US Census Bureau 2018.
- Foster, Lucia, John Haltiwanger, and Cody Tuttle**, “Rising Markups of Changing Technology?,” mimeograph, University of Maryland 2022.
- Ganapati, Sharat**, “The Modern Wholesaler: Global Sourcing, Domestic Distribution, and Scale Economies,” Technical Report, Yale mimeo 2016.
- Grossman, Sanford J. and Oliver D. Hart**, “The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration,” *Journal of Political Economy*, 1986, 94, 691–719.
- Haltiwanger, John, Ron S. Jarmin, and Javier Miranda**, “Who Creates Jobs? Small Versus Large Versus Young,” *The Review of Economics and Statistics*, 2013, 95, 347–361.
- Hart, Oliver D. and John Moore**, “Property Rights and the Nature of the Firm,” *Journal of Political Economy*, 1990, 98, 1119–58.
- Haskel, Jonathan and Stian Westlake**, “Capitalism without capital,” in “Capitalism without Capital,” Princeton University Press, 2017.
- Herrendorf, Berthold, Richard Rogerson, and Akos Valentinyi**, “Two Perspectives on Preferences and Structural Transformation,” *American Economic Review*, 2013, 103 (7), 2752–89.
- , —, and —, “Growth and Structural Transformation,” in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Amsterdam: Elsevier North Holland, 2014.
- Holmes, Thomas J. and John J. Stevens**, “An Alternative Theory of the Plant Size Distribution, with Geography and Intra- and International Trade,” *Journal of Political Economy*, 2014, 122 (2), 369–421.
- Hombert, Johan and Adrien Matray**, “Can Innovation Help US Manufacturing Firms Escape Import Competition from China?,” *The Journal of Finance*, 2018, 73 (5), 2003–2039.
- Hottman, Colin, Stephen Redding, and David Weinstein**, “Quantifying the Sources of Firm Heterogeneity,” *Quarterly Journal of Economics*, 2016, 131, 1291–1364.
- Hsieh, Chang-Tai and Esteban Rossi-Hansberg**, “The Industrial Revolution in Services,” 2019. University of Chicago.

- Jarmin, Ron S. and Javier Miranda**, “The Longitudinal Business Database,” *Center for Economic Studies Working Paper*, 2002, 02 (17).
- Kamal, Fariha**, “A Portrait of Factoryless Goods Producers,” in Nadim Ahmad, Brent Moulton, J. David Richardson, and Peter Van De Ven, eds., *The Challenges of Globalization in the Measurement of National Accounts*, University of Chicago Press, 2020.
- Kehoe, Timothy J., Kim J. Ruhl, and Joseph B. Steinberg**, “Global Imbalances and Structural Change in the United States,” *Journal of Political Economy*, 2018, 126 (1), 761–796.
- Khandelwal, Amit**, “The Long and Short (of) Quality Ladders,” *Review of Economic Studies*, 2010, 77 (4), 1450–1476.
- Lashkari, Danial, Arthur Bauer, and Jocelyn Boussard**, “Information Technology and Returns to Scale,” mimeo, Boston College 2021.
- Magyari, Ildikó**, “Firm Reorganization, Chinese Imports, and US Manufacturing Employment,” Working Paper 17-58, Center for Economic Studies 2017. Columbia University, mimeograph.
- Matsuyama, Kiminori**, “A Ricardian Model with a Continuum of Goods under Nonhomothetic Preferences: Demand Complementarities, Income Distribution and North-South Trade,” *Journal of Political Economy*, 2000, 108, 1093–1120.
- , “Structural Change in an Interdependent World: A Global View of Manufacturing Decline,” *Journal of the European Economic Association*, 2009.
- , “Engel’s law in the global economy: Demand-induced patterns of structural change, innovation, and trade,” *Econometrica*, 2019, 87 (2), 497–528.
- Melitz, Marc J.**, “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, 2003, 71 (6), 1695–1725.
- Mengus, Eric and Tomasz Michalski**, “Within-firm Services and Firm Capabilities,” mimeograph, HEC Paris 2022.
- Mion, Giordano and Linke Zhu**, “Import competition from and offshoring to China: A curse or blessing for firms?,” *Journal of International Economics*, 2013, 89 (1), 202 – 215.
- Ngai, L. Rachel and Christopher A. Pissarides**, “Structural Change in a Multisector Model of Growth,” *American Economic Review*, 2007, 97 (1), 429–443.
- Oulton, Nicholas**, “Must the growth rate decline? Baumol’s unbalanced growth revisited,” *Oxford Economic Papers*, 10 2001, 53 (4), 605–627.
- Pierce, Justin R. and Peter K. Schott**, “A Concordance between Ten-Digit U.S. Harmonized System Codes and SIC/NAICS Product Classes and Industries,” *Journal of Economic and Social Measurement*, 2012, 37, 61–96.
- and —, “Trade Liberalization and Mortality: Evidence from US Counties,” Working Paper 22849, NBER 2016.
- Teece, David J.**, “Towards an economic theory of the multiproduct firm,” *Journal of Economic Behavior & Organization*, 1982, 3 (1), 39–63.
- Williamson, Oliver E.**, “The Economics of Organization: The Transaction Cost Approach,” *The American Journal of Sociology*, 1981, 87 (3), 548–577.

