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The "Weighty" Manufacturing Sector
Transforming Raw Materials into Physical Goods

Erica R. H. Fuchs, Christophe Combemale, Kate S. Whitefoot, and Britta Glennon

1.1 Introduction

Manufacturing has historically played a significant role in productivity and R&D. Jorgenson (2001) suggests that advances in microprocessors alone were associated with 50 percent of total factor productivity growth in the US and worldwide in the 1990s. This outsized role in R&D and productivity appears to continue today, even with significant changes across the sector in technology and globalization. US manufacturing is a disproportionate source of private R&D spending relative to its share of employment and global value added (GVA)[1,2] and has higher than average labor productivity relative to other sectors.[3]

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1. The ratio of R&D spending in manufacturing relative to its share to GVA share went from 4.52 in 1997 to 5.45 in 2015 (i.e., a 21 percent relative increase). The share of research funding proportional to employment in manufacturing grew from 1982 to 2015 and was "overrepresented" on a per-capita basis by a factor of 5 relative to other sectors. The manufacturing share of GDP parallels the trajectory of its share of GVA.

2. The manufacturing share of GDP parallels the trajectory of its share of GVA.

3. Manufacturing productivity per capita employed (measured as its share of the US GVA versus its share of employment) is higher than that of the overall US economy by a factor of

For the manufacturing sector as a whole, the past few decades have been marked by increases in R&D and productivity and a declining share of the US economy as other sectors grew faster. US manufacturing value added (MVA)[4] has grown in real terms from the 1980s to the present (as far back as public data allow us to observe) in addition to real growth in US private R&D spending by manufacturing industries. However, both absolute employment and share of total US employment in the sector have declined over the same period.[5] Despite MVA growth, manufacturing today accounts for a smaller share of total US value added than it did in the 1980s and 1990s.[6] While a majority of US industrial R&D spending still occurs in manufacturing, this too is a declining share of the US total. Manufacturing is a sector whose apparent role in the economy on these important dimensions would seem to be in decline, but it remains unusually productive per employee and highly research intensive.

Despite these average trends and commonalities, drawing implications from sector-wide manufacturing trends can be misleading because of the variation in these indicators across manufacturing subsectors. By definition, the manufacturing sector includes all establishments engaged in mechanical, physical, or chemical transformation of materials, substances, or components into new products (US Census Bureau 2017). The industries in the sector vary widely with respect to value added, workforce size and composition, and level of R&D effort. At the five-digit NAICS code level, the top sources of employment are animal processing, aerospace products, and printing (on various materials, including textiles, metals, and plastics); the top sources of revenue are petroleum refineries and automotive; and the top source of R&D spending is pharmaceuticals followed by semiconductors and other electronic components.

The rate and direction of technology change also varies greatly across subsectors. Indeed, industrial R&D spending is not only disproportionately driven by manufacturing, it is also disproportionately driven by the top five subsectors: pharmaceuticals, semiconductors and other electronic components, automobiles and light duty vehicles, communications, and aerospace. Unpacking the relationship among globalization, innovation, and labor outcomes requires not only understanding how the manufacturing sector can be different than other sectors, but also addressing the sector's diversity. Here, deep subsector-level knowledge and empirical detail may prove particularly

1.39. Manufacturing's share of GVA relative to its share of employment has grown since 1997 (the first available US MVA data) from a ratio of shares at 1.18 to a ratio of 1.40 in 2016.

4. Manufacturing value added is calculated (as in the US Census Bureau 2018) by the difference between input costs and output values from a firm or other entity.

5. US manufacturing employment also went from 19 percent of total employment in 1982 to 8.7 percent in 2015 (and is still falling slightly as of 2019, beyond our R&D funding dataset, at 8.5 percent).

6. MVA share of US GVA shifted from 16.7 percent in 1997 to 12.1 percent in 2015 (i.e., a 27.9 percent relative decline).

valuable for unpacking the puzzling (and sometimes conflicting) results in today's state-of-the-art analyses.

This chapter is structured as follows. We begin with a brief history of manufacturing technologies and systems. Second, we provide a birds-eye view of the trends in manufacturing based on available data on manufacturing value added, R&D spending, and human capital and demographic composition of the labor force. Third, we explore why manufacturing contributes to a majority (66 percent) of US industrial R&D spending but a much smaller (12 percent) proportion of US domestic value added. Fourth, we highlight subsectoral level differences in our birds-eye view measures, and potential subsectoral differences in the dichotomy between US industrial R&D spending and US value added (and potential explanations for that dichotomy). Finally, we engage with the existing literature and discuss implications of the chapter's findings for the relationship among globalization, innovation, and labor outcomes.

1.2 A Brief History of Manufacturing Technologies and Systems

US manufacturing began in the seventeenth and eighteenth centuries as a craftwork system imported from Europe to the American colonies. Craftwork was performed by skilled artisans, often working with tools that they owned themselves. Labor was organized into master craftsmen with apprentices or in small firms. In this period, most craftwork was for domestic consumption, and exports were dominated by raw materials (Shepherd and Williamson 1972).

In the mid-eighteenth century, what later came to be known as the first industrial revolution emerged in Great Britain. This revolution would eventually reach its maturity in the United States during the first quarter of the nineteenth century (Crafts 1996). The first industrial revolution shifted the sources of production power from human and animal toward chemical sources such as coal and wood, and water sources such as riverside mills (Crafts 1996). Faced with abundant materials but scarce, relatively skilled labor, US manufacturers in this period strongly favored innovations in mechanization (even compared with Great Britain; Rosenberg 1972). This mechanization reduced the demand for labor on the production line but increased material waste and produced new demands for skilled machinists to construct the machines. At the same time as the demand for skilled machinists grew, the shift in production organization from artisanal work to factory production saw a decline in the demand for skilled artisanal labor while shifting demand toward less skilled production labor in the factory (Goldin and Katz 1998).

After the first and into the second industrial revolution, US manufacturing saw the emergence, national prominence, and international export of the "American system," a mechanized approach to producing separate, interchangeable parts that made up final goods (Hounshell 1984). Eli Whitney originally popularized the concept of interchangeable parts in response to the needs of American small arms manufacture for high performance and easier repair, maintenance, and logistics (Hounshell 1984). Progress toward interchangeability was further developed by such entities as the Springfield Armory (Ford 2005). In addition to facilitating higher production volumes, interchangeability also expanded opportunities for the division of labor (Tyson 1990). Novel modes of organizing production activity at larger scales were driven in large part by the demand of US armories that emerged in the late eighteenth century and proliferated in the first quarter of the nineteenth century. Production volumes grew around US conflicts, such as the Mexican-American War and the American Civil War as well as arms production for national and international use in the later nineteenth and early twentieth centuries (Malone 1988; Smith 1980, 1985).

By the 1870s and the coming of the second industrial revolution, major productivity gains had been achieved through specialized labor and tools (Atack, Margo, and Rhode 2019) and innovations in power sources (e.g., from coal to oil; Mokyr 1992). As infrastructure, transportation, and communication technologies expanded and improved, production was able to further increase in scale, scope, and complexity. Along with increases in these dimensions came an enlarged role for salaried managers who did not own the industrial enterprises but rather were organized according to functions in the overall system of the firm, such as sales, purchasing, or research (Chandler 1990).

The organizational implications of the increasing scale economies of production gave rise in the early twentieth century to what became known as the American system of mass production (Hounshell 1984). Under mass production, further division of labor and specialization were made possible by the realization of interchangeable parts combined with a high degree of product and process standardization under organizational structures, such as the assembly line and scientific management approaches pioneered by Frederick Winslow Taylor (Chandler 1990; Hounshell 1984; Taylor 1914). These innovations also drove a further complementarity between capital and low skilled labor (Lafortune, Lewis, and Tessada 2019). Standardization of tools, processes, and products would remain a driving feature of production into the post-war era (Mowery and Rosenberg 1999).

After a slowdown in productivity growth in manufacturing from the 1960s to the 1970s (Hulten and Schwab 1984), US manufacturing in the mid-1970s and 1980s experienced what some have referred to as the third industrial revolution (Greenwood 1997; Mowery 2009). Manufacturing tasks shifted from humans and active machine control toward industrial robots and computer numerical control (CNC) systems (Bollinger and Duffie 1988; Moore 1997; Nichols 1976). Flexible manufacturing exploited CNC and other systems to allow medium-sized batch production. This batch production enabled product variety over the low-variety scale economies of mass production (Browne et al. 1984; Buzacott and Yao 1986). Human resource management approaches, such as employee training programs and flexible job assignments, also expanded (Bartel 1994; Ichniowski, Shaw, and Prennushi 1995).

In contrast to the American system of mass production, shifts associated with the third industrial revolution coincided with higher demand for skilled labor (Autor and Dorn 2013; Autor, Levy, and Murnane 2003; Katz and Murphy 1992). In some contexts, changes in the methods of production coincided with changes in the organization of production: from mass production, product standardization, and strict task specialization for equipment and personnel toward flexible manufacturing and lean production approaches (Mansfield 1993; Ohno 1988). Lean manufacturing, pioneered at Toyota through the Toyota Production System (TPS), differed from the material-rich roots of early US manufacturing by focusing on minimizing material as well as other resource wastage (Shah and Ward 2003; Womack, Jones, and Roos 1990). The system established just-in-time manufacturing strategies, which encouraged firms to entwine production and supply chains with the goal of narrowing the lead time between production and suppliers and time in production (Cheng and Podolsky 1996; Sakakibara et al. 1997). Among US manufacturers, lean manufacturing methods were adopted, among other places, in metal fabrication and computer, electrical machinery, and automotive production (Swamidass 2007). US firms did not adopt all dimensions of TPS, due to concerns about possible limitations on creativity and innovation (Mehri 2006), keeping many traditional compensation and labor relations arrangements (Doeringer, Lorenz, and Terkla 2003).[7]

Throughout the third industrial revolution, multiple manufacturing contexts actively pursued increasing the modularity of designs, led by computer hardware and other electronics. Modular computer systems composed of smaller, simpler subsystems (including such elements as hard disk drives and microprocessors) paralleled rapid innovations in component-specific performance that did not require costly (from the perspective of both time and money) total-system overhauls. In some cases, this modularity in design was mirrored in the design of organizations and supply chain composition of modern industries (Baldwin and Clark 2000, 2003; Colfer and Baldwin 2016). Suppliers also often took an active role in the innovative process (Helper and Sako 1995). Increasing modularity, including in the organization of suppliers, coincided with an increasing globalization of manufacturing supply chains (Gereffi, Humphrey, and Sturgeon 2005). At the same time, system-level innovations were often associated with (often temporary) reintegration of modular elements to facilitate technologies

7. While strong performers adopting TPS realized inventory-to-sales reductions, weaker performers saw an increase in their ratio of inventory to sales (Swamidass 2007).

that affected characteristics across modular boundaries. The integrated circuit, a key innovation in microprocessors that enabled technology across the US economy (Bresnahan and Trajtenberg 1995), was itself an integration of components (Moore 1965); other components, such as lasers, saw continuing integration during the twentieth and twenty-first centuries (Liu et al. 2007). Drawing on industries such as computer hardware and other electronics, academics hypothesized a dynamic of modularity, and integration in contrast, increasing and decreasing apace with technological shifts (Chesbrough 2003).

Organizational innovations and production technologies continue to evolve in the twenty-first century. Though lean and flexible approaches have become prominent trends in manufacturing, the American system of mass production continues in new permutations, as does the development of new automation and information technologies that hold potential to transform the nature of work (Bartel, Ichniowski, and Shaw 2007; Mindell 2015). Automation has begun to include collaborative dimensions, bringing workers into direct production roles supported by robots (Cherubini et al. 2016; Kaber and Endsley 2004). However, collaborative robots are in their infancy and are unlikely to be appropriate in all settings (Hayes and Scassellati 2013). Additive manufacturing approaches present new possibilities for small batch, high variety production with the promise of mass customization in such industries as food, metals, and plastics (Atzeni and Salmi 2012; Fralix 2001; Herrigel 2010; Mellor, Hao, and Zhang 2014) and material savings complementary to lean manufacturing approaches. That said, additive manufacturing is likely to be limited, at least in the near term, in the complexity of components that it can build and the degree of economically feasible customization that it enables, limiting its appropriateness in a wide range of contexts (Bonnín-Roca et al. 2017a). Through all these changes, large scale, mechanized systems with intellectual roots in nineteenth- and even eighteenth-century US manufacturing continue to play a major role informed by subsequent innovations (Achillas et al. 2015; Hu 2013; Kumar and Ando 2010).

1.3 Manufacturing Value Added and R&D

Global measurements of manufacturing value added and R&D offer an important birds-eye perspective on the US and world economies.

1.3.1 US and Global Value Added

Value added is the amount (in our data, dollars) contributed by an entity to the value of a good or service (US Census Bureau 2018). Value added thus comes from the changes made to an intermediate good or service (the price minus all inputs). While value added is a useful economic indicator, in that it isolates an individual firm or nation's contribution in the global supply chain, it has several limitations. First, market power can affect prices of goods, which can then affect the measurement of value added. Second, our global manufacturing value added statistics are from the World Bank Database. The World Bank measures of value added come from its national accounts data. As not all national accounts are handled in the same way, cross-country comparisons are imprecise. The World Bank lacks gross (and thus nonmanufacturing sector) value added data for many countries, including China. We therefore limit our international comparisons of gross value added across all sectors to Appendix A (this section includes international comparisons of manufacturing value added only).[8] The World Bank data on MVA includes more countries, although notably the World Bank only starts including China as of 2004. Our US domestic value added data by sector thus comes from the Bureau of Economic Analysis (BEA). The BEA’s data collection on value added by industry follows the North American Industry Classification System (NAICS) codes, whereas the World Bank’s data collection across countries follows the International Standard Industrial Classification (ISIC) codes.[9] These sector classification differences in part explain the numerical differences between figure 1.1 (World Bank) and figure 1.2 (BEA).

The US has seen a decline in its global share of MVA since 2000. While US MVA grew in real terms (indeed, at a higher rate than the growth of key manufacturing countries, such as Germany or Japan), it did not outpace the overall growth of the rest of the world. In particular, the US decline in global share of MVA is due in large part to the significant rise in China’s MVA, leaving the US with a reduced share.

US manufacturing has seen a decline in its share of US value added (Bureau of Economic Analysis 2019). While manufacturing value added stagnated in real terms in 1997–2015, other sectors, such as services, grew. Thus, the relative role of manufacturing in the overall value added of the economy decreased (see figure 1.2). Outside of services, manufacturing, and information (reported in figure 1.2), the largest nongovernmental sectors by

8. The United States has seen growth in its GVA over the past 25 years, and modest growth in its share of world GVA from 2011 to 2016 after a year-on-year decline since 2001 (World Bank 2019). The US share of GVA is likely less than reported by the World Bank and perhaps is declining more sharply due to growth in unmeasured nations.

9. Moreover, the World Bank has changed which versions of the ISIC codes it uses, with data up to 2008 reflecting Revision 2 and a shift toward ISIC Revision 3 thereafter. After 2008, however, some international comparative data continue to follow ISIC Revision 2, and the World Bank notes that it attempts to reconcile these with its Revision 3 standard. The ISIC Revision 2 system did not break out manufacturing by industry or subsector, and this rougher classification likely resulted in the discrepancies between World Bank and BEA values for US MVA that are observable in figures 1.1 and 1.2. Even the ISIC Revision 3 codes differ slightly from the NAICS categorization and could result in further discrepancies. For example, ISIC Revision 3 includes recycling (absent from NAICs) but no category for “miscellaneous manufacturing” (NAICS 339). We thus reserve World Bank data for rough international comparisons of manufacturing and do not attempt a subsectoral international comparison.

