

The “Weighty” Manufacturing Sector: Transforming raw materials into physical goods

Erica R.H. Fuchs^{1,2}, Christophe Combemale¹, Kate S. Whitefoot¹, Britta Glennon³

¹Carnegie Mellon University, ² NBER and ³The Wharton School of the University of Pennsylvania

Abstract

The manufacturing sector encompasses a diverse set of industries that are involved in the transformation of raw materials into physical goods. Over the last two decades, the U.S.’s manufacturing value added (MVA) has slightly grown, however, the U.S.’s percentage of global MVA has declined due to China’s exponential rise. The U.S.’s relatively high R&D spending on manufacturing (66% of industrial R&D) and comparatively low manufacturing value added (14%) can in part be explained by foreign multinationals’ globalization of manufacturing facilities in the last decade. As a whole, the manufacturing sector involves higher value added per capita employed, a greater proportion of the labor force with education at the high school level or below while having on average higher wages for that labor force, higher industry spending on R&D, and fewer private equity/venture capital deals financing new ventures than non-manufacturing industries such as services (including software). The above said, drawing implications from sector-wide trends can be misleading because of the variation in these indicators across sub-sectors. Considering the sector’s diversity will be critical to understanding productivity and labor outcome effects, and appropriate policy responses, if any.

1. Introduction

Manufacturing has historically played a significant role in productivity and R&D. Jorgenson (2001, 2016) suggests that advances in microprocessors alone were associated with 50% of total factor productivity growth in the U.S. and world-wide in the 1990s. This outsized role in R&D and productivity appears to continue to today even with significant changes across the sector in technology and globalization. U.S. 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 sectors³.

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 U.S. economy as other sectors grew faster. U.S. 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 U.S. private R&D spending by manufacturing industries. However, both absolute employment and share of total U.S. employment in the sector have declined over the same period.⁵ Despite MVA growth, manufacturing today accounts for a smaller share of total U.S. value added than it did in

¹ The ratio of R&D spending within manufacturing relative to its share to GVA share went from 4.52 in 1997 to 5.45 in 2015 (i.e. a 21% 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.

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 U.S. GVA versus its share of employment) is higher than that of the overall U.S. economy by a factor of 1.39. Manufacturing’s share of GVA relative to its share of employment has grown since 1997 (the first available U.S. 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 U.S. Census Bureau’s Annual Survey of Manufactures) by the difference between inputs costs and output values from a firm or other entity.

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

the 1980s and 1990s.⁶ While a majority of U.S. industrial R&D spending still occurs within manufacturing, this too is a declining share of the U.S. 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 sub-sectors. The manufacturing sector by definition includes all establishments engaged in mechanical, physical, or chemical transformation of materials, substances, or components into new products. (NAICS 2017). The industries within the sector vary widely with respect to value added, workforce size and composition, and level of research and development 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, 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 disproportionately driven by the top five subsectors: pharmaceuticals, semiconductors and other electronic components, automobiles and light duty vehicles, communications, and aerospace. Unpacking the relationship between 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 valuable to unpacking the puzzling and at times conflicting results in today's state-of-the-art analyses.

This chapter takes the following structure: 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%) of U.S. industrial R&D spending but a much smaller (12%) proportion of U.S. domestic value added. Fourth, we highlight sub-sectoral level differences in our bird-eye view measures, and potential sub-sectoral differences in the dichotomy between U.S. industrial R&D spending and U.S. 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 between globalization, innovation, and labor outcomes.

2. A Brief History of Manufacturing Technologies and Systems

U.S. manufacturing began in the 17th and 18th centuries as a craftwork system imported from Europe to the American colonies (Epstein, 1993). 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-18th 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

⁶ MVA share of U.S. Gross Value Added shifted from 16.7% in 1997 to 12.1% in 2015 (i.e. a 27.9% relative decline.)

States during the first quarter of the 19th 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, U.S. manufacturers in this period strongly favored innovations in mechanization (even compared with Great Britain) (Rosenberg, 1975). This mechanization reduced the demand for labor on the production line but increased material waste and produced new demand 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 within the factory (Goldin and Katz 1998).