A Appendix Tables and Figures

In this appendix, we provide supporting tables and figures discussed in the text.

A.1 Headline numbers for payroll

Table A1: Payroll Growth in M and NM from 1977 to 2019, by Firm Type and Margin

Panel A: “Census” (Upper Bound)								
	Manufacturing Pay				Non-Manufacturing Pay			
	1977	2019	Change	Share of Change	1977	2019	Change	Share of Change
M Firms	234	733	500	1.00	165	1682	1518	0.25
Continuers	87	306	219	0.44	70	1066	996	0.17
Net Birth/Death	147	427	280	0.56	94	616	522	0.09
NM Firms					335	4838	4503	0.75
Continuers					59	1048	989	0.16
Net Birth/Death					276	3790	3514	0.58
Total	234	733	500	1.00	500	6520	6021	1.00

Panel B: “HJM Firms” (Upper Bound)								
	Manufacturing Pay				Non-Manufacturing Pay			
	1977	2019	Change	Share of Change	1977	2019	Change	Share of Change
M Firms	234	733	500	1.00	219	2620	2401	0.40
Continuers	158	474	316	0.63	175	2037	1862	0.31
Net Birth/Death	75	259	184	0.37	43	583	540	0.09
NM Firms	0	0	0	0.00	281	3901	3620	0.60
Continuers					72	1046	974	0.16
Net Birth/Death					209	2855	2646	0.44
Total	234	733	500	1.00	500	6521	6021	1.00

Source: LBD and authors’ calculations. Table presents manufacturing (M) and non-manufacturing (NM) payroll levels in 1977 and 2019, the change in these levels, and the share of the change accounted for by M firms, NM firms, and continuers versus net/birth withing these firm types. M pay is the sum of payroll at all US establishments in the LBD classified in manufacturing. NM pay is the sum of payroll at all US establishments in the LBD classified outside manufacturing. Census M firms (top panel) are those that ever have an M plant between 1977 and 2019. HJM M firms (bottom panel) are those that ever have an establishment that was ever in a firm with an M plant in the same year. Continuing Census firms are those for which the Census *lbdid* exists in both years. HJM continuing firms are those with an establishment in 2019 that existed in 1977. Pay is in millions. There are 27.5 thousand continuing Census M firms in both years, out of 5.42 million firms in 2019. There are 46 thousand continuing HJM M firms in 2019.

A.2 Reduced-form analysis

The regression sample consists of firms that continue through 2007 and own one or more manufacturing plants in 1997. Table A2 documents the levels and shares of M and NM employment in 1997, and the changes in this employment from 1997 to 2007 accounted, for by this sample. The left panel presents statistics for M employment. In 1997, the start of our long-difference, the regression sample accounts for over 60 percent of total M employment, and 10 percent of NM employment. These continuing M firms account for one quarter of the aggregate decline in M over the period, though this is partially due to the fact that firms without auxiliaries increase their M employment, while firms with auxiliaries experience net declines in M employment equal to one-third of the aggregate decline.