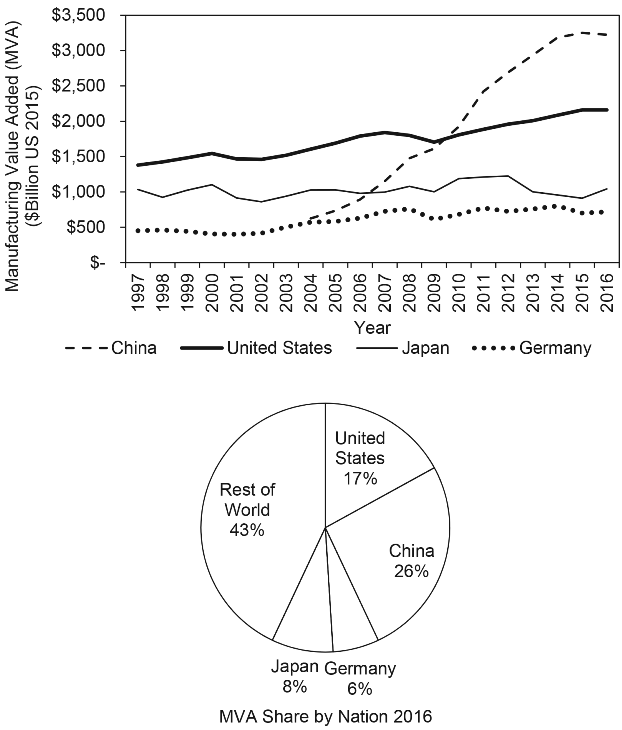


Fig. 1.1 Global manufacturing value added of top four manufacturing nations, 1997–2016

value added are finance (21 percent) and retail and wholesale trade (10 percent). Though the greatest proportional growth in 1997–2015 was in mining (89 percent increase in value added 1997–2015), the largest real growth was in services and finance, with manufacturing among the slowest growing sectors proportionately and in real terms (Bureau of Economic Analysis 2019).

In short, the manufacturing industry in the US offers an undersized—and shrinking—contribution to domestic value added.

1.3.2 US and Global R&D Spending

Our data on global industrial R&D spending is based on the OECD Science, Technology and Patents Database.[10] The OECD database consists of the OECD nations and 28 nonmember countries (including all countries

10. International R&D spending statistics are collected by the European Union and the OECD. The European Union's World Input Output Database (WIOD) covers the 28 EU countries and 15 other major countries, including the US and China. However, the WIOD database lacks detailed breakouts of the sources of R&D spending, such as industry and government.

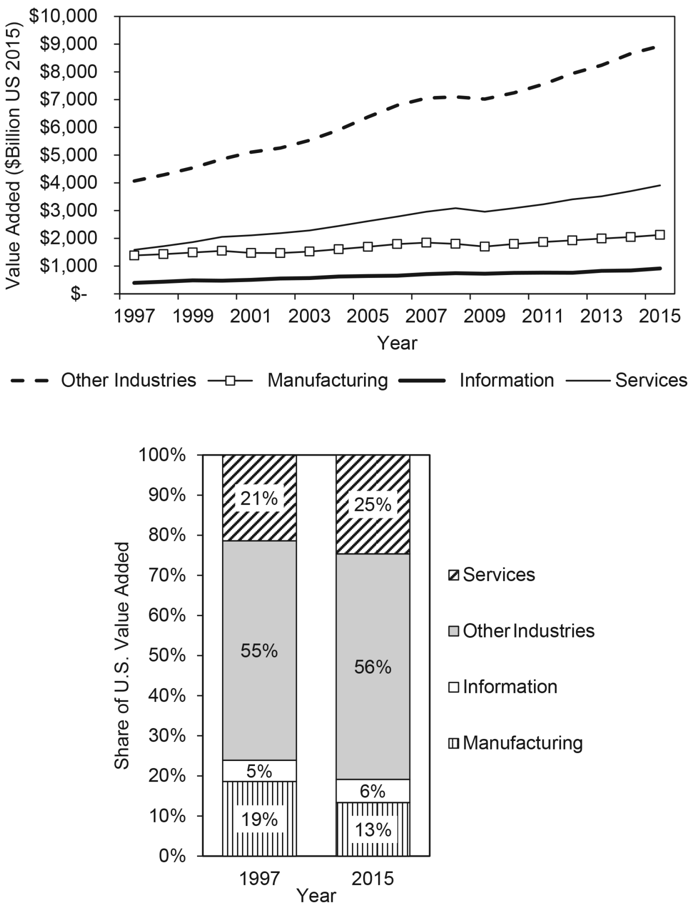


Fig. 1.2 US domestic value added, by sector
Source: Bureau of Economic Analysis (2019).

in the G20), with data covering the US, China, and some other nations beginning in 2008 only. While the OECD data does not include sectoral-level data, it captures industrial R&D activity in each nation distinctly from government spending for each sector (including manufacturing).[11] Similar to value added, the OECD database on R&D spending has limitations for cross-country comparisons: While the National Science Foundation (NSF), on which OECD bases its US R&D calculations, excludes historical and other nonscientific research, the definition of R&D used by OECD in tabu-

11. Internationally, federal R&D spending is a greater share of expenditure relative to industrial spending than it is in the United States.

lating the R&D spending of EU nations and possibly others in the database includes a broader set of cultural and historical research.[12]

For sectoral level comparisons of industrial R&D spending in the US, we use the NSF Science and Technology Indicator data.[13] The OECD data are submitted by nations following the Frascati Manual (OECD 2015): for each nation, these data report all spending on R&D by establishments in a focus country's borders (regardless of the country in which those establishments have their headquarters), combined with the R&D spending of foreign subsidiaries not within the focus country's borders, but whose parent company is headquartered in the focus country.[14] While the NSF also reports these values (referred to by NSF as "US world-wide R&D spending," and which match OECD's numbers), as our focus in later sections is on R&D spending by business establishments located in the US, we use NSF's (smaller) US domestic industrial R&D values rather than the worldwide spending. As can be seen in comparing figures 1.3 and 1.4, the difference between the NSF's US world-wide R&D spending (as used in the OECD global industrial R&D spending data) and the NSF US domestic industrial R&D spending in 2015 was about $50 billion or 21 percent.

Under OECD's measurement, Chinese establishments and Chinese-owned subsidiaries account for the most R&D spending internationally. While US manufacturing R&D has increased since 1980s, growth has stagnated since 2008. The same trends are true in Japan and Germany (the nations with the third and fourth greatest R&D spending by manufacturing business establishments located within them). In contrast, R&D expenditures by manufacturing business establishments located in China have more than doubled in the same period, exceeding spending in the US in 2013 (OECD 2019).[15] Figure 1.3 captures these trends in R&D spending by

12. The OECD (2015) definition of R&D is: "Research and development (**R&D**) comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge (including knowledge of man, culture and society) and the use of this knowledge to devise new applications."

13. Historic NSF R&D indicators classify firms into industries and sectors based on the industry that receives the plurality of R&D funding for the firm. Although more recent NSF work (NSF 2019) has sought to classify R&D indicators based on the revenue sources of firms, we focus in this chapter on the historic data.

14. It is thus possible for international aggregate statistics to double-count R&D spending when the country in which a multinational enterprise in headquartered counts the R&D spending of that enterprise's foreign affiliates, and the country where those affiliates are located also counts the R&D spending of those affiliates.

15. While offering the most complete international data on R&D spending by nation and industry, the OECD Science, Technology and Patents Database is based on a different definition of R&D spending from that used by the US government (and OECD notes that US R&D inputs to its database are based on a different definition). OECD's R&D "comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge (including knowledge of man, culture and society) and the use of this knowledge to devise new applications." The inclusion of social sciences expands the scope of relevant R&D activity outside that used in the US and thus may understate the level of non-social science R&D spending in the US relative to other countries.

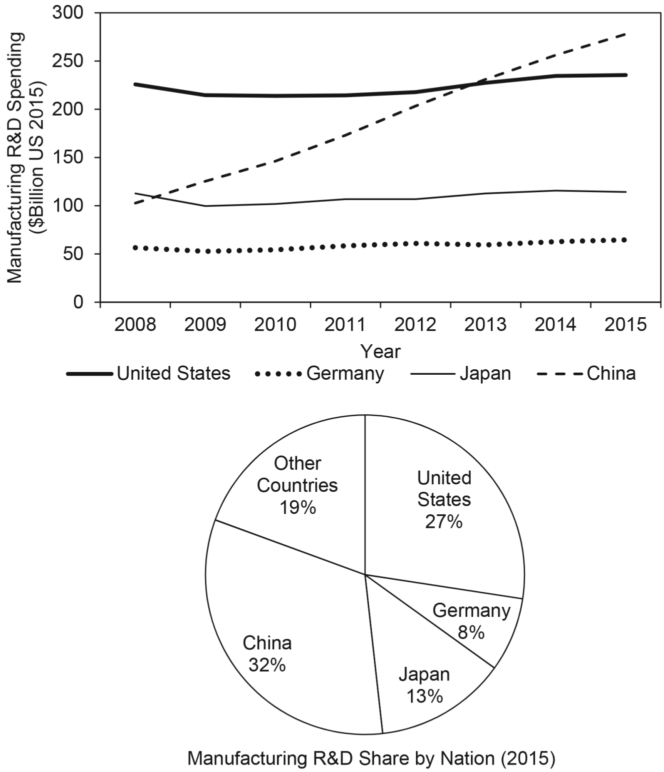


Fig. 1.3 Expenditures on manufacturing R&D by business establishments located in a country, top four nations

Source: OECD (2019).

Note: Other countries are OECD nations + Taiwan + Argentina + Romania.

manufacturing business enterprises in key nations. The named countries' shares of global R&D activity by manufacturing business enterprises are overstated in the figure, because the dataset for 2015 (the latest available year with broad, reliable international data) includes data from China, the US, Japan, Germany, the OECD nations, Taiwan, Argentina, and Romania, but not the rest of the world.

Among the nations captured by the OECD data (OECD Nations and China, Taiwan, Argentina, and Romania), 72 percent of industrial R&D expenditures recorded by OECD were in manufacturing. In China, that share was 88 percent, while in OECD's figures, the share of US industrial R&D expenditure in manufacturing was only 66 percent. That is, the US spends proportionally less on manufacturing R&D than do OECD members and other nations.

Between 1982 and 2015, the US rate of federal R&D funding declined as a relative share of total R&D funding (National Science Foundation n.d., American Association for the Advancement of Science 2019), with industrial R&D funding growing relative to federal funding over the same period (see appendix J). Industrial and federal R&D show significant differences in the funding of basic versus applied research: while 30–36 percent of overall federal funding was allocated to basic research during 2006–2015, in 2015 only 5.5 percent of industry R&D spending was directed toward basic research, the rest going to applied research and development.[16] Arora, Belenzon, and Patacconi (2015) show declining R&D spending and capability-building by US companies in basic research. Fleming et al. (2019) suggest that companies are increasingly relying on federally supported research.

In the US, manufacturing remains the dominant source of industrial R&D. Industrial R&D spending originating from manufacturing grew significantly in real terms during 1982–2015 (National Science Foundation n.d.). However, after 1997, this growth in manufacturing R&D was accompanied by growth in R&D spending from other sectors, including services and information, such that the overall share of industrial R&D spending from manufacturing has actually declined (see figure 1.4).

In short, R&D spending by manufacturing sector business establishments located in the US continues to dominate US-based industrial R&D spending, far outstripping that spent by other sectors. This dominance is in stark contrast to manufacturing's comparatively small role in contributing to US value added.

1.4 The US Manufacturing Labor Force

The IPUMS Current Population Survey Annual Social and Economic Complement microdata from 1968 to 2018 reveal differences between the US manufacturing and nonmanufacturing labor force along several demographic dimensions, including educational attainment, age, gender, and wage and salary income groups.[17] Figure 1.5 shows the magnitude of the labor force each year in manufacturing and nonmanufacturing; during this period, growth in the US labor force has come entirely from the nonmanufacturing sector, with a reduced manufacturing labor force post-1981.

1.4.1 Human Capital and Demographics of the Labor Force

Educational attainment, as measured by years of formal education, has risen for the overall labor force, manufacturing sector, and manufacturing subsectors. Across the economy, the proportion of workers with a high school (HS) education or less has declined across the past five decades. Ber-

16. Federal funds to industry were also disproportionately allocated to applied R&D, with 8 percent of funds going to basic research.

17. Each individual observation in the data is weighted by the Annual Social and Economic Complement population weight.

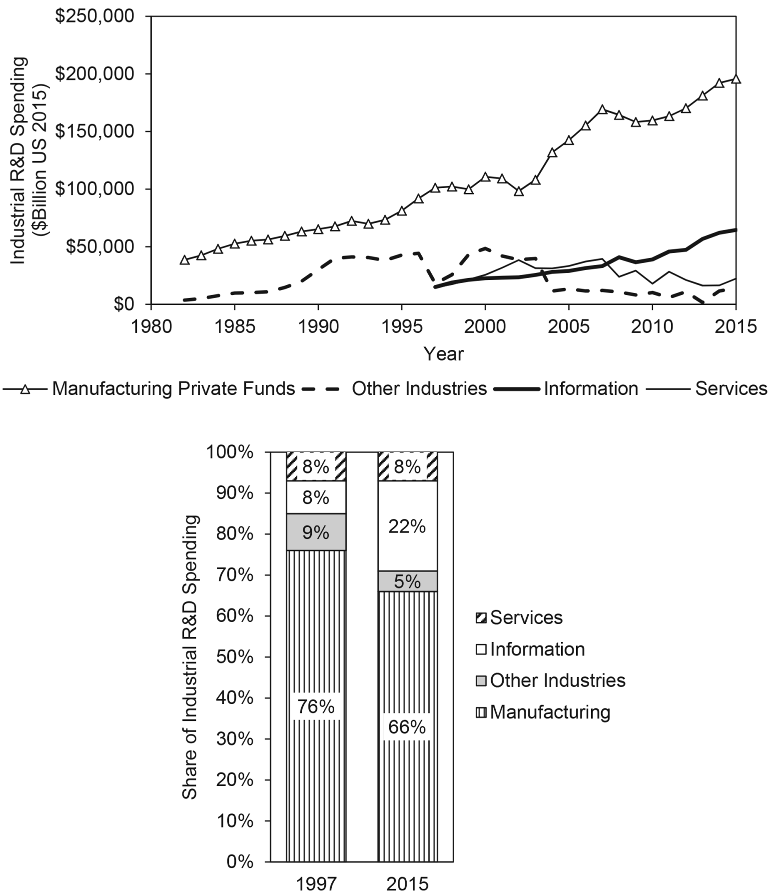


Fig. 1.4 US industrial R&D spending, by sector

Source: National Science Foundation (n.d.).

Note: While manufacturing and overall R&D data extend to 1982, we use 1997 as a basis of comparison, because it is the first year for which information and service data are available.

man, Bound, and Griliches (1994) argue that labor-saving technological change is the leading cause of this trend. Berman, Bound, and Machin (1998) find further international evidence of manufacturers increasing demand for skilled workers and increasing skill premiums, in line with the skill-biased technological change hypothesis.

However, the manufacturing sector still provides many jobs for workers with less education, especially in contrast with other sectors. As can be seen in figure 1.6, the manufacturing sector (solid line) consistently has a higher proportion of workers with a HS education or less relative to nonmanufacturing sectors (dashed line); each year, the manufacturing labor force has

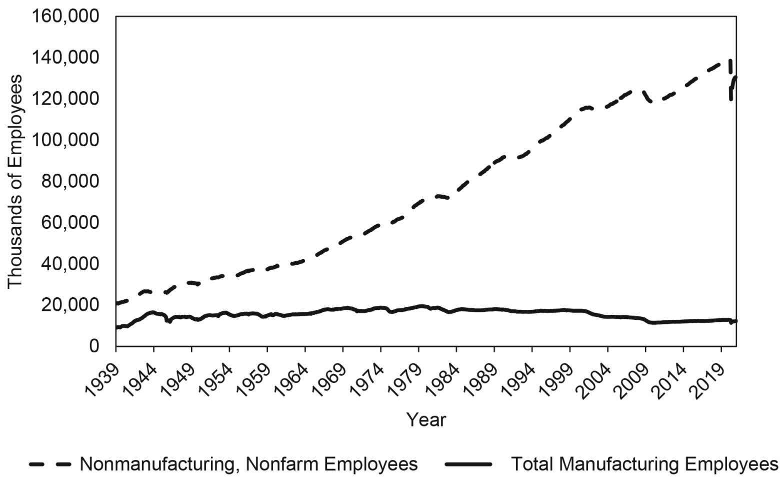


Fig. 1.5 Absolute magnitude of the US nonmanufacturing and manufacturing labor force

Source: St. Louis Fed.

Note: In this figure, 2014 is omitted to allow for use of consistent weighting by the ASEC population weight, as the CPS underwent an experimental redesign.