After the first and into the second industrial revolution, U.S. 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, easier repair, maintenance and logistics (Hounshell 1984). Progress toward interchangeability was further developed by entities such 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 U.S. armories which emerged in the late 18th century and proliferated in the first quarter of the 19th century. Production volumes grew around U.S. 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 19th and early 20th centuries (Smith 1980; Smith 1985; Malone 1988).

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 1998). 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 within 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 20th 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 (Taylor 1914; Hounshell 1984; Chandler 1990). These innovations also drove a further complementarity between capital and low skilled labor (Lafortune, Lewis and Tessada 2019). Standardization in 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 1970s (Hulten and Schwab 1984), U.S. 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 (Nichols 1976; Bollinger and Duffie 1988; Moore 1997). 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 (Katz and Murphy 1992; Autor, Levy and Murnane 2003; Autor and Dorn 2013). 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 (Ohno 1988; Mansfield 1993). Lean manufacturing, pioneered at Toyota through the Toyota Production System (TPS), differed from the material-rich roots of early U.S. manufacturing by focusing on minimizing material as well as other resource wastage (Womack, Jones and Roos 1990; Shah and Ward 2003). 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 within production (Cheng and Podolsky 1996; Sakakibara, Flynn and Schroeder 1997). Among U.S. manufacturers, lean manufacturing methods were adopted, among other places, in metal fabrication, computer, electrical machinery and automotive production (Swamidass 2007). U.S. firms did not adopt all dimensions of TPS, including due to concerns around 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. This modularity in design in some cases 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 2006). At the same time, system-level innovations were often associated (often temporary) reintegration of modular elements to facilitate technologies that affected characteristics across modular boundaries. The integrated circuit, a key innovation in microprocessors and enabling technology across the U.S. economy (Bresnahan and Trajtenberg 1995), was in itself an integration of components (Moore 1965); other components, such as lasers, saw continuing integration during the 20th and 21st 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).

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

Organizational innovations and production technologies continue to evolve in the 21st 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 (Mindell 2015; Bartel, Ichniowski and Shaw 2007). Automation has begun to include collaborative dimensions, bringing workers into direct production roles supported by robots (Kaber and Endsley 2004; Cherubini et al 2016). Although, collaborative robots are in their infancy and are unlikely to be appropriate to 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 (Fralix 2001; Atzeni and Salmi 2012; Mellor, Hao and Zhang 2014; Herrigel 2010) and material savings complementary to lean manufacturing approaches (Yossi 2013). 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 (Sheffi 2013; Bonnin-Roca et al 2017a). Through all of these changes, large scale, mechanized systems with intellectual roots in the 19th and even 18th century history of U.S. manufacturing continue to hold a major role informed by subsequent innovations (Kumar and Ando 2010; Hu 2013; Achillas et al 2015).

3. Manufacturing Value Added and Research and Development

Global measurements of manufacturing value added and research and development offer an important birds-eye perspective on the U.S. and world economy.

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. (NAS 2015). Value added thus comes from the *changes* 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 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 approached in the same way, cross-country comparisons are imprecise. The World Bank lacks gross (and thus non-manufacturing sector) value added data for many countries, including China. We therefore limit our international comparisons of gross value added across all sectors to the appendix (this section includes international comparisons of manufacturing value added only).⁸ The manufacturing value added World Bank data includes more countries, although notably only starts including China as of 2004. Our U.S. 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

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

countries follows the International Standard Industrial Classification (ISIC) codes.⁹ These sector classification differences in part explain the numerical differences between Figure 1 (World Bank) and Figure 2 (BEA).

The U.S. has seen a decline in its global share of MVA since 2000. While U.S. 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 U.S.'s decline in global share of MVA is due in large part to the significant rise in China's MVA, leaving the U.S. with a reduced share.