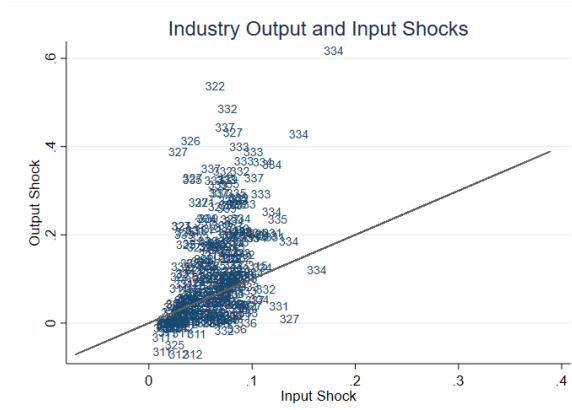
The right panel of Table A2 shows that the regression sample accounts for 20 percent of the aggregate increase in NM employment over the period, with 18 percentage points of the rise occurring in firms with auxiliaries at the start of the period. In Online Appendix Table G12, we decompose NM employment into Management and Professional, Scientific and Technical Services (NAICS 54 and 55) versus other NM. The regression sample also contains 20 percent of aggregate US employment in the former in 1997, and accounts for 23 percent of its increase over the period.

Table A2: Employment in Regression Sample Relative to Economy Totals

	M Employment				NM Employment			
	1997		Δ 1997-2007		1997		Δ 1997-2007	
	Level	Share	Level	Share	Level	Share	Level	Share
Firms in Regression Sample	10.00	0.61	-0.77	0.26	8.75	0.10	3.90	0.20
Firms without Auxiliaries in 1997	3.85	0.24	0.26	-0.09	0.29	0.00	0.41	0.02
Firms with Auxiliaries in 1997	6.15	0.38	-1.03	0.34	8.45	0.10	3.49	0.18
Firms Outside Regression Sample	6.38	0.39	-2.24	0.74	78.04	0.90	15.59	0.80
Economy Total	16.38	1.00	-3.01	1.00	86.79	1.00	19.49	1.00

Source: EC and authors' calculations. Table presents manufacturing (M) and non-manufacturing (NM) employment levels and shares in 1997 and changes from 1997 to 2007 for firms in the regression sample, by their auxiliary status in 1997. Regression sample contains 73,500 continuing firms with M employment in 1997, of which 3,600 have an auxiliary establishment. Administrative Records from the Census of Manufactures are excluded from the regression sample since all their sales and input purchases are imputed. Employment is in millions.

Figure A1: Changes in Chinese Market Share in Output vs Inputs, by Industry



Source: Comtrade, Bureau of Economic Analysis and author's calculations. Figure presents the change in Chinese market shares in Europe from 1997 to 2007 in a six-digit NAICS industry (output shock) versus the expenditure-weighted average change in that industry's inputs (input shock). We label each industry using its three-digit NAICS root.

Table A3: Summary Statistics of the Industry Shocks

	Positive	Median	Mean	Min	Max	Std Dev
Output Shock	91%	0.085	0.113	-0.071	0.617	0.113
Input Shock	99%	0.049	0.047	-0.003	0.164	0.028

Source: Comtrade, Bureau of Economic Analysis and author's calculations. Table presents summary statistics for industry-level output and input shocks. The input shock here is based solely on the weighted-average of an output industry's input expenditure shares across industries, using weights from the 1997 BEA Input-Output tables. Positive reports the percent of industries with positive shocks.

Table A4 presents correlation coefficients between the endogenous measures of Chinese import penetration in the United States versus the plausibly exogenous measures of Chinese market share gains in Europe in firms' output and input industries. For each pair of variables, we report the raw correlation coefficient as well as the correlation coefficient after residualizing the variables using the regression controls.