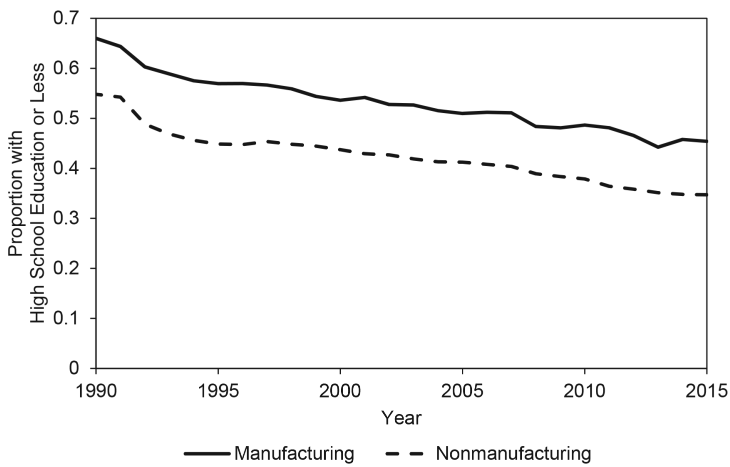


Fig. 1.6 Manufacturing and nonmanufacturing labor force educational attainment exhibiting a consistent difference

Source: IPUMS-CPS ASEC microdata (1990–2015).

8–12 percentage points more workers with HS education or less relative to the nonmanufacturing sector.

The manufacturing industry's labor force has remained nearly completely private wage or salary workers: 98 percent in 1975 and 95 percent in 2015. The proportion of the manufacturing labor force earning less than $10,000

(2017 dollars) remains less than the proportion of the nonmanufacturing labor force (8 percent manufacturing, 19 percent nonmanufacturing). The proportion of the manufacturing labor force whose earnings fall between $10,000 and $250,000 is also higher than the nonmanufacturing labor force (91 percent manufacturing, 81 percent nonmanufacturing).

1.5 Manufacturing Share of Value Added and Share of R&D Funding

1.5.1 Disproportionate R&D Funding from Manufacturing Relative to MVA

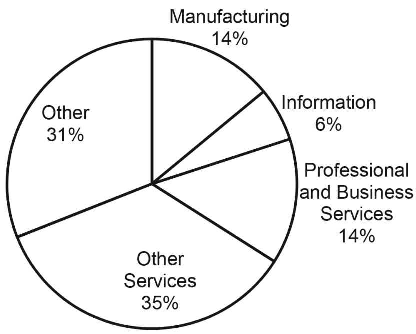
As described in sections 1.1 and 1.3, manufacturing historically and currently makes up a disproportionate source of industrial R&D funding in the US: about 96 percent in 1982 and about 66 percent in 2015. Though shrinking proportionally, R&D funds from manufacturing grew in real terms by 197 percent in the same period. Manufacturing represents a much smaller proportion of US nongovernmental value added (14 percent), and manufacturing's proportion of value added has been declining since 1997 (the earliest available BEA data), when MVA share of total value added stood at 19 percent. At that time, the manufacturing share of industrial R&D spending was 76 percent. With a proportional decline in R&D share of 13 percent and a proportional decline of MVA share of 26 percent since 1997, the proportional difference between manufacturing subsector's contribution to US R&D spending and to value added has been growing. As can be seen in figure 1.7, this difference between a sector's contribution to US industrial R&D spending versus a sector's contribution to US value added, while most pronounced in manufacturing, is not unique to the sector. For example, the information sector comprises 22 percent of US industrial R&D spending but 6 percent of US value added. In contrast, professional, scientific, and technical services comprise 7 percent of US industrial R&D spending but a much larger percentage of US value added. Uncovering the sources of these differences in other sectors is outside the scope of this chapter but is an important broader phenomena to unpack in the US economy.[18]

1.5.2 Hypotheses, Evaluation, and a Partial Explanation

We propose and evaluate three hypotheses for what might in part account for the disproportionate share of US industrial R&D spending from manufacturing: (1) Other sectors of the economy underreport their R&D spend-

18. More recent work by NSF (2019) has sought to reclassify R&D spending based on the dominant revenue source of a firm, rather than on the dominant industry focus of its R&D. This approach suggests that about 40 percent of industrial R&D performance occurs in firms whose primary revenue source is manufacturing. This figure is less than the 66 percent of industrial R&D spending with a manufacturing focus but remains much greater than the share of manufacturing in US value added. We choose to focus on industrial R&D spending by sector of spending rather than by revenue stream, as our interest is in manufacturing as a destination of R&D activity.

A. US Value Added (Nongovernment)



B. US Industrial R&D Spending

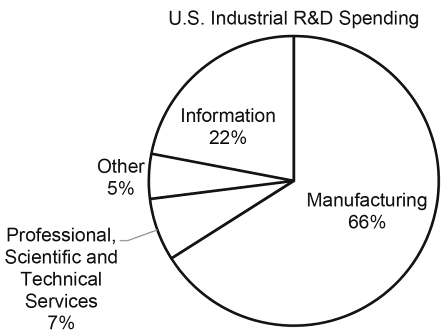


Fig. 1.7 Share of value added and industrial R&D spending by sector, 2015

Source: A: BEA: *The Use of Commodities by Industries.* B: NSF.

Note: Professional and Business Services includes Professional, Scientific and Technical Services.

ing, possibly due to incentives in the R&D tax credits available under the US tax code or because research activities that are not performed through traditional R&D channels are not counted by NSF. (2) The returns from manufacturing R&D accrue to nonmanufacturing sectors, for instance, through R&D embodied in manufactured capital or through the development of general-purpose technologies (GPTs) using manufacturing R&D funds. (3) The returns to domestic manufacturing R&D are realized abroad, for instance, by multinational firms, and thus are not reflected in value added statistics from US manufacturing. Our ingoing hypothesis was that all three hypotheses could be acting simultaneously.

We do not find strong evidence to support our first two hypotheses. We briefly discuss our conclusions regarding hypotheses 1 and 2 here, and provide the details of our explorations of the first two hypotheses in appendix K. We present our findings regarding hypothesis 3 in greater depth in the next section.

For hypothesis 1, we were not able to find clear incentives for other sectors of the economy to underreport their R&D spending under the US Research and Development Tax Credit. We find that personnel expenditures and, in small firms, payroll taxes, can be offset by R&D tax credits, suggesting that there are strong incentives for software and other technology firms to report their R&D activities. Firms may in fact have less incentive to report the capital-intensive R&D activities more common to manufacturing, because the credit excludes spending on fixed capital. We also find that one possible form of R&D spending not counted by the NSF, venture capital (VC) funding, is disproportionately directed toward sectors other than manufacturing. That said, even counting all VC funding as a form of R&D spending still leaves manufacturing the majority source of industrial R&D spending (although at this extreme only by a very small margin). It is important to note that the definition of R&D used both in NSF's data collection and for the R&D Tax Credit does not include the development of internal capabilities or of incremental product improvements. For example, there is significant patenting in finance (Lerner et al. 2020) and software (Branstetter et al. 2019), but some of those patents are, for example, for new algorithms consumed internally by the firm. Manufacturing also has cases where firms develop, for example, their own equipment for internal use. These activities would not count as R&D according to NSF's definition. Future work is needed to unpack whether such internal R&D expenditures are more significant in some sectors than in others.

Hypothesis 2 proposes that the disproportionate share of US industrial R&D from manufacturing is in part due to the returns from manufacturing R&D accruing to nonmanufacturing sectors, for instance, through R&D embodied in manufactured capital or through the development of general-purpose technologies (GPTs) using manufacturing R&D funds. We do not find evidence to support an outsized role for manufacturing in producing capital that embodies R&D. Leveraging the World Input-Output Database (WIOD), we conduct a rudimentary regression analysis of output and value added of other sectors on intensity-adjusted R&D stock from manufacturing subsectors (described in detail in appendix K.2). Preliminary evidence based on the rudimentary regression instead suggest that the magnitude of embodiment may be greater for nonmanufacturing sectors, such as information. We also do not find any preliminary evidence to support GPT as a primary explanation for the outsized role of manufacturing overall. A GPT is defined as having (1) general applicability (i.e., it performs some generic function vital to the functioning of a large number of products or processes that use it); (2) technology dynamism (i.e., continuous innovation over time improves the efficiency with which the general function is performed, benefiting existing users and prompting further sectors to adopt the GPT);

and (3) innovation complementarities (i.e., technology advances in the GPT make it more profitable for users to innovate in their own technologies) (Rosenberg and Trajtenberg 2004). We do not find any association between value added in nonmanufacturing sectors and their manufacturing inputs. We do not do a sufficient test to track whether innovation in one sector leads to innovation in another sector. GPT dynamics have clearly been a significant part of the story historically in some sectors, such as microprocessors (Jorgenson 2001).[19]

1.5.2.1 MVA Returns Abroad: A Partial Solution to the Puzzle

In this section, we examine the hypothesis that returns to domestic manufacturing R&D are realized abroad and therefore are not reflected in value added statistics that are bounded by country borders (hypothesis 3). We do so by looking at the activities of US multinational companies (MNCs) in the US and at their foreign affiliates, using publicly available BEA data from the US Direct Investment Abroad surveys (Bureau of Economic Analysis 2019). Statistics on value added and R&D performed in the US exclude the foreign affiliate activities of multinational firms and may hide some significant activity undertaken by these firms. The focus on multinational firms is especially significant given their disproportionate role in performing R&D; the National Center for Science and Engineering Statistics[20] reports that US multinational companies performed 79 percent of all R&D conducted by US-located businesses.

Figure 1.8 illustrates that concentrating attention on US MNCs—and including all their global activity—significantly shrinks the gap between value added and R&D performed for manufacturing firms vs. nonmanufacturing firms. Panel A is a bar graph representation of the pie chart from figure 1.7 and shows the original motivating puzzle: manufacturing firms contribute disproportionately to R&D, and yet very little value added results from this. Panel B focuses attention on US multinational firms and—importantly—includes both the parent activities and the foreign affiliate activities. By concentrating attention on MNCs—and their global activity—the gap between value added and R&D for manufacturing firms compared to nonmanufacturing firms shrinks significantly.

Figure 1.9 provides some insight into why the gap shrinks so much when looking at MNC global activity rather than domestic activity alone: a larger share of value added is abroad compared to R&D, which is highly concentrated in the US.

The picture becomes even more clear when we take this one step further

19. Jorgenson's (2001) approach is a technology-specific analysis of quality improvements in information technology relative to pricing, which then informs a model of the production possibility frontier of the US economy and its shifts relative to the quality of IT equipment. We were unable to replicate this detailed analysis for goods and services throughout manufacturing.

20. Moris (2016).

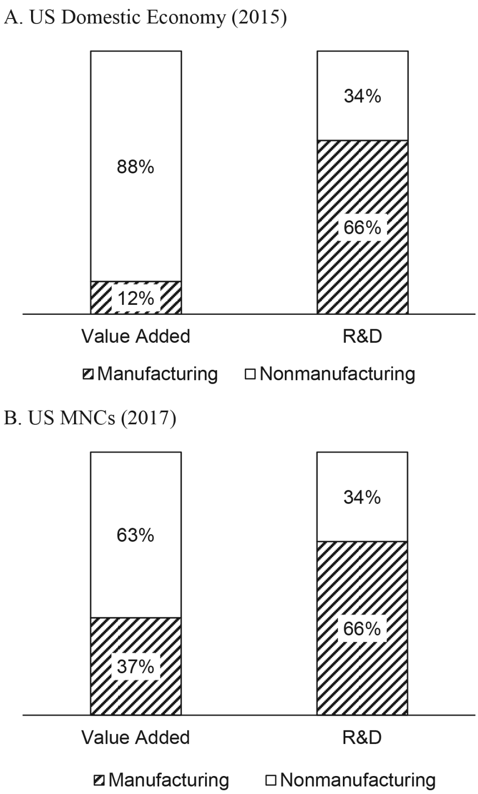


Fig. 1.8 Share of value added and R&D contributed to by manufacturing vs. nonmanufacturing firms
Source: BEA.

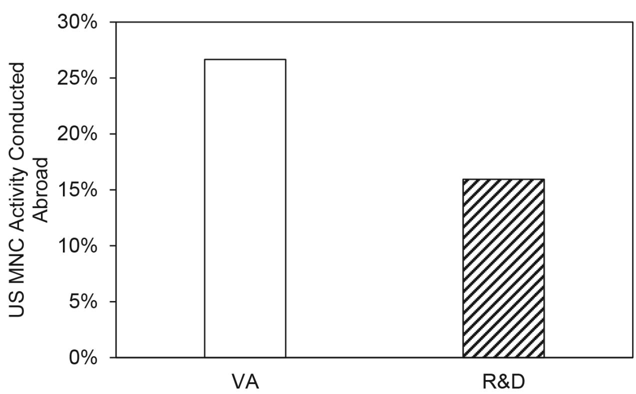


Fig. 1.9 Percentage of US MNC activity conducted abroad in 2017
Source: BEA.

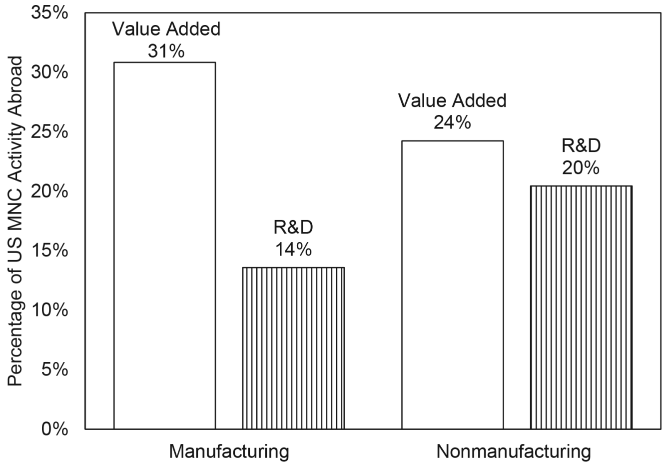


Fig. 1.10 Percentage of US MNC activity conducted abroad in 2017, by sector
Source: BEA.

and consider how US MNCs in the manufacturing sector geographically distribute their value added and R&D activities relative to those in the nonmanufacturing sector. Figure 1.10 illustrates this point: US MNCs in the manufacturing sector do only 14 percent of their R&D activities abroad, while those in the nonmanufacturing sector do 20 percent of their R&D activities abroad, as of 2017. In contrast, they are much likely to have value added abroad; 31 percent of manufacturing value added is at their foreign affiliates, while only 24 percent of nonmanufacturing value added is at their foreign affiliates.

The above data support our hypothesis and suggest that a significant part of the gap between manufacturing's share of R&D spending and their realization in value added can be explained by recognizing that production is no longer constrained by national borders, while manufacturing R&D—in general terms—is more constrained.

1.5.2.2 R&D Increasingly Moving Abroad, but Less So in Manufacturing

R&D is increasingly moving abroad, especially in services and some manufacturing sectors. Although we document in section 6.2.3 that R&D is more concentrated at home than production is, when explaining the differences in manufacturing's contribution to R&D vs. value added in US domestic borders, it is important to recognize that (1) R&D is increasingly moving abroad, and (2) the concentration of R&D at home is only true for some sectors.

As shown in figure 1.11, there has been tremendous growth—in real terms—of foreign R&D. Since the late 1990s, the amount of R&D conducted overseas by US MNCs has grown nearly fourfold.

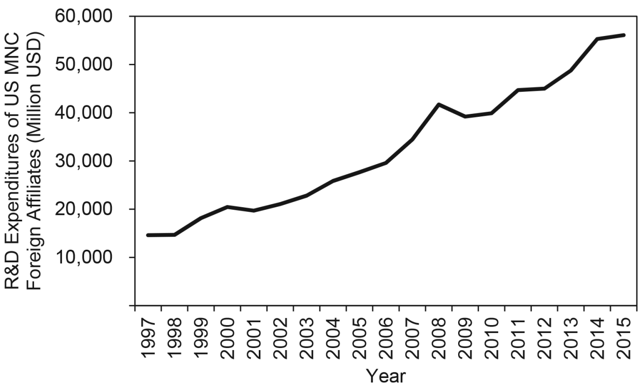


Fig. 1.11 R&D expenditures of US MNC foreign affiliates (millions USD)
Source: BEA.

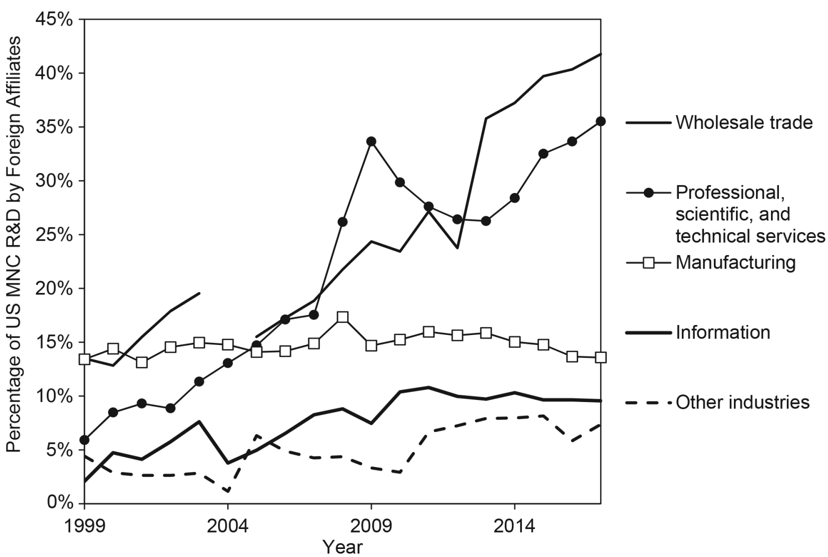


Fig. 1.12 Percentage of R&D conducted at foreign affiliates, by sector
Source: BEA.