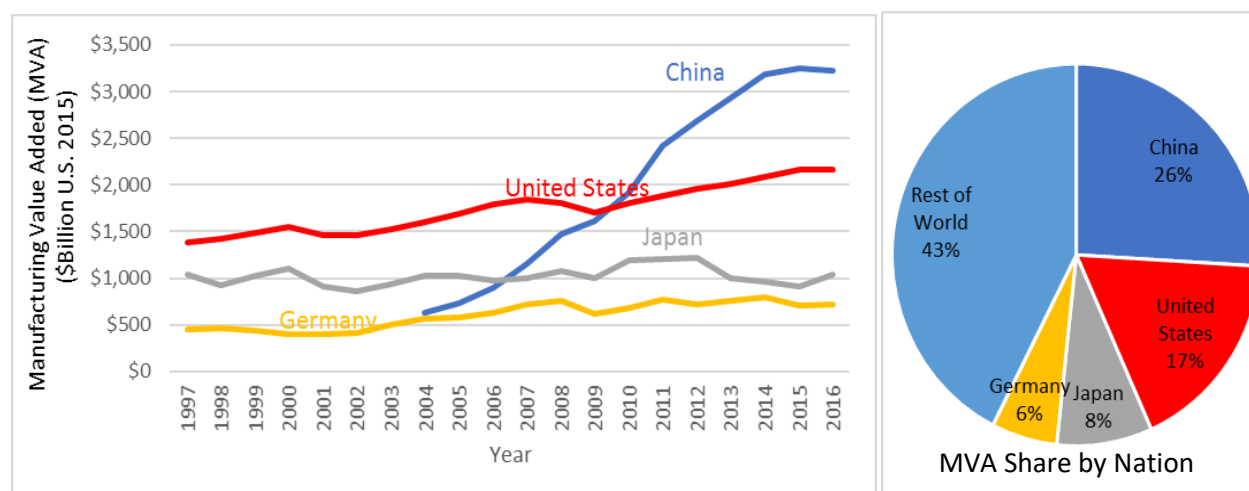


Figure 1 Global Manufacturing Value Added of Top 4 Manufacturing Nations (1997-2016)

U.S. manufacturing has seen a decline in its share of U.S. value added (BEA 2019). While manufacturing value added stagnated in real terms in the period 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 2). Outside of services, manufacturing and information (reported in the following table), the largest nongovernmental sectors by value added are finance (21%) and retail and wholesale trade (10%). Though the greatest proportional growth in 1997-2015 was in mining (89% increase in VA 1997-2015), the largest real growth was in services and finance, with manufacturing among the slowest growing sectors proportionately and in real terms (BEA 2019).

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 U.S. MVA observable in Figure 1 and Figure 2 (note e.g. that). 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 sub-sectoral international comparison.

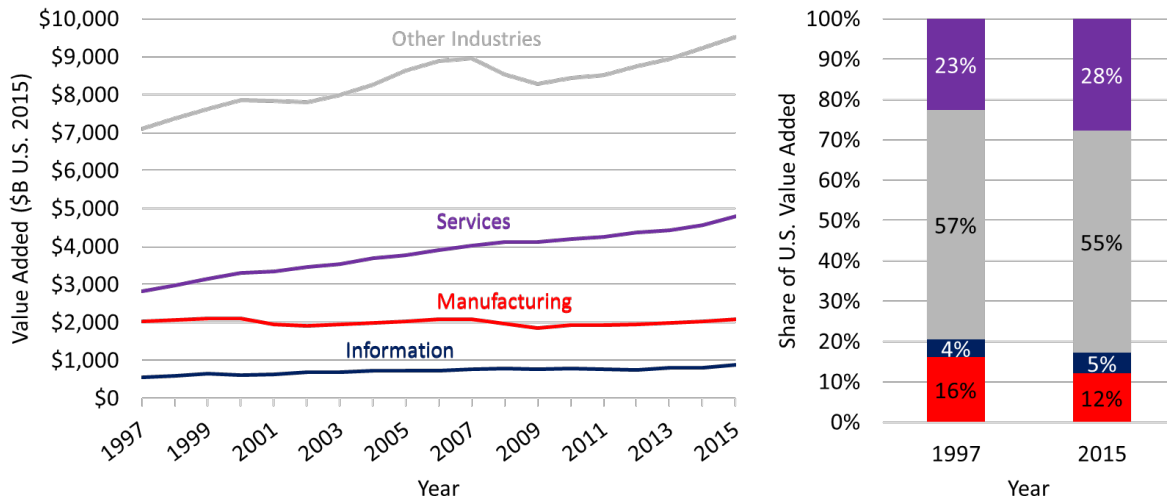


Figure 2 U.S. Domestic Manufacturing Value Added by Sector (BEA 2019)