Table A4: Correlations in Firms' US and EU Chinese Input and Output Exposure Measures

	$\Delta ChinaImpPen_f^{US,Output}$		$\Delta ChinaImpPen_f^{US,Input}$		$\Delta Output_f$	
	raw	resid	raw	resid	raw	resid
$\Delta ChinaImpPen_f^{US,Input}$	0.418	0.151				
$\Delta Output_f$	0.523	0.408	0.306	0.163		
$\Delta Input_f$	0.177	0.087	0.656	0.525	0.170	0.050

Source: Comtrade, Bureau of Economic Analysis and author's calculations. Table presents correlations between changes in Chinese market shares in Europe ($\Delta Output_f$ and $\Delta Input_f$) and Chinese import penetration in the US ($\Delta ChinaImpPen_f^{US,Output}$ and $\Delta ChinaImpPen_f^{US,Input}$) in both firms' output products and inputs for the regression sample of 73,500 firms. We report correlations for raw variables and after residualizing them with the following regression controls: $\ln(Emp_f^{1997})$, firm age, the log number of establishments, the share of sales in manufacturing, the share of materials in manufacturing costs, these shares interacted with Aux_f^{1997} and $\ln(Emp_f^{1997})$, and four-digit NAICS fixed effects.

A.3 Additional Results and Mechanisms

Table A5 presents our estimates of the impact of input and output shocks on import growth, pivoting and the manufacturing shares of sales and employment. Table A6 studies the impact of output and input shocks on firm exit. We use two definitions of firm exit. Our first definition corresponds to our definition of Census firms in the rest of the paper. Additionally, we examine the robustness of our results to the HJM definition of exit: a firm in our regression sample exits under HJM's definition if it exits under Census definition and if none of its plants in 1997 survives by 2007. We modify our regression sample to include initial manufacturing firms that did not survive from 1997 to 2007.

A.4 Plant-level switching

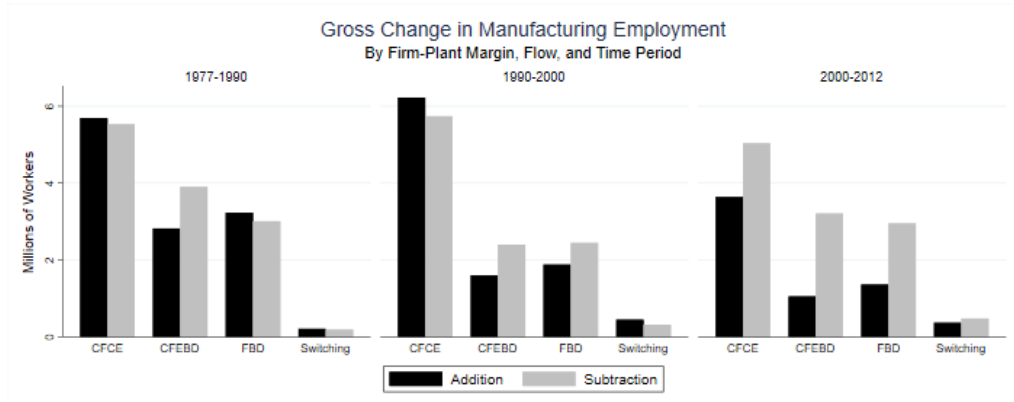
In related work, Bloom et al. (2019) document increased plant-level industry switching in response to increased Chinese import penetration in high-wage commuting zones. While they find large marginal effects on this dimension, we caution that this does not translate to large level effects. Figure A2 shows that net switching leads to manufacturing increases during the 1990s and small reductions in the 2000s. Even the gross flows from switching are quite small, and dwarfed by other flows.