Figure 1.12 and figure 1.13 illustrate that the expansion abroad has largely been driven by nonmanufacturing sectors. In particular, the services sector—and especially the professional, scientific, and technical services sector—has dramatically increased the amount of R&D conducted at foreign affiliates rather than at the US parent company location. In contrast, at the aggregate level, the manufacturing industry as a whole has continued to keep the vast majority of its R&D at home.

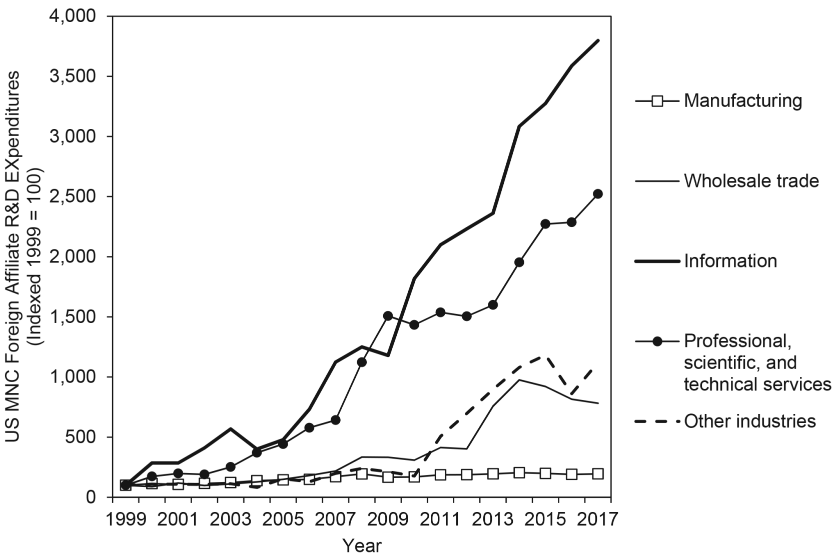


Fig. 1.13 R&D expenditures by US MNC foreign affiliates, by industry of foreign affiliate, indexed (1999 = 100)

Source: BEA.

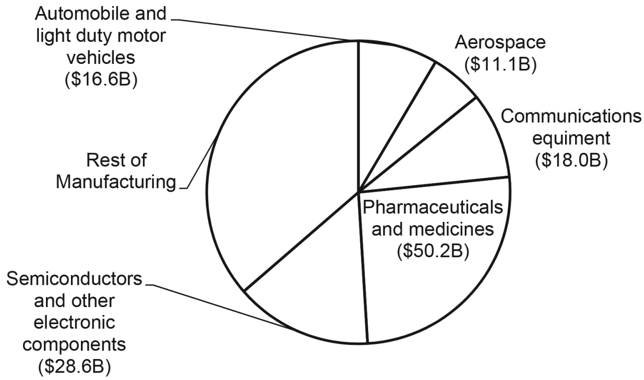
1.6 Manufacturing Subsectoral Variations in the Concentration of Value Added, R&D Funding, Employment, and Revenue

Today, the US manufacturing sector is composed of industries that vary in the level of spending that they dedicate to R&D, with key industries representing dominant sources of current investment. The disproportionate role of manufacturing in R&D activity becomes starker when considering the top five manufacturing subsectors by R&D spending. These subsectors contributed 42 percent of US industrial R&D Spending in 2015 (National Science Foundation n.d.), despite representing only 18 percent of manufacturing value added and thus 2.1 percent of total value added in the economy (Bureau of Economic Analysis 2019; US Census Bureau 2018). The role of these key subsectors offers further insight into the puzzle of outsized manufacturing R&D spending versus value added.

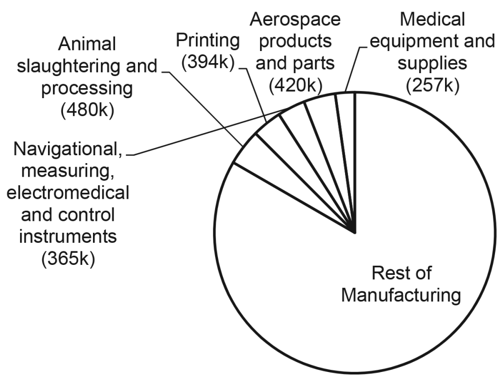
In contrast to manufacturing industrial R&D spending, MVA is not dominated by any core sector or sectors, nor are the top subsectors necessarily the largest by R&D spending. Appendix L shows the share of total MVA by the top five subsectors by MVA and by industrial R&D spending.

Figure 1.14 illustrates the concentration of R&D spending, employment, and value added in the manufacturing sector by four-digit NAICS subsector. As the figure illustrates, the industries that provide the most funding for industrial R&D are not necessarily the largest employers or sources of value

A. Industry R&D Spending ($Billion), NSF, Top 5 Industries



B. Industry Employment (thousands), ASM, Top 5 Industries



C. Industry Receipt ($Billion), ASM, Top 5 Industries

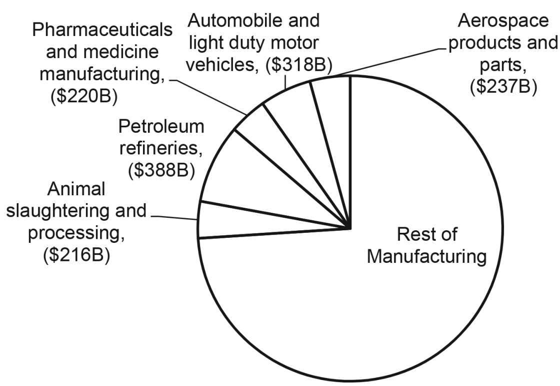


Fig. 1.14 Concentration of R&D spending, employment, and value added in manufacturing, 2015

added. Pharmaceuticals rank as the top R&D spending industry and the top source of value added, while animal slaughtering is the top employer. Only aerospace overlaps the top five ranking for all three indicators. The largest industries by value added include only two of the five largest by R&D funding (pharmaceuticals and aerospace) and only one of the largest by employment (aerospace).

The pharmaceutical industry leads manufacturing R&D spending with 26 percent of the total, followed by semiconductors and electronic components with 15 percent of the total and communications, automobile and aerospace manufacturing contributing a cumulative 23 percent, for a total of 64 percent of Industry R&D funded by the top five industries. The gap between pharmaceuticals and medicines and the next largest subsector by R&D spending, semiconductors and other electronic components, is just over twice the gap between the second and third largest industries. Thus, not only are the largest five sectors by R&D spending disproportionately dominant, but the concentration continues to scale within the top five.

Employment and value added show a wider dispersion across manufacturing industries. The five largest manufacturing industries by revenue make up 24 percent of total manufacturing revenue, while the five industries with the highest employment represent 15 percent of total employment. While the pharmaceutical industry is a major source of R&D funding, it does not solely drive the disproportionate concentration of R&D funding among type funds: even without pharmaceuticals, the next four industries account for 38 percent of R&D spending by manufacturing, more than half again the concentration of employment or revenue among top five sectors and more than twice the concentration among the second through fifth place sectors.

The top five manufacturing industries by R&D funding are consistent from 1994[21] to the latest NSF data by sector in 2015. Figure 1.15 illustrates that while the overall composition was consistent, the relative positions of top industries by R&D funding evolved over this period. The automotive industry, which ranked fourth for R&D funding in 2015, was the largest manufacturing funder of R&D from 1994 to 2003, with pharmaceuticals and medicines dominating from 2004 to 2015. While pharmaceuticals and semiconductors grew in R&D funding after 2004, aerospace, automotive, and communications equipment manufacturing appeared to largely stagnate or decline throughout the period, except for modest growth in communications R&D funding after 2011. The relative composition of R&D funding in manufacturing has shifted over the 2004–2015 period, with the bottom three industries remaining fairly close to one another in level of funding

21. The NSF annual reports on "Research and Development in Industry" include annual data extending back to 1982, but classification shifts from the 1993 to 1994 reports limit comparisons before 1994: the composition of the top five sectors may have changed prior to 1994, but comparison is infeasible before and after the reclassifications.

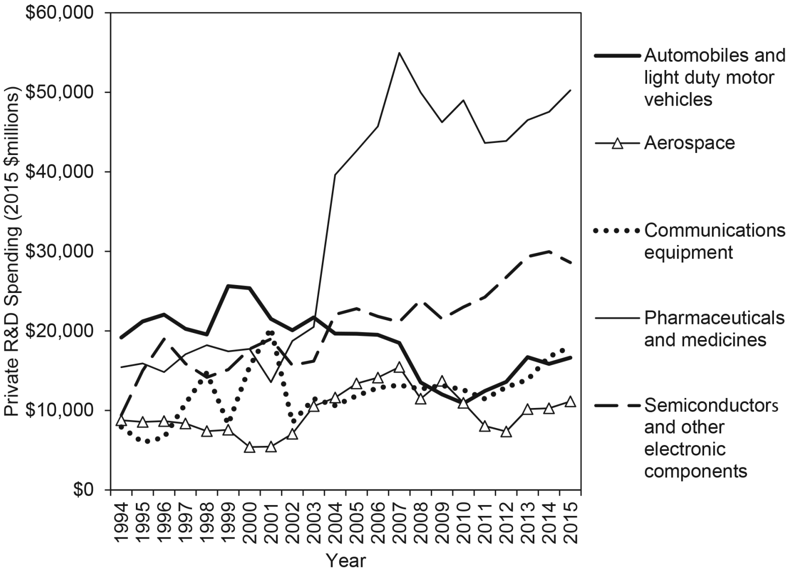


Fig. 1.15 Industrial R&D funding by top five R&D funders in manufacturing, 1994–2015 (NSF)

and a growing gap between both the top and bottom three and between pharmaceuticals and semiconductors.

1.7 Subsectoral Nuances in the Offshore Realization of Manufacturing R&D Returns

1.7.1 Globalization of MVA and R&D Subsector Story

To better understand the dichotomy between MVA and industrial R&D spending, we looked at the changes in share of intermediates imported for the subsectors in the ISIC classification that most closely correspond to the manufacturing subsectors under NAICS with the top industrial R&D spending.[22] While US manufacturing overall saw a 10 percent increase in the share of intermediates imported from 2005 to 2014 (the latest available data from WIOD), the manufacturing subsectors with the highest industrial R&D spending experienced far greater shifts in their share of intermediate inputs imported than did manufacturing overall (see figure 1.16). Motor vehicles and machinery had nearly double an increase in their share of inter-

22. While some research (e.g., Los, Timmer, and de Vries 2015) has imputed value added from the input-output data of the WIOD, sectoral and gross national value added data are not collected for all countries in the WIOD, and available measures of input and output by national industry or sectors may overstate value added by omitting inputs from countries in the database.

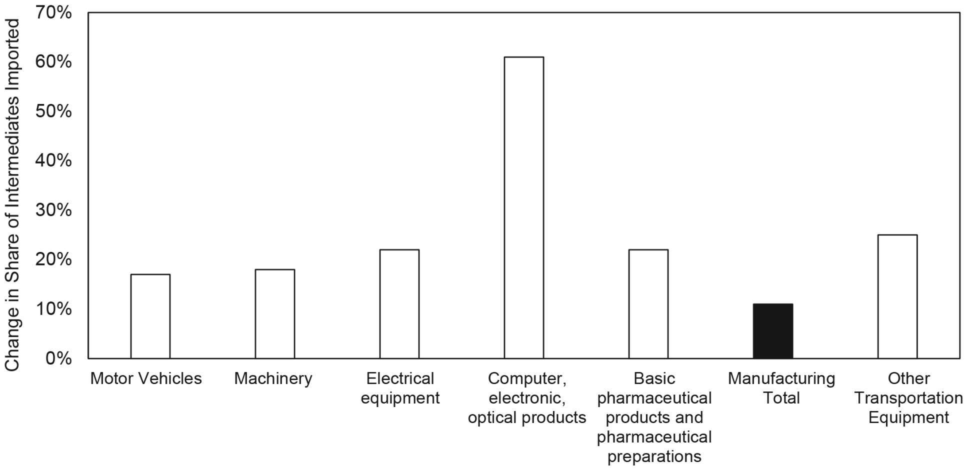


Fig. 1.16 Manufacturing subsector differences in shifting inputs offshore, 2005–2014

Source: World Input Output Database.

Note: Classification system used is ISIC, not NAICS as in NSF R&D and ASM data.

mediates imported, at 17 percent and 18 percent, respectively, compared to manufacturing on average. The largest industrial R&D spending subsector in manufacturing, pharmaceuticals, saw a 22 percent in its share of intermediate inputs imported between 2005 and 2014. Meanwhile, computer, electronic, and optical products saw a 61 percent increase in the share of intermediates imported. While these R&D-intensive subsectors showed strong increases in importing, further research would be necessary to understand what in these sectors was and was not shifted abroad and why.

Although in aggregate, US MNCs in the manufacturing industry concentrate their R&D activity in the US, figure 1.17 demonstrates the degree to which this varies. Industries like petroleum conduct almost no R&D abroad, while textiles and printing conduct almost a third of their R&D at their foreign affiliates.

In short, while US MNCs continue to concentrate their R&D activity predominately in the US, even as they have expanded production overseas, R&D is increasingly a global activity—particularly in the services sector and some manufacturing sectors.

1.7.2 Globalization of MVA: Labor Subsector Story

The realization of MVA returns abroad in key manufacturing subsectors by R&D spending also aligns with differences in the educational demand of those subsectors relative to the rest of manufacturing. While the overall manufacturing distribution of employment and wages is characterized by higher employment and wages for non-college educated workers (see section 1.4), we show in figure 1.18 that the largest manufacturing subsectors

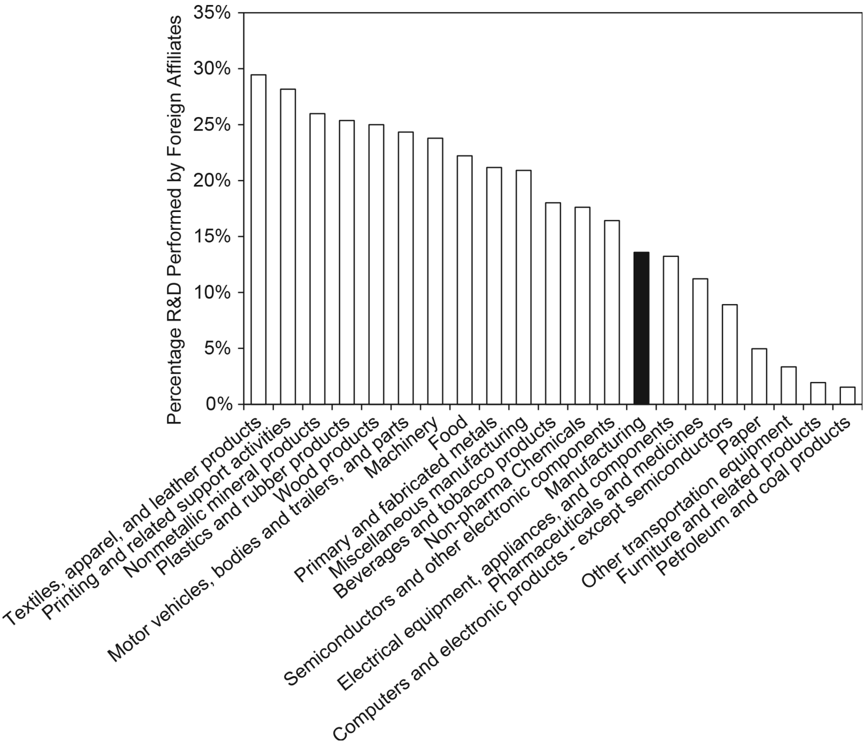


Fig. 1.17 Percentage of R&D performed at US MNCs foreign affiliates, 2017
Source: BEA.

by R&D spending (panel A) tend to skew less toward HS-level employees than the largest subsectors by employment (panel B).[23]

Our findings suggest that the role of manufacturing in R&D spending may be relatively decoupled from the sector's overall labor profile, so that value added gains from R&D may not translate directly into value added or employment growth for HS-intensive subsectors. Of the five largest subsectors by R&D spending, all but motor vehicle manufacturing have proportionally fewer employees with HS education or less than do nonmanufacturing industries. The contrast is especially apparent between high-employment, low-R&D subsectors, such as animal slaughtering and processing, and the high-R&D subsectors. Aerospace, the only subsector in the top five by R&D spending and employment, highlights the potential decoupling of high-R&D spending from HS employment, with a lower proportion of HS employees than manufacturing overall and nonmanufacturing industries.