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

3.2 U.S. 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 non-member countries (including all countries in the G20), with data covering the U.S., 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 within 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 NSF, on which OECD bases its U.S. R&D calculations, excludes historical and other nonscientific research, the definition of R&D used by OECD in tabulating 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 within the U.S. 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 within 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

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

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

¹² OECD's definition of R&D (2019): "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: while 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.

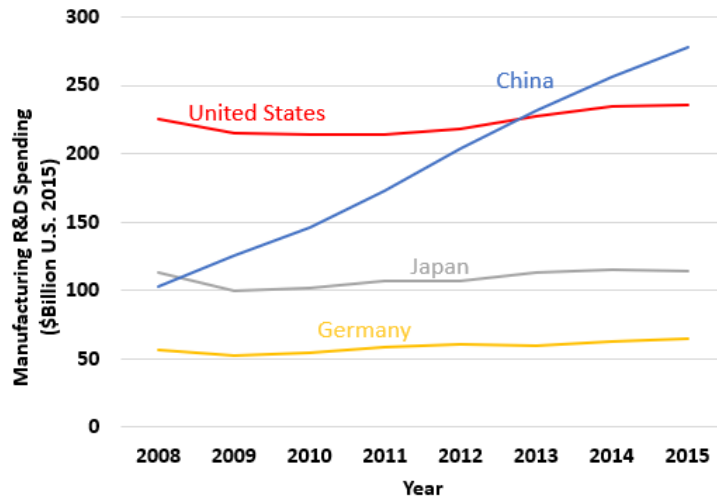
in the focus country.¹⁴ While the NSF also reports these values (referred to by NSF as “U.S. world-wide R&D spending,” and which match OECD’s numbers), as our focus in later sections is on R&D spending by business establishments located in the U.S., we use NSF’s (smaller) U.S. domestic industrial R&D values rather than the world-wide spending. As can be seen in comparing Figures 3 and 4, the difference between the difference between the NSF’s U.S. world-wide R&D spending (as used in the OECD global industrial R&D spending data) and the NSF U.S. domestic industrial R&D spending in 2015 was about \$50B or 21%.

Under OECD’s measurement, Chinese establishments and Chinese-owned subsidiaries account for the most R&D spending internationally. While U.S. 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 each). In contrast, R&D expenditures by manufacturing business establishments located in China have more than doubled in the same period, exceeding spending in the U.S. in 2013 (OECD 2019).¹⁵ Figure 3 captures these trends in R&D spending by manufacturing business enterprises in key nations. The named countries’ share of global R&D activity by manufacturing business enterprises is overstated in the figure, because the dataset for 2015 (the latest available year with broad, reliable international data) includes data from the China, the U.S., Japan, Germany, the OECD nations, Taiwan, Argentina, and Romania, but not the rest of the world.

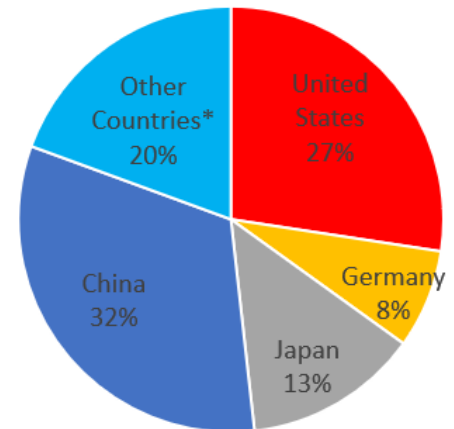
Among the nations captured by the OECD data (OECD Nations and China, Taiwan, Argentina and Romania), 72% of industrial R&D expenditures recorded by OECD were in manufacturing. In the China that share was 88%, while in OECD’s figures the share of U.S. industrial R&D expenditure in manufacturing was only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

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 U.S. government (and OECD notes that U.S. R&D inputs to its database are based on a different definition). OECD’s 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.” The inclusion of social sciences expands the scope of relevant R&D activity outside that used within the United States and thus may understate the level of non-social science R&D spending in the U.S. relative to other countries.