Table A5: Effects of Output and Input Shocks on Additional Firm Outcomes

	Import	Pivot		Δ Manuf Share of:	
	Growth	Sales	Emp	Sales	Emp
Output Shock	-0.108 (0.327)	-0.152 (0.220)	-0.138 (0.219)	0.097 (0.078)	0.083 (0.080)
Output Shock $\times Aux_f^{1997}$	-1.521*** (0.289)	0.209** (0.098)	0.212** (0.103)	-0.273** (0.132)	-0.214** (0.106)
Output Shock $\times \ln(Emp_f^{1997})$	0.076 (0.077)	0.055 (0.036)	0.051 (0.037)	-0.036* (0.020)	-0.029 (0.021)
Input Shock	1.420 (1.443)	0.409 (0.451)	0.380 (0.459)	-0.094 (0.160)	-0.035 (0.159)
Input Shock $\times Aux_f^{1997}$	1.473*** (0.515)	0.098 (0.175)	0.181 (0.178)	-0.175 (0.152)	-0.184* (0.108)
Input Shock $\times \ln(Emp_f^{1997})$	-0.399 (0.302)	-0.101 (0.103)	-0.092 (0.106)	0.016 (0.038)	-0.003 (0.038)
R^2	0.107	0.087	0.081	0.080	0.061

Source: Comtrade, Bureau of Economic Analysis, EC and author's calculations. Table presents results from estimating equation (32) via OLS. Aux_f^{1997} is an indicator for whether the firm has one or more auxiliary establishments in 1997. Import growth is measured as Davis-Haltiwanger-Schuh (DHS) growth rates: $DHS(x)_f = (x_f^{2007} - x_f^{1997}) / ((x_f^{2007} + x_f^{1997})/2)$. Pivot is measured by equation (3) using sales and employment shares by industry within the firm, respectively. All regressions include firm-level controls for Aux_f^{1997} , $\ln(Emp_f^{1997})$, firm age, the log number of establishments, the share of sales in manufacturing, the share of materials in manufacturing costs, these shares interacted with Aux_f^{1997} and $\ln(Emp_f^{1997})$, and 4-digit NAICS fixed effects. Standard errors two-way clustered by firm's primary output and input NAICS. Our regression sample contains 73,500 firms.

Figure A2: Gross Manufacturing Employment Changes by Margin



Source: LBD and authors' calculations. Figure displays gross flows of US manufacturing employment for continuing establishments within continuing firms (CFCE), establishment births and deaths within continuing firms (CFEBD), firm births and deaths (FBD), and establishment industry switching (Switching).

Table A6: Effects of Output and Input Shocks on Firm Exit

Dependent variable is an indicator equal to one if firm exits between 1997 and 2007

	Census Definition of Firm Exit			HJM Definition of Firm Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
Output Shock	0.096 (0.088)	0.091 (0.088)	0.038 (0.126)	0.053 (0.068)	0.049 (0.069)	-0.074 (0.099)
Output Shock $\times Aux_f^{1997}$		0.244** (0.113)	0.131 (0.128)		0.183* (0.102)	0.036 (0.094)
Output Shock $\times \ln(Emp_f^{1997})$			0.019 (0.027)			0.043** (0.020)
Input Shock	0.063 (0.124)	0.057 (0.131)	-0.764** (0.381)	-0.046 (0.109)	-0.047 (0.115)	-0.503* (0.288)
Input Shock $\times Aux_f^{1997}$		0.038 (0.195)	-0.499** (0.218)		-0.048 (0.174)	-0.369* (0.193)
Input Shock $\times \ln(Emp_f^{1997})$			0.240** (0.093)			0.134** (0.066)
R-squared	0.117	0.117	0.118	0.105	0.105	0.106
Observations	168,000	168,000	168,000	168,000	168,000	168,000

Source: Comtrade, Bureau of Economic Analysis, Economic Census and author's calculations. Table presents results from estimating equation (32) via OLS. Dependent variable is an indicator equal to one if firm exits over between 1997 to 2007. Aux_f^{1997} is an indicator for whether the firm has one or more auxiliary establishments in 1997. All regressions include firm-level controls for Aux_f^{1997} , $\ln(Emp_f^{1997})$, firm age, the log number of establishments, the share of sales in manufacturing, the share of materials in manufacturing costs, and four-digit NAICS fixed effects. Columns (2), (3), (5), and (6) also control for the input and output shares interacted with Aux_f^{1997} , and columns (3) and (6) additionally control for the input and output shares interacted with $\ln(Emp_f^{1997})$. Standard errors two-way clustered by firm's primary output and input NAICS. Regression sample contains 168,000 firms.