23. The figure reports on some subsectors at higher levels of aggregation than the NSF data due to imperfections in data cross-walking between the IPUMS database and NAICS classification, but the aggregation occurs across sectors with similar R&D spending and offshoring profiles (e.g., motor vehicles and aerospace).

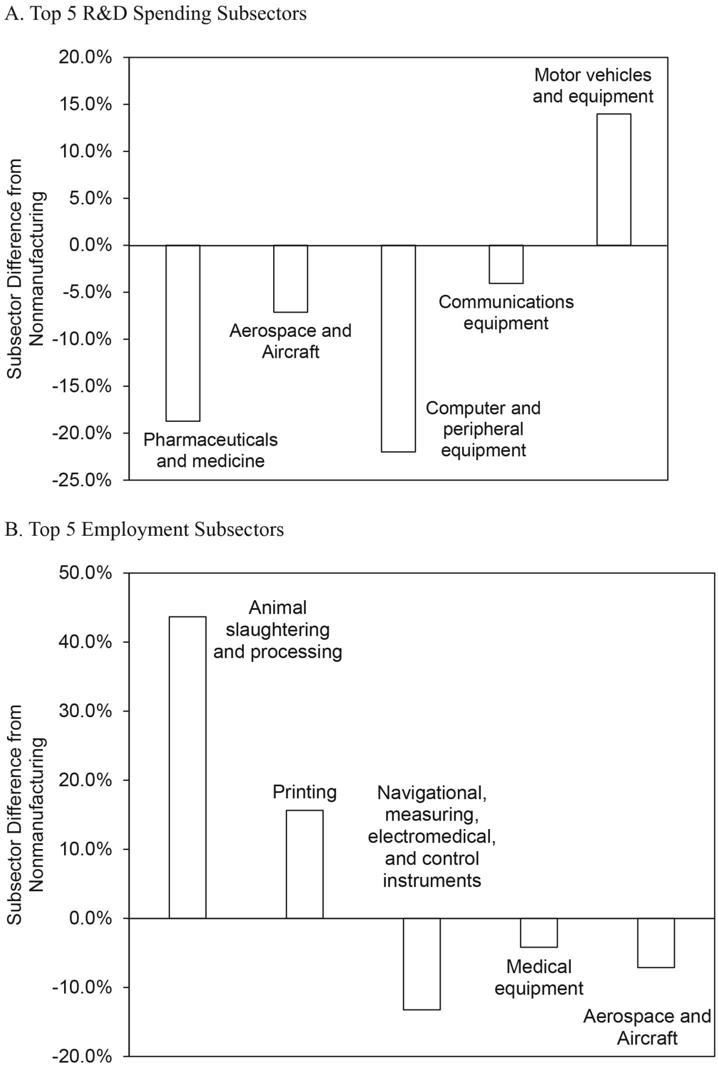


Fig. 1.18 Manufacturing industry differences from share of high-school level employees in nonmanufacturing, 2015

Source: IPUMS-CPS ASEC microdata, 2015.

It is also important to note that significant employment in other sectors (e.g., retail and warehousing services) is connected to the output of manufacturing industries and that innovative effort in manufacturing can have effects along the supply chain. Sectoral and subsectoral boundaries do not fully capture the characteristics (e.g., educational) of workforces, which may be affected by innovations coming out of manufacturing.

1.8 Discussion: Potential Relationships between Manufacturing Location, Innovation, and Labor Outcomes—A Need for Technology Differentiation

1.8.1 The Potential Relationship between Manufacturing and Innovation

Economic theory suggests that shifts in manufacturing away from a nation may hurt wages there, but global innovation and productivity gains will not suffer (Samuelson 2004). However, empirical research suggests that, at least in certain contexts, moving the location of manufacturing can alter whether and which next-generation products are profitable (Fuchs and Kirchain 2010, Fuchs et al. 2011). Production characteristics (wages, yields, downtimes, organization of production) can differ greatly across nations (especially developed and developing ones). In two cases—automobile bodies and high-end optoelectronic components for communications—when US firms shifted production to developing East Asia, differences in these production characteristics meant that products developed in the US based on the most advanced technologies were no longer immediately profitable. The overseas firms stopped producing these products and, in optoelectronics, also stopped innovation (measured as patenting) in the most advanced products in all their locations overseas and in the US (Fuchs and Kirchain 2010; Yang, Nugent, and Fuchs 2016).

Recent work has further underscored the potential negative relationship between overseas activities and innovation. Dorn et al. (2020) find that foreign competition (in the form of import substitution) reduces US innovation. One potential mechanism behind this finding could be cost reductions giving a longer life to older-generation products by raising the barrier for next-generation products to be profitable. We find that while US multinationals in the manufacturing sector have increased their industrial R&D spending proportionally in the US and at foreign locations, as of 2013, the most industrial R&D spending on manufacturing globally is occurring in China. Notably, Branstetter et al. (2018) find—in contrast to software, where a growing number of patents are in developing countries or "new knowledge hubs" (like China)—a disproportionate number of manufacturing patents remain in "old knowledge hubs" (like Germany).[24] It is unclear whether it will just be a matter of time for levels of manufacturing pat-

24. Branstetter et al. (2021) find that the largest fraction of patents in emerging economies is in services, while developed countries continue to do a disproportionate amount of manufacturing patenting. Such results could be suggestive of less manufacturing innovation in developing countries or could reflect the fact that process innovations are dominant in developing countries, and process innovations are less likely to be patented. Patenting by developing countries with high manufacturing value added (in particular, China), is slowly growing in some manufacturing subsectors but not equally across all.

ents in China to catch up to levels of manufacturing value added (China's manufacturing value added superseded that of the US in 2010) and R&D spending (OECD's measure of R&D spending by establishments located in China and Chinese foreign subsidiaries exceeded that of US-based establishments and US foreign subsidiaries), and how that will differ by subsector and technology.

Indeed, more research is needed on the relationship between manufacturing location and innovation, and how that may differ by technological and industrial context. Increased distance, electronic dependence, time zone changes, and national differences all can reduce knowledge flows (Gibson and Gibbs 2006). In certain contexts—particularly, unfamiliar, unstructured problems—problem solving can require physically present experts to recognize embedded clues, exploit specialized tools, and find and interpret relevant information (Tyre and von Hippel 1997). Yang, Nugent, and Fuchs (2016) find that offshoring by US firms to developing East Asia (including producers in Taiwan, Singapore, Malaysia, and Shenzhen) is associated with fewer patents in the most advanced products by the firms, but more patents in other technological areas likely to be related to general production. Branstetter et al. (2021), exploiting a policy shock in Taiwan that allowed Taiwan's electronic and IT firms to legally offshore their manufacturing to China, find that offshoring has a negative impact on firm innovation as measured by patents. In addition to negatively affecting the level of innovation, they find that the offshoring shock shifted the direction of innovation in offshored products toward process innovation. That said, they argue that firms did not experience an across-the-board decline in innovation, but rather a reallocation of innovation away from offshored parts of their R&D portfolio and toward the non-offshored parts. The findings of Yang et al. (2016) suggest that in some cases, firms are not necessarily offshoring production activities in which it is no longer desirable to innovate. Indeed, the high share of US manufacturing R&D spending performed by MNCs and the realization of value added overseas raise the possibility that offshored activities may still be desirable and productive foci for domestic R&D funding.

Fuchs (2014) suggests that three conditions shape the impact of manufacturing location on global technology development: (i) the number of manufacturing facilities that a firm can sustain (potentially influenced by the ratio of their minimum efficient plant size to the size of the market and their share thereof); (ii) the location of product and process design expertise and whether the designers need to be physically present at the production line; and (iii) the importance, security, and enforcement of intellectual property rights. These conditions particularly affect early-stage high technology start-ups involving early-stage advanced materials and processes (Fuchs 2014). Challenges separating design from manufacturing are common for early-stage products in industries, such as semiconductors (Lécuyer 2006), pharmaceuticals (Pisano 2000), and additive manufacturing (Bonnín-Roca et al. 2017b), in which product innovations are fundamentally linked to advances in process. In these contexts, a lack of codified knowledge about the relationships between inputs and outputs, and the underlying science supporting outcomes, leads to low yields and can make production more of an "art" than a science in the early stages of new products (Bohn 2005, Bonnín-Roca et al. 2017b; Fuchs and Kirchain 2010). A small market compared with the production output required to take advantage of economies of scale is also common for early-stage high technology start-ups, forcing them to choose just one manufacturing location. In contrast, firms that can sustain multiple manufacturing facilities and don't struggle with separating design from production could potentially leverage location-based differences in production characteristics to diversify their product development portfolio and potentially increase their innovation.

Furthermore, national differences in consumer preferences may also have a role in incentives for innovation. Today approximately one-third of conventional vehicles are produced in China, but more than half of electric vehicles are produced in China. While the conventional vehicles are produced predominantly by joint ventures with multinational firms, the electric vehicles are produced predominantly by independent domestic Chinese firms. Helveston et al. (2015) find that, all else being equal, consumers in China are more willing to pay for electric vehicles than are consumers in the US. Local and national policy can then further shift the playing field. Helveston et al. (2019) finds a combination of local and national policies in China associated with significant regional experimentation in electric vehicle technologies by independent domestic manufacturers. Specifically, joint venture requirements may be creating disincentives for multinationals or their Chinese joint venture counterparts to undertake electric vehicle production or innovation in China, leaving open—with a combination of supportive resources and protectionism from regional governments—for independent domestic Chinese firms to move into the Chinese electric vehicle market (Helveston et al. 2019).

1.8.2 Technology Change in Manufacturing and Labor Outcomes

Recent research has investigated how employment and labor skill demands in manufacturing, and industry more broadly, are associated with globalization, technology change, changes in what is being manufacturing, and other factors. The adoption of new technologies in manufacturing has the potential to alter the demand for labor, including biases toward certain types of skill (Card and Dinardo 2002). There is a documented polarization of skill demand (measured as education or wage percentile) in the US economy, which Autor and Dorn (2013) attribute to a combination of sectoral shifts in demand toward low-skill service work and increases in automation (capital intensity). Research suggests that automation (measured as increases in capital to labor share) shifts manufacturing labor demand away from middle income jobs, as capital substitutes for labor in routine tasks and (Autor, Levy, and Murnane 2003; Autor and Dorn 2013). In particular, industrial robots may reduce employment and wages overall (Acemoglu and Restrepo 2017). Contributing at the high end of the observed polarization, technological shifts in production toward continuous processing may also drive an increase in the demand for worker skill (Goldin and Katz 1998), shifting from line operators toward labor involved in equipment support. Some technology changes may shift the skill requirements of an occupation (e.g., more operators pressing buttons and monitoring equipment than hand-assembling parts) while keeping the demand for labor in that occupation constant; other technology changes may shift skill requirements, such as a shift in the demand for occupations (e.g., fewer operators and more engineers). In the context of optoelectronic semiconductors, Bartel et al. (2004, 2007) suggest that information technology adoption in production facilities, coincides with increased skill requirements for machine operators, particularly in technical and problem-solving dimensions. In contrast, Combemale et al. (2021) find that automation polarizes the demand for skill in manufacturing operator occupations, eliminating demand for middle-skilled tasks while shifting demand toward low- and high-skilled tasks. Relatedly, Combemale et al. (2021) find that parts consolidation drives a convergence in skill demand toward middle skills (again in the context of optoelectronic semiconductors). Of potential policy interest, Combemale et al.'s work finds that competing technologies with seemingly comparable production cost outcomes can be associated with different outcomes for labor and skill demand.

1.9 Conclusions, Potential Policy Implications, and Future Work

The manufacturing sector dominates industrial R&D spending in the US as measured; however, manufacturing's share of US value added and share of US domestic employment have been in decline. This disproportionate contribution of manufacturing firms to US-based industrial R&D compared to total US employment or US gross value added is in part driven by the offshoring of manufacturing facilities from the US to other nations, and in particular China, without equivalent offshoring of US-based manufacturing R&D. The US manufacturing sector's dominant role in private funding of R&D is driven by five industries: aerospace, automobile, pharmaceuticals, semiconductors and telecommunications. Further research is necessary to understand the relationship between offshoring of manufacturing facilities and research in each of these industries and in specific technologies in these industries and technology directions. The changes, however, have not been small: according to the WIOD, between 2005 and 2014 US-based firms in motor vehicles increased intermediate inputs imported by

18 percent, pharmaceuticals increased intermediated imported by 22 percent (classification ISIC, not NAICS).

The manufacturing sector is not alone in disproportionately contributing to US-based R&D compared to value added: the information sector's fraction of US-based R&D spending is also greater than its fraction of US-based value added, although the difference is not quite as large as for manufacturing. While globalization still plays a dominant role, the information sector's greater contribution to US-based R&D than value added is in part driven by different underlying factors. Multinationals in the information sector conduct a greater proportion of their R&D at foreign affiliates than do multinationals in the manufacturing sector (the latter whose R&D spending has risen equally in the US and at foreign affiliates). Furthermore, the information sector receives a significant amount of funding from private equity and venture capital, which don't count toward R&D spending even though some of those funds likely contribute to R&D activities. In contrast, the proportion of deals by count (2 percent) and monetary volume (3 percent) aimed at manufacturing industries is comparatively quite small. This lower investment in manufacturing is perhaps surprising, given that Lerner (2000) finds that VC in manufacturing is more productive (measured by patents per dollar) than corporate R&D. However, the capital intensity of manufacturing (Levinson 2017; Pierce and Schott 2016) might contribute to this pattern: large manufacturing firms are likely better positioned to capture the returns of their basic research efforts (Cohen and Klepper 1996).

While inputs to the innovation process (e.g., industrial R&D expenditures) are clearly high in manufacturing, it is more difficult to measure outputs. Patents are often not the dominant mechanism used by manufacturing firms to appropriate innovation (Arora, Cohen, and Walsh 2015; Cohen, Nelson, and Walsh 2000; Levin et al. 1987). The research insights available into manufacturing innovation outputs, however, primarily use patents as measures of innovation. Trade theory suggests that shifts in manufacturing away from a nation may hurt wages there, but global innovation and productivity gains will not suffer (Samuelson 2004). However, empirical research has found that at least in certain contexts, moving the location of manufacturing can alter whether and which next generation products are profitable (Fuchs and Kirchain 2010, 2011). Likewise, Dorn et al. (2020) find that foreign competition (in the form of import substitution) reduces US innovation (measured in patents). Branstetter et al. (2021) find that the largest fraction of patents in emerging economies is in services, while developed countries continue to do a disproportionate amount of manufacturing patenting. However, manufacturing patenting in China has been rising, and it is unclear how long it will be until—like manufacturing value added and manufacturing industrial R&D expenditures—manufacturing patenting (and innovation) in China will also supersede that in the US, and in which industrial and technological contexts. Indeed, in some industrial and technological contexts, China's patenting and innovation activities likely already do supersede those in the US. More research is imperative on the global innovation landscape in manufacturing using measures other than patents, how the relationship between manufacturing and innovation differs by technological and industrial context, and how to think about the role of manufacturing in the US economy.

While the size of the US manufacturing labor force has remained relatively constant in the past half century, growth in US jobs outside manufacturing has led to manufacturing being a small fraction of today's overall US labor force. That said, in those US jobs that remain, manufacturing is an outsized employer of non-college educated workers, and generally has better-paying jobs than nonmanufacturing. It is important to separate the employment profile of manufacturing from its role in industrial R&D spending: the industries that drive manufacturing R&D spending tend to employ a more educated workforce than the rest of manufacturing. Industries such as food manufacturing, which help drive the sector's greater-than-average employment of less-educated workers, are relatively small contributors to the sector's R&D spending. It is also important to note that many manufacturing companies employ workers in establishments classified as part of retail, wholesale, and services that complement the production of manufactured goods (Whitefoot, Valdivia, and Adam 2018). Along with globalization, the adoption of new technologies in manufacturing over time is contributing to changes in the nature and demand for labor, including biases toward certain types of skill (Card and Dinardo 2002). Further research will be necessary to determine the relative contribution of offshoring, import competition, and technology change to observed economy-wide polarization in wages and education (Autor and Dorn 2013), and how different technologies may lead to different labor outcomes (Combemale et al. 2021).

Appendix A

The Share of Manufacturing in US GVA and the Share of the US in Global Manufacturing and GVA

Figure 1.A.1 illustrates the continually declining share of US GVA from manufacturing over the 20 years from 1997 to 2017. While US MVA rose in real terms over the same period, its relative contribution to the economy shrank. The US share of global MVA and GVA both declined from 1997 to 2017: the decline of manufacturing as a share of the US economy is mirrored in the steeper decline of the US share of global MVA, relative to world GVA (figure 1.A.2).

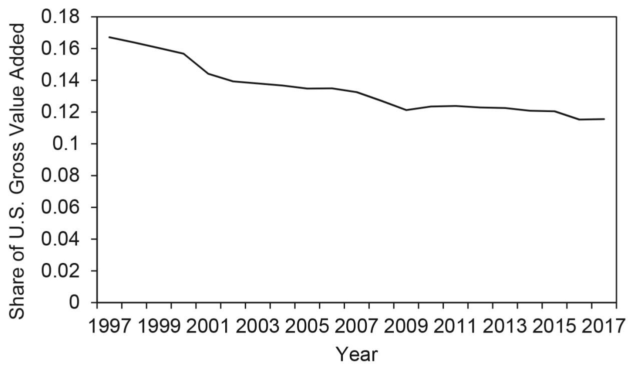


Fig. 1.A.1 Manufacturing share of US GVA, 1997–2017

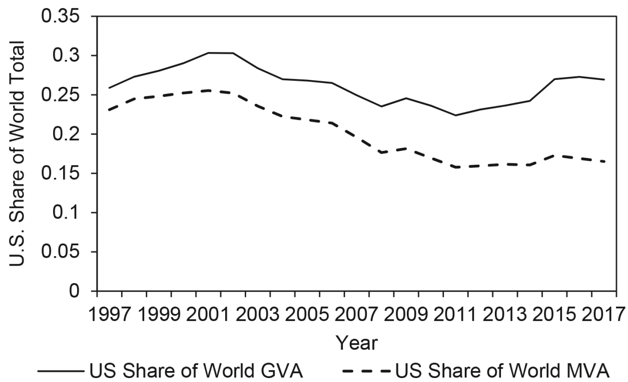


Fig. 1.A.2 US share of world MVA and GVA, 1997–2017

Appendix B

Additional Visualizations of the Manufacturing Labor Force

Subsector analysis reveals heterogeneity among leading R&D and employment subsectors. Figure 1.B.1 displays the difference in educational attainment of a few selected subsectors relative to the nonmanufacturing sector. These subsectors include the top five subsectors by private R&D spending and the top two subsectors by employment in 2015. As can be seen, the manufacturing subsector that contributes the most to employment—the food manufacturing subsector—has on average a 10 percent higher proportion of employees with HS education or less than nonmanufacturing sectors have. It also had an approximately 12 percentage higher proportion of employees

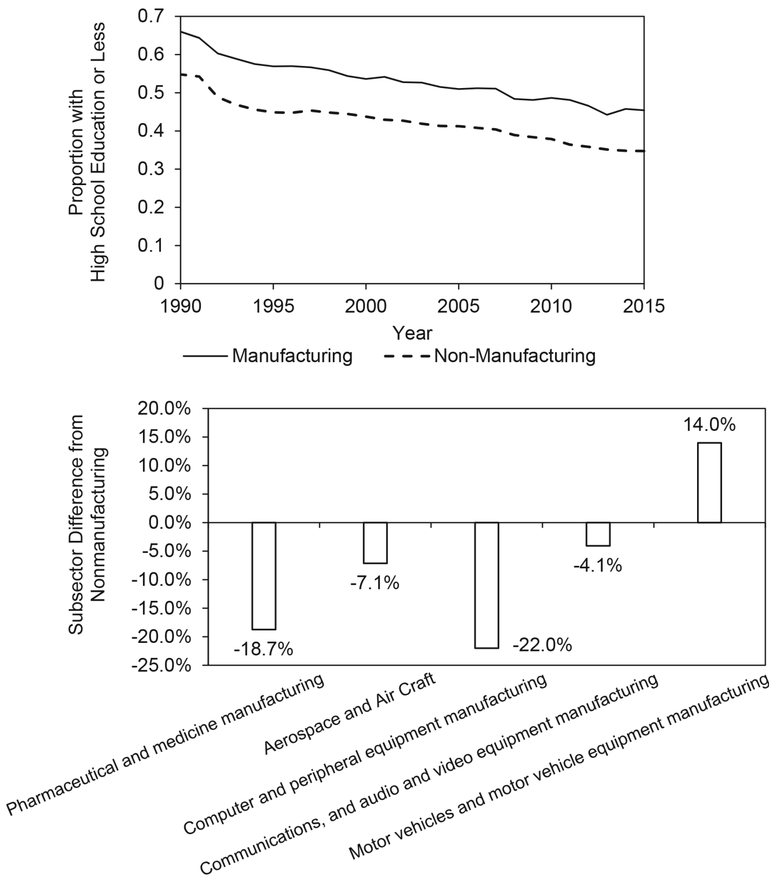


Fig. 1.B.1 Select manufacturing subsectors difference from nonmanufacturing's educational attainment, 2015

Source: Flood et al. (2020) (IPUMS-CPS ASEC microdata 2015).

Note: the NAICS imperfectly crosswalks to the Industry Codes in the IPUMS-CPS data, given the level of aggregation for our analysis aerospace and automotive subsectors were combined as were navigating instruments and medical equipment.

with HS education or less than the overall workforce proportion in the 1970s, with that gap widening in the recent decade to around 22 percentage points (IPUMS). Other subsectors with a relatively large proportion of workers with HS education or less include apparel, textile, furniture, leather, and lumber manufacturing. In contrast, the top R&D spending manufacturing subsectors have larger proportions of their labor force who are higher educated: consider the chemical/drug subsector and the communications subsector, which both contain a larger proportion of higher educated workers than do nonmanufacturing sectors.

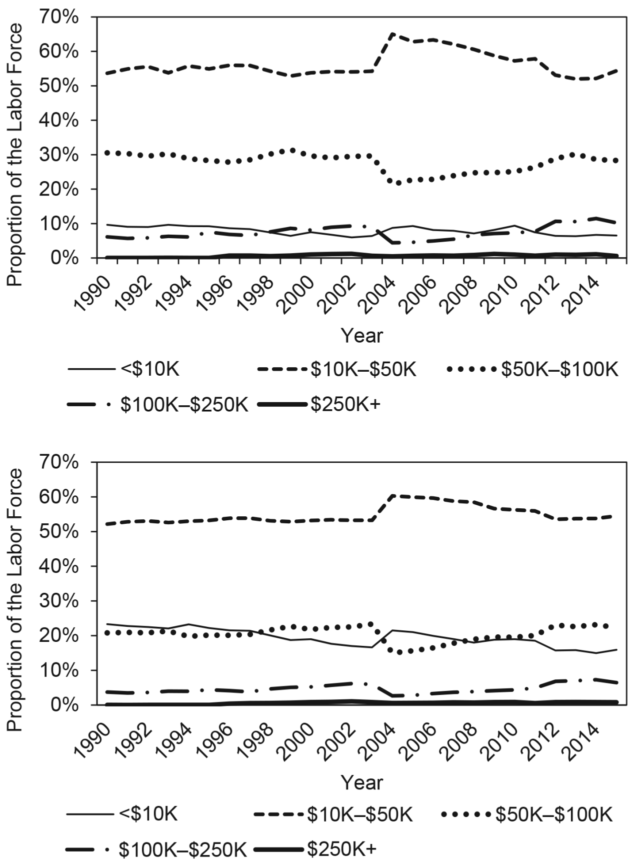


Fig. 1.B.2 Individual wage and salary income categories

Source: CPS microdata, 1990–2015.

Note: Data interval set for consistent industry classifications starting from 1990 industry reclassification by IPUMs.

Worker class falls into one of four categories: private wage or salary worker, federal or state government employee, self-employed (incorporated or unincorporated), or unpaid family worker. The manufacturing industry's labor force has remained nearly completely private wage or salary workers: 98 percent in 1975 and 95 percent in 2015. In the nonmanufacturing sector, private wage and salary workers have increased over time: 67 percent in 1975 and 74 percent in 2015. Figure 1.B.2 shows annual individual wage and salary income, CPI adjusted to 2017 dollars, between 1988 and 2018 (as shown in figure 1.B.2). While the proportion of nonmanufacturing workers with earnings less than $10,000 declines over time, the proportion of the manufacturing labor force earning less than $10,000 (2017 dollars)

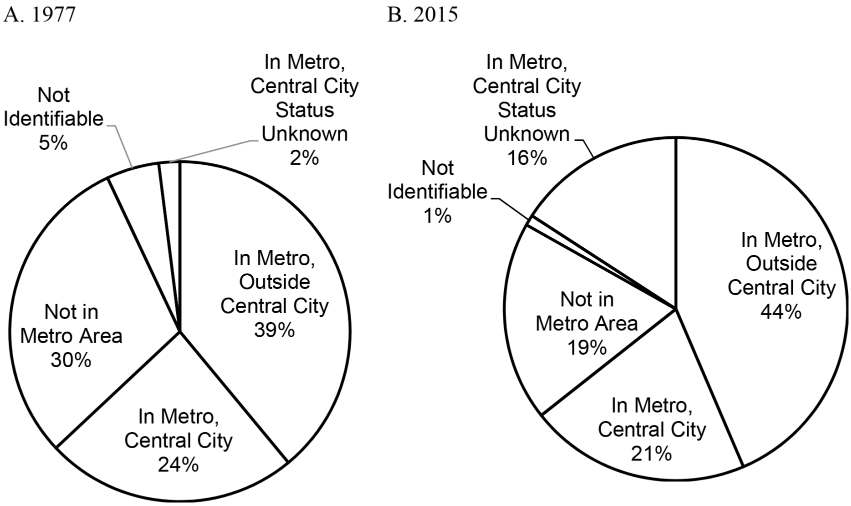


Fig. 1.B.3 Geographic location of the manufacturing labor force
Source: IPUMS-CPS ASEC microdata.

remains less than the proportion of the nonmanufacturing labor force. The total proportion of the manufacturing labor force whose earnings fall in the categories between $10,000 and $250,000 is also higher than that for the nonmanufacturing labor force.

It is well known that given manufacturing's floor space requirements and the higher cost of building space per square foot in metro areas and their central cities, manufacturing firms are often located outside of central cities/metropolitan statistical areas. Figure 1.B.3 exhibits the manufacturing labor force's geographic location in 1977 and 2015.

The age distribution of the manufacturing labor force is quite similar to the nonmanufacturing workforce for prime aged workers (ages 25 to 64). Across time, the manufacturing labor force consistently has a lower proportion of participants aged 16–19 and 20–24 and consistently has a larger proportion of participants aged 25–64 relative to the nonmanufacturing labor force. As can be seen in figure 1.B.4, in manufacturing, the proportion of labor force participants aged 16–19 and 20–24 has fallen across time. Meanwhile, the largest mass of the labor force has been increasing in age across time: the largest proportions of workers were aged 35–44 in the 1990s, and aged 45–54 in the mid-2000s. Finally, the proportion of participants aged 65 and older in manufacturing is consistently lower relative to the nonmanufacturing labor force, although it has increased slightly.

Figure 1.B.5 shows the gender composition of the manufacturing and

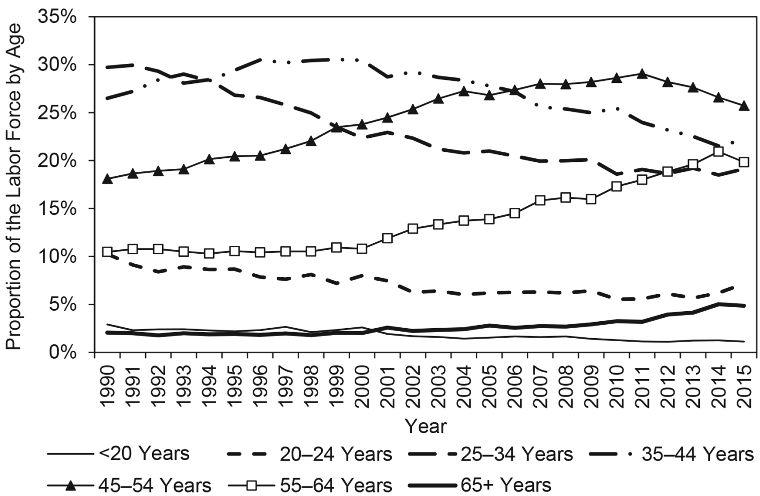


Fig. 1.B.4 Manufacturing labor force age distributions
Source: Flood et al. (2020) (IPUMS-CPS ASEC microdata, 1990–2015).

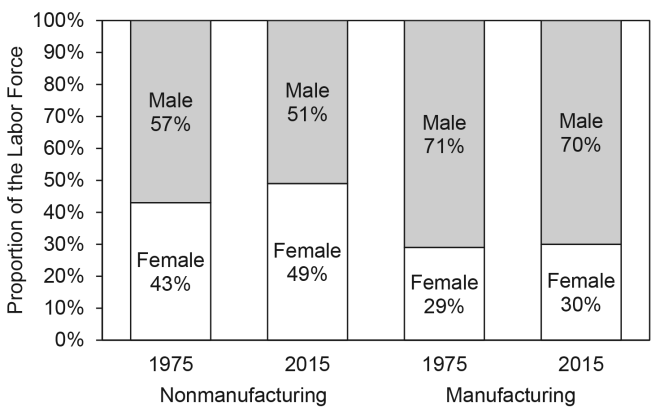


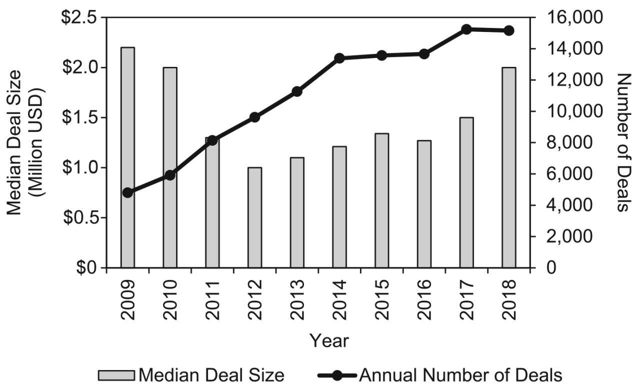
Fig. 1.B.5 Gender composition of the nonmanufacturing and manufacturing labor force
Source: Flood et al. (2020) (snapshots of 1975 and 2015).

nonmanufacturing labor force in 1975 and 2015. Across both nonmanufacturing and manufacturing sectors, the majority of the labor force is composed of male workers; however, manufacturing sectors have proportionately fewer female workers and thus more male workers. Across time, the gap in the labor force composition of manufacturing is quite stagnant, whereas nonmanufacturing subsectors have made progress toward parity.

Appendix C
Private Equity/Venture Capital Measures

Figure 1.C.1 shows the trends in median deal size and annual number of deals for nonmanufacturing and for manufacturing industries. As seen in figure 1.C.2, the US's percentage of global PE/VC deals in manufacturing dominate that of China, Germany, and Japan; however, PE/VC to manufacturing industries in China and Germany feature a higher median and mean deal size. Figure 1.C.3 features a similar visualization of the global distribution of nonmanufacturing deals. Note that the global geographic dispersion of PE/VC deals is quite similar for both manufacturing and nonmanufacturing industries.

A. Nonmanufacturing Industries, US



B. Manufacturing Industries, US

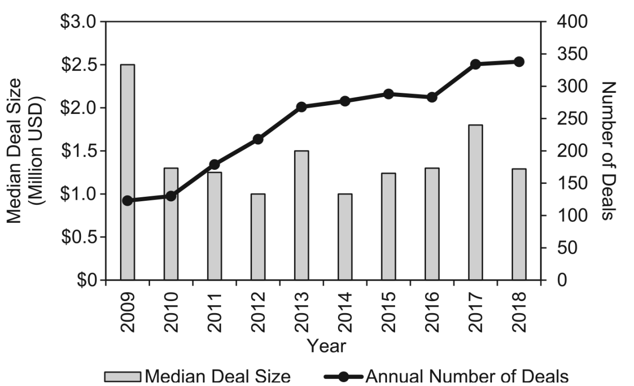
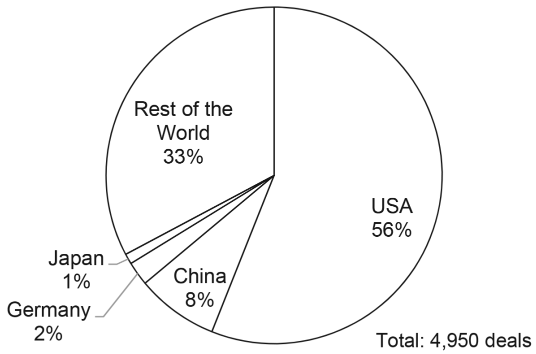


Fig. 1.C.1 PE/VC in nonmanufacturing industries and PE/VC in manufacturing industries, each with median deal size

Source: Data retrieved from CB Insights (2019).

A. Share of Global Manufacturing Industries PE/ VC Deals by Country. 2009–2019



B. Median and Mean deal Size by Geography

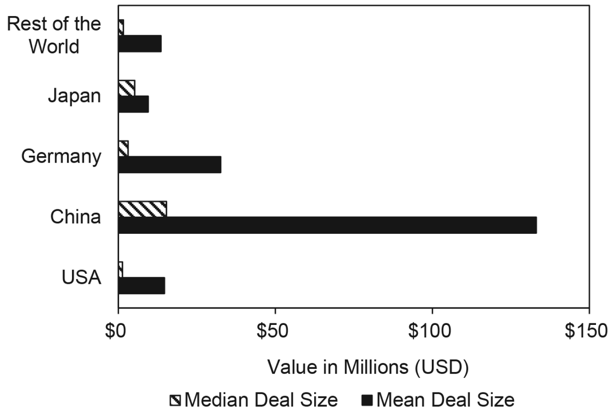
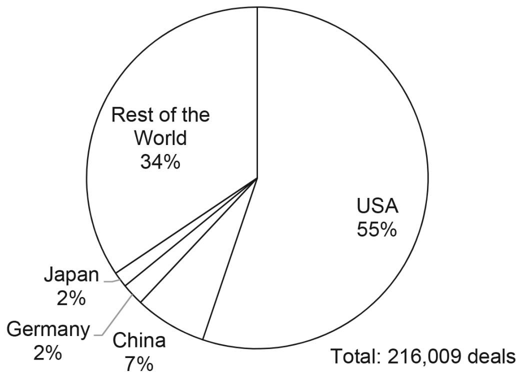


Fig. 1.C.2 Comparison of global manufacturing industries PE/VC, inclusive of top four countries by MVA

Source: Data retrieved from CB Insights (2019).

A. Share of Global Nonmanufacturing Industries PE/ VC Deals by Country, 2009–2019



B. Median and Mean Deal Size by Geography

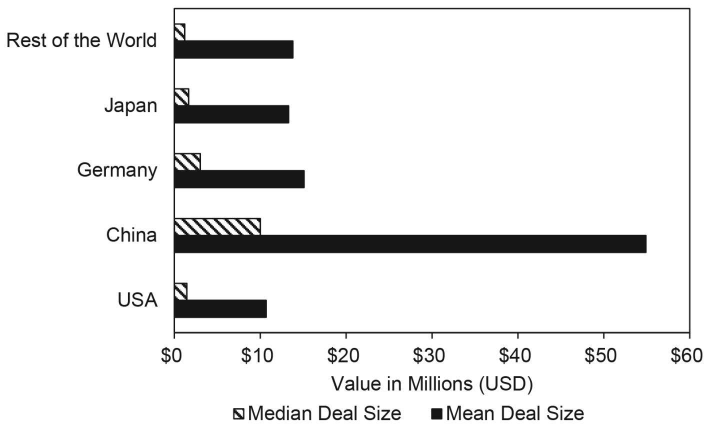


Fig. 1.C.3 Comparison of global nonmanufacturing industries PE/VC, inclusive of top four countries by MVA

Source: Data retrieved from CB Insights (2019).

Appendix D

"Public VC": Data Visualization of SBIR and STTR Awards

The distribution of Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) awards by funding agency are exhibited in figure 1.D.1 (data from SBIR.gov).[25] Notably, most of the awards have been given by two agencies: the Departments of Defense and of Health and Human Services.

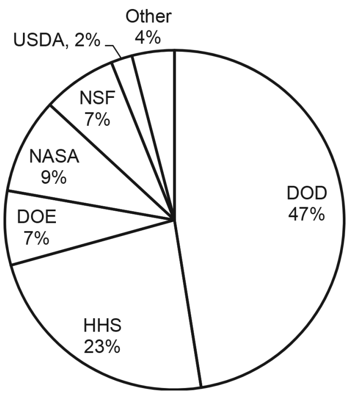


Fig. 1.D.1 Distribution of SBIR and STTR awards by federal funding agency
Source: SBIR.Gov, July 2019.

Appendix E

Firm Counts and Firm Size Distribution

The total number of firms (irrespective of industry) in the US has ranged from over 6.05 million firms in 2007 to 5.96 million firms in 2016, featuring a trough closely coincident with the business cycle: declining to 5.68 million firms in 2011, before increasing again (US Census Bureau, "Statistics of US Businesses, 2007–2016"). The proportion of manufacturing firms relative to the total number of firms' averages ~4.5 percent between 2007 and 2016 and has featured a slight decline in recent years, attributable to the lack of a sustained expansion in manufacturing firm counts relative to nonmanufacturing firm counts following the Great Recession. The proportion of information sector firms to all firms has been relatively stable at ~1.2 percent over the same period.

There are several differences between the firm size distribution of US firms in nonmanufacturing versus those in manufacturing (see figure 1.E.1). The

25. "Other" agencies include DHS, ED, EPA, DOT, DOI, and NRC.

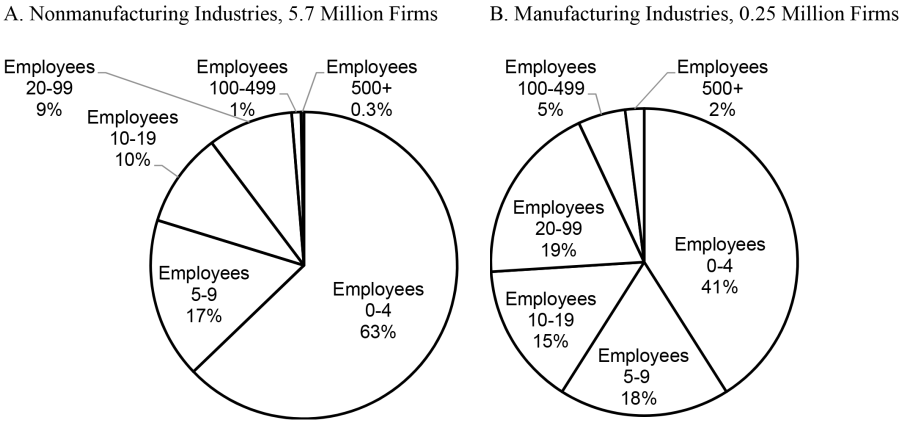


Fig. 1.E.1 Firm size distributions, 2015

Source: Data retrieved from Census Statistics of US Businesses.

Note: Nonmanufacturing Industries calculated by subtracting manufacturing firm counts (NAICS codes 31–33) from the total firm counts using the 2015 Census Statistics of US Businesses.

firm size distribution across nonmanufacturing firms is monotonic, that is, the density of firms in each category declines as the firm size grows. In contrast, manufacturing proceeds from 41 percent of firms with 0–4 employees, to 18 percent with 5–9 employees, to 15 percent with 10–19 employees, then a larger proportion 19 percent with 20–99 employees and 5 percent with 10–499 employees. These results may suggest that given manufacturing's capital intensity in many sectors, fewer firms find having 10–19 employees to be an efficient scale. In contrast, the 0–4 employees may reflect machining shops and similar undertakings.

Buera, Kaboski, and Shin (2011) argue that manufacturing, with larger scales of operation, is relatively more exposed to financial frictions than are other sectors. The differences between small and large manufacturing firms across the business cycle is explored in Gertler and Gilchrist (1994), who find that in a high interest rate environment, small firms shed inventories and contract relatively more than large firms. Davis and Haltiwanger (1992) document the countercyclical nature of the job reallocation rate,[26] which they argue is driven by larger, older, multi-establishment manufacturers. Comparatively, manufacturing has a lower proportion of firms with 0–4 employees and a higher proportion of each of the other categories. Overall, large firms (500 or more employees) comprise .3 percent of all nonmanufacturing firms; however, in manufacturing, large firms comprise 1.5 percent of all manufacturing firms. That is, the manufacturing firm size distribution

26. Davis and Haltiwanger (1992) define the job reallocation rate to be the sum of the gross job destruction and gross job creation rates. Their study employs data from 1972 to 1986 and finds these rates to be 11.3 percent and 9.2 percent, respectively.

has proportionally 5 times as many large firms as the overall distribution. In other words, large (500+ employees) manufacturing firms made up 20 percent of all large (500+ employees) firms in the US in 2015. The relatively larger proportion of large manufacturing firms is consistent with Neumark, Wall, and Zhang (2011), who document the importance of large firms in manufacturing to job creation. Dunne, Roberts, and Samuelson (1989) provide one explanation for the presence of more large firms. These authors argue that manufacturing firms' plant failure rates fall with plant size and age, however there is a tradeoff between a manufacturer's rate of growth and probability of failure. Klepper and Simons (2000) also address the effects of firm size (among other factors) on the US tire industry, arguing that larger and older firms influence technological evolution in the industry, increasing their survivability. Still, the disproportionate presence of large firms is quite interesting, given that the literature has documented a wage premium paid to workers of large US manufacturing employers which can only be partially explained by observable characteristics of the workers and establishments (Troske 1999). It has also been documented that larger firms proportionally face higher relative prices of labor than their smaller competitors (Söderbom and Teal [2003] in the case of African manufacturing firms).

Appendix F

Science and Technical Employees by Sector

Manufacturing represents 20 percent of employment for engineers, mathematical and computer science and scientific occupations, compared with 8 percent employment share for information and 5 percent share for R&D service companies.

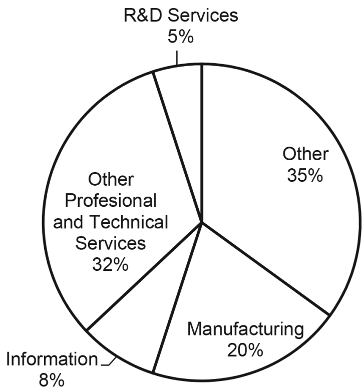


Fig. 1.F.1 Share of industrial STEM employees by sector
Source: Data from Bureau of Labor Statistics, 2019.

Appendix G

Example of Data Format

Table 1.G.1 BEA input-output subsector data format example

Industry Code	Commodities/Industries Name	111CA Farms	113FF Forestry, fishing, and related activities
111CA	Farms	71893	901
113FF	Forestry, fishing, and related activities	23901	9627
211	Oil and gas extraction	. . .	. . .
212	Mining, except oil and gas	2771	2
213	Support activities for mining	. . .	. . .
22	Utilities	4500	139

Appendix H

Linear Regression of Inputs and Intensity-Adjusted R&D by Sector

In addition to our production function estimation approach, we also attempt a very simple linear regression of output and value added over intensity-adjusted R&D stock from key R&D spending subsectors. For example, we use the change in the ratio of value added by a subsector to the output of

Table 1.H.1 Regression outputs for change in value added over output (annual)

Change in subsector value added/output (R^2 = .274)	Coefficient	Standard error	p-value
Intercept	1.70E−03	1.23E−03	0.17
Change in gross value added (US economywide)	1.29E−16	6.90E−17	0.06
Change in inputs (sector)	−6.71E−07	3.81E−08	0.00
Machinery intensity adjusted 3-year R&D	2.81E−11	1.02E−10	0.78
Computer and electronic intensity adjusted 3-year R&D	3.06E−12	2.69E−12	0.26
Motor vehicles, bodies and trailers, and parts intensity adjusted 3-year R&D	−5.39E−12	5.66E−12	0.34
Publishing industries, except internet (includes software) intensity adjusted 3-year R&D	1.18E−10	7.10E−11	0.10
Computer systems design and related services intensity adjusted 3-year R&D	−3.34E−10	6.40E−10	0.60
Miscellaneous professional, scientific, and technical services intensity adjusted 3-year R&D	9.84E−12	8.46E−12	0.24

Sources: Bureau of Economic Analysis (2019), NSF (2019).

that subsector as a measure of the productivity of inputs to a sector, and then regress this value on intensity-adjusted R&D stock from key subsectors.

We are unable to find evidence in these preliminary regressions to suggest that the returns to manufacturing R&D are captured by consumers of manufactured goods in a manner accounting for the underrepresentation of manufacturing in overall value added.

Appendix I

Regression Outputs for Estimation of Subsector Output with Time Fixed Effects

To account for possible exogenous factors in each year of our time series (curtailed at either end by the limitations of our NSF time series R&D data and the construction of our intensity-adjusted measure of R&D stock), we conduct and report on an estimation of the regression model in table 1.I.1 extended to include time fixed effects for each year. We do not find that this revised model affects our evaluation that there is little initial evidence to support the R&D embodiment hypothesis for the dominance of manufacturing R&D spending.

Table 1.I.1 Regression outputs for estimation of subsector output with time fixed effects

Dependent variable: ln(Output) (R^2 = .86)

Independent variable	Coefficient	Standard error	*p*-value
Intercept	0.394	0.186	0.034
ln(Intensity-adjusted top manufacturing R&D stock)	0.022	0.007	0.002
ln(Intensity-adjusted service and information R&D stock)	0.122	0.011	4.84E−24
ln(Inputs from other sectors)	0.952	0.013	1E-25
Time-fixed effects (year)			
2002	−0.066	0.065	0.305
2003	−0.086	0.065	0.185
2004	−0.087	0.065	0.178
2005	−0.104	0.065	0.108
2006	−0.097	0.065	0.134
2007	−0.117	0.065	0.072
2008	−0.114	0.065	0.079
2009	−0.051	0.065	0.435
2010	−0.057	0.065	0.381
2011	−0.046	0.064	0.471
2012	−0.051	0.064	0.432
2013	−0.036	0.064	0.578
2014	−0.048	0.064	0.456

Sources: Bureau of Economic Analysis (2019), NSF (2019).

Appendix J

US R&D Funding by Federal Government and Industry

Figure 1.J.1 illustrates industrial R&D spending overtaking federal R&D spending, growing most acute after the 1980s.

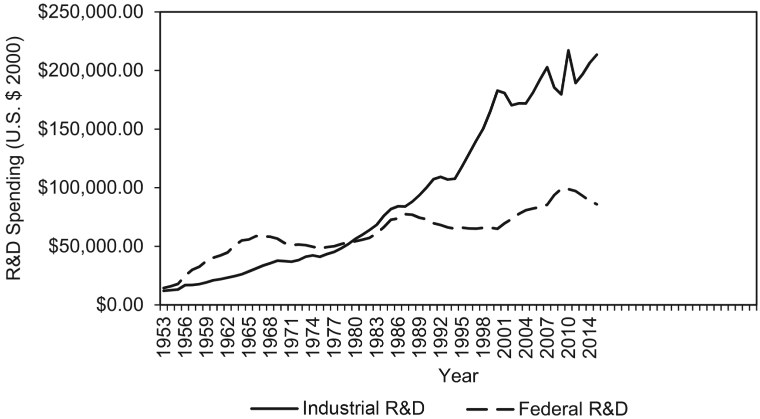


Fig. 1.J.1 Industrial and federal R&D, 1953–2015 (NSF, AAAS)

Appendix K

Exploration of Alternative Hypotheses

K.1 Mismeasurement and Reporting Incentives

We examine three possible sources of mismeasurement of R&D spending and conclude that they cannot account for the dominance of manufacturing R&D spending.

The first possible source is measurement error through sampling bias in the NSF's data collection process for industrial R&D spending. The NSF used the "Business R&D and Innovation Survey" (BRDIS) from 2008 until the 2016 survey cycle. The BRDIS defines R&D as "planned, creative work aimed at discovering new knowledge or developing new or significantly improved goods and services."[27] R&D returns manifest outside of manu-

27. This definition includes (a) activities aimed at acquiring new knowledge or understanding without specific immediate commercial application or use (basic research); (b) activities aimed at solving a specific problem or meeting a specific commercial objective (applied research); and (c) systematic use of research and practical experience to produce new or significantly improved goods, services, or processes (development). The term "research and development" does not include expenditures for: routine product testing, quality control, and technical services unless

facturing, or manufacturing does not appropriate all returns. The survey covers a population consisting of all firms in the Business Register, with or without known R&D activities. As part of the survey, firms are asked to report whether they engage in R&D activity and how many employees are engaged. NSF notes the risk of bias from different definitions of R&D but identifies government contractors and R&D service companies as the major risk items, possibly overstating their level of R&D spending activity. Industrial R&D funding as reported by NSF does not include funds from the federal government for performance, so that federal funding activity is not included in the dominance of manufacturing industrial R&D spending (NSational Science Foundation n.d.), and R&D service providers are already measured in the NSF data to account for a share of industrial R&D spending less than one-sixth that of manufacturing. These potential sources of measurement error in the NSF's survey methodology appear unlikely to account for the dominance of manufacturing in R&D spending.

The second possible source of mismeasurement is that some spending activities that further R&D objectives are not included in traditional R&D spending channels. For example, venture capital investment is not factored into industry R&D spending as measured by NSF, but nevertheless may support innovation effort from firms that engage in research-like activity (Kortum and Lerner 2001). The Venture Capital and Private Equity (VC/PE) market's nominal value of \$0.53 trillion during 2009–2015 (CB Insights 2019) compares with nominal private industrial R&D spending of \$1.76 trillion from 2009 to 2015. Assuming that every dollar spent in the VC and PE market was a form of R&D investment and given that about 3 percent of VC/PE spending went to manufacturing, manufacturing would still represent at least 52 percent of nominal combined industrial and VC R&D spending. Even under the most expansive assumptions about the share of VC spending dedicated to research activities, manufacturing would remain the majority source of combined VC and traditional R&D spending (at least 52 percent; see figure 1.K.1).

The third possible source of error that we examine is differences by sector in the incentives to report R&D spending. US firms have a financial incentive to report their R&D activities under the terms of the Federal R&D Tax Credit, in place since 1981 and established in perpetuity since the 2015 PATH Act. The terms of the credit have been consistent since before the PATH Act, however (Holtzman 2017). The terms for accessing the tax credit for R&D activity could produce different incentives to report R&D. The credit is available to businesses developing "new, improved, or technologically advanced products or trade processes" (IRS 2020). Qualified applications

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they are an integral part of an R&D project; market research; efficiency surveys or management studies; literary, artistic, or historical projects, such as films, music, or books and other publications; or prospecting or exploration for natural resources.

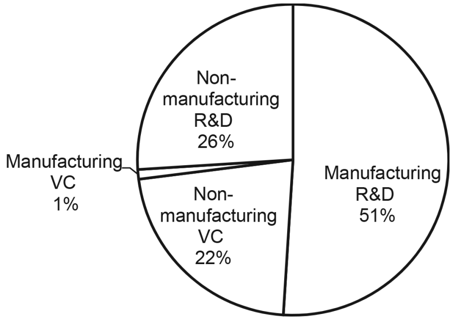

Fig. 1.K.1 Manufacturing and nonmanufacturing shares of R&D and venture capital spending, 2009–2015

include wages for qualified services, supplies used and consumed in R&D, contract research expenses on behalf of government, and basic research payments to qualified institutions. The credit also places constraints on qualified activities, which must be intended to resolve technological uncertainty; consist of a process of experimentation to resolve that uncertainty; and rely on engineering, computer science, biological science, or physical science.

Under the conditions for the credit, manufacturing firms may have less incentive to report R&D than other sectors have, not more. The credit notably excludes fixed capital, while wages, contracts and supplies are creditable (IRS 2020). Given the capital intensity of manufacturing R&D (Nadiri and Mamuneas 1991), there may be less incentive for manufacturing firms to report their R&D spending than for other, less capital-intensive sectors (such as information). The credit is also not available for incremental product development (such as post-launch software fixes). One major change brought by the PATH act is that startup businesses with no federal tax liability and gross receipts of less than $5 million may take the R&D tax credit against their payroll taxes. While NSF does not report data on firm R&D spending by revenue, US firms with fewer than 100 employees accounted for 6.3 percent of US industrial R&D in 2016 (after the PATH act took effect) (NSF 2019), insufficient to displace the dominance in prior years of manufacturing, even if other sectors had proportionately more firms with revenues less than $5 million.

Finally, we note in figure 1.K.2 that among the largest publicly traded US firms by R&D spending (PricewaterhouseCoopers 2019), manufacturing remains a dominant sector that key firms outside manufacturing (such as Google, Amazon, and Microsoft) help drive the spending of top firms. That is, these firms claim heavy R&D spending but do not displace the dominance of manufacturing, even under the whole population measure of the top 340 publicly traded US firms used by PricewaterhouseCoopers.

A. U.S. R&D Spending by Top 340 Public Firms: Share by Sector (2018), PwC 2019

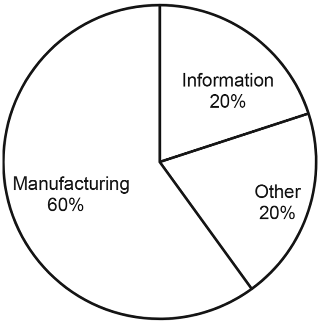

Fig. 1.K.2 R&D spending, by sector

Table 1.K.1 Top 10 US firms by R&D spending, 2018

2018 Spending rank	Company name	Sector
1	Amazon.com, Inc.	Retail
2	Alphabet, Inc.	Information
3	Intel Corporation	Manufacturing
4	Microsoft Corporation	Information
5	Apple, Inc.	Manufacturing
6	Johnson & Johnson	Manufacturing
7	Merck & Co., Inc.	Manufacturing
8	Ford Motor Company	Manufacturing
9	Facebook, Inc.	Information
10	Pfizer, Inc.	Manufacturing

K.2 Returns across Sectors and General-Purpose Technologies

Our second hypothesis, that the returns to manufacturing R&D may accrue in other sectors of the US economy, is motivated by the literature on General Purpose Technologies (Aghion and Howitt 2000; Helpman and Tratjenberg 1996). Under this framework, manufacturing could generate R&D returns that are not accounted for until they are sold in other sectors, for example. Manufacturing R&D could also generate technical knowledge that is adapted and appropriated by other sectors.

Our first subcase is motivated by descriptions of GPT embodied in capital (cf. Aghion and Howitt 2000). We evaluate this subcase of the GPT hypothesis using input-output accounts data by subsector from the Bureau of Economic Analysis (2019). This dataset, collected at the annual level, relates the inputs from individual subsectors of the US economy to other US subsectors and reports the output and value added of each subsector, with subsectors reported at four- and five-digit NAICS code levels. In total, the dataset covers 71 subsectors of the economy, each described in terms of the dollar value of its inputs from and outputs to the other 70. We select the 66 of these 71 subsectors that are nongovernmental and construct a time series dataset from 1997 to 2017 relating the inputs from each subsector to every other subsector and subsector outputs and value added by year. For intertemporal comparison, all annual input, value added, and output data were adjusted to 2015 dollars in our analysis.

We undertake a simple first-order statistical evaluation of the embodiment hypothesis to suggest whether an outsized productivity effect from manufacturing R&D might supply an explanation for its dominant role in R&D spending.

To reconstruct the possible embodiment of R&D in the outputs of manufacturing subsectors, we create a composite variable intensity-adjusted embodied R&D stock going into each nongovernmental subsector from each top R&D spending nongovernmental subsector (including manufacturing industries but also subsectors under information and technical services). This embodied stock is calculated for each year and subsector in the time series and has the form:

$$S_{j,i,t} = \frac{I_{j,i,t}}{\sum_{k=1}^{66} I_{j,k,t}} R_{i,t}$$

where $S_{j,i,t}$ is the intensity-adjusted embodied R&D stock in subsector j from sector i at time t; $I_{j,i,t}$ is the input to subsector to j from i in time t; $\sum_{k=1}^{66} I_{j,k,t}$ is the sum of nongovernmental inputs to subsector j; and $R_{i,t}$ is a research spending term for subsector i in time t. We test several different constructions of $R_{i,t}$ to account for lags between R&D spending and the realization of returns. We find that the "best" fit formulation is a 3-year running average from subsector spending in $t-2$ to spending in t, as measured by NSF (thus limiting the upper bound of our time series to 2015).[28]

As a preliminary estimate of a relationship between this embodied R&D stock and subsectoral output, we use a Cobb-Douglas production function of the form:

$$O_{j,t} = a\left(\sum_{k=1}^{66} I_{j,k,t}\right)^{\alpha}\left(\sum_{i\in M} S_{j,i,t}\right)^{\beta}\left(\sum_{i\in V} S_{j,i,t}\right)^{\gamma}$$

where $O_{j,t}$ is the output of subsector j in time t; a, α, β, γ are constant terms; $\sum_{k=1}^{66} I_{j,k,t}$ is the value of intermediate inputs to $O_{j,t}$; $\sum_{i\in M} S_{j,i,t}$ is the sum of intensity-adjusted embodied R&D stock from subsectors $i \in M$, where M is the set of high R&D spending subsectors in manufacturing; and $\sum_{i\in V} S_{j,i,t}$

28. We also test alternate formulations for our intensity measure $I_{j,i,t} / (\sum_{k=1}^{66} I_{j,k,t})$, including 3- and 5-year averages to reflect accumulation of R&D-embodying stock, with no improvement of fit.

is the same for V the set of information and service subsectors with high R&D spending. The analysis reported below excludes high R&D spending subsectors that produce end consumer goods (e.g., pharmaceuticals) and focuses instead on machinery, electronics, and various transportation goods.

We perform a simple regression analysis estimating $\ln(O_{j,t})$, giving an equation of the form:

$$\ln(O_{j,t}) = \ln(a) + \alpha \ln\left(\sum_{k=1}^{66} I_{j,k,t}\right) + \beta \ln\left(\sum_{i \in M} S_{j,i,t}\right) + \gamma \ln\left(\sum_{i \in V} S_{j,i,t}\right)$$

In table 1.K.2, we report the results of our regression estimating subsectoral output from inputs and intensity-adjusted R&D stock from manufacturing and from service and information (see appendix I for estimation output with annual time fixed effects—these effects do not affect our evaluation). Though a basic first evaluation, this simple analysis does not give any preliminary suggestion that manufacturing R&D stock in other sectors is disproportionately contributing to output relative to information and technical services, which it far outweighs in spending. We note that the coefficient for top manufacturing subsector R&D stock is in fact less than one-fifth the coefficient for service and information R&D stock—if manufacturing R&D spending is embodied in inputs to other subsectors, service and information inputs may outweigh it. Thus, embodiment of R&D spending does not appear to account for the dominance of manufacturing.

We also perform several simple linear regressions relating variation in value added, output and year-on-year change in these measures to R&D stock from specific subsectors, without any further evidence of a dominant role for manufacturing (see appendix I).

In this rudimentary analysis, we do not find evidence to support GPT as the sole explanation for the outsized role of manufacturing in R&D across all manufacturing subsectors. GPT not being an explanation for all manufacturing subsectors, however, does not rule out it being an explanatory

Table 1.K.2 **Regression outputs for estimation of subsectoral output**

Dependent variable: ln(Output) ($R^2 = .86$)			
Independent variable	Coefficient	Standard error	*p*-value
Intercept	0.394	0.186	0.034
ln(Intensity-adjusted top manufacturing R&D stock)	0.022	0.007	0.002
ln(Intensity-adjusted service and Information R&D stock)	0.122	0.0118	4.84E−24
ln(Inputs from other sectors)	0.952	0.0128	1.E−25

Sources: Bureau of Economic Analysis (2019), NSF (2019).

Note: Assuming an intercept $a = 1$, $\ln(a) = 0$ does not alter the finding that manufacturing R&D stock contributes a smaller effect than services and information or other sectors.

factor for some subsectors, such as innovation in microprocessors enabling innovation in other sectors throughout the economy (Jorgenson 2001).

The second subcase is that manufacturing is a source of GPTs that are adopted and adapted by other sectors. A GPT is a technology of generic function and general applicability, whose efficiency improves over time by continuous innovation, and it enables innovation and improvement by users in their own technologies (Rosenberg and Tratjenberg 2004). The third element of this definition suggests sector- or firm-specific R&D investment supported by the GPT (Helpman and Tratjenberg 1996; Jovanovic and Rousseau 2005), while many of the sectors and subsectors whose growth outperformed that of manufacturing were not engaged intensively in R&D (BEA 2019). Jorgenson (2001) finds that up to half of US economic growth in the 1990s was associated with advances in information technology and hardware (a form of GPT), including microprocessors (a manufactured good). While we were unable to unable to construct technology-specific factor productivity analysis (cf. Jorgenson 2001), we also note that top manufacturing R&D spenders include pharmaceuticals and other consumable end-use products, which do not fit the profile of GPT. That is, top sources of manufacturing R&D spending generate products that are not generalist in their function (e.g., pharmaceuticals) or that would directly facilitate further innovation in other sectors in the same manner as information technology or microprocessors. While manufacturing and the semiconductor subsector in particular have historically been a source of GPT, it does not appear that manufacturing R&D spending across all sectors engaged in producing GPTs nor that the emergence of GPTs from manufacturing is a plausible explanation for its disproportionate share of R&D activity.

Appendix L

Figure 1.L.1 displays the share of overall manufacturing value added from both the top five manufacturing subsectors by value added and the top five manufacturing subsectors by R&D spending. We see that the top five manufacturing subsectors by R&D have a total value added about a third lower than the top five subsectors by value added. Two subsectors, aerospace and pharmaceuticals, are both among the top five largest subsectors by MVA and R&D spending, but the remaining top subsectors by R&D spending are outweighed in value added by less R&D-intensive subsectors.

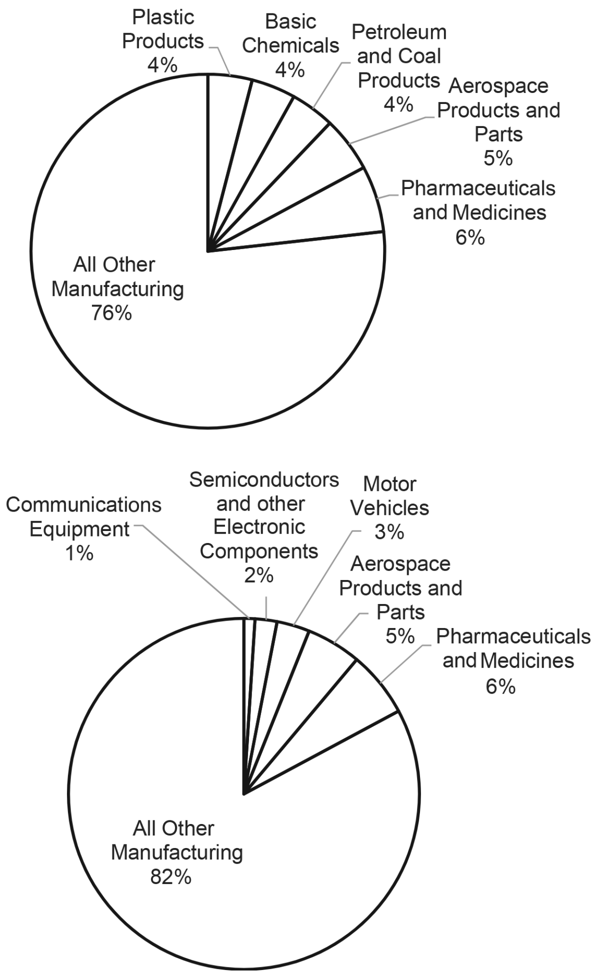

Fig. 1.L.1 Share of total manufacturing value added by subsector, 2015 (ASM)

Appendix M

US Share of R&D Spending by Top 1,000 Firms by R&D Spending Worldwide

A. U.S. Share of Manufacturing R&D Spending from Top 1000 World Firms by R&D Spending

B. U.S. Share of Nonmanufacturing R&D Spending from Top 1000 World Firms by R&D Spending

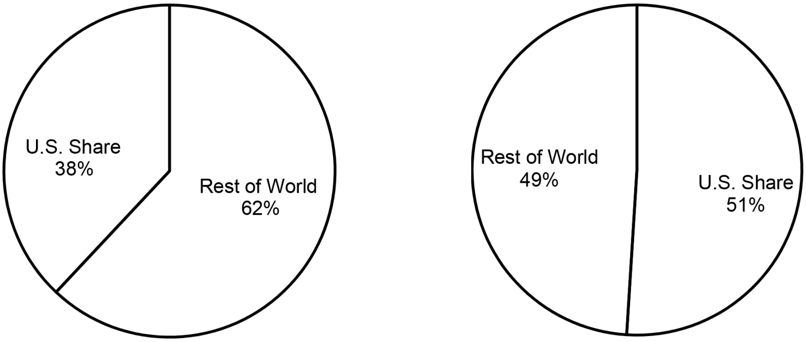

Fig. 1.M.1 US share of manufacturing and nonmanufacturing R&D spending by top 1,000 world firms by R&D spending

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