*OECD Nations + Taiwan + Argentina + Romania



Manufacturing R&D Share by Nation (2015)

Figure 3 Expenditures on Manufacturing R&D by Business Establishments Located in a Country: Top 4 Nations (OECD 2019)

Between 1982 and 2015, the U.S. rate of federal R&D funding declined as a relative share of total R&D funding (NSF 2018, AAAS 2018), with industrial R&D funding growing relative to federal funding over the same period (See Appendix K). Industrial and federal R&D show significant differences in the funding of basic versus applied research: while 30-36% of overall federal funding was allocated to basic research over the period of 2006-2015, in 2015 only 5.5% of industry R&D spending was directed toward basic research, the rest going to applied research and development.¹⁶ Arora et al (2015) show declining R&D spending and capability-building by U.S. companies in basic research. Fleming et al (2019) suggest that companies are increasingly relying on federally-supported research.

Within the United States, manufacturing remains the dominant source of industrial R&D. Industrial R&D spending originating from manufacturing grew significantly in real terms over the period 1982-2015 (NSF 2018). 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 4).

¹⁶ Federal funds to industry were also disproportionately allocated to applied research and development, with 8% of funds going to basic research.

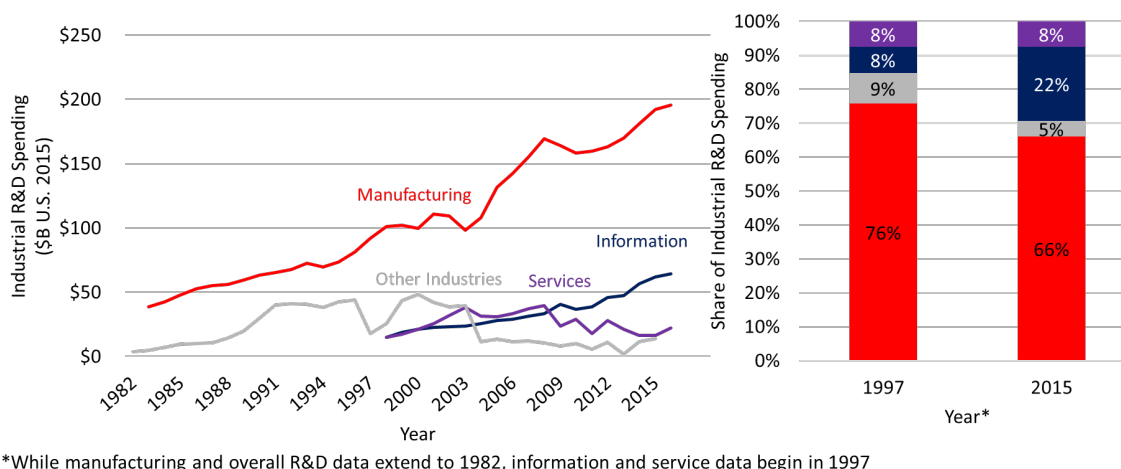


Figure 4 U.S. Industrial R&D Spending by Sector (NSF 2018)

In short, R&D spending by manufacturing sector business establishments located in the U.S. continues to dominate U.S.-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 U.S. value added.

4. The U.S. Manufacturing Labor Force

The IPUMS CPS Annual Social and Economic Complement microdata from 1968 to 2018 reveal differences between the U.S. manufacturing and non-manufacturing labor force along several demographic dimensions, including educational attainment, age, gender, and wage and salary income groups.¹⁷ Figure 5 shows the magnitude of the labor force each year in manufacturing and nonmanufacturing; during this period, growth in the U.S. labor force has come entirely from the non-manufacturing sector, with a reduced manufacturing labor force post-1981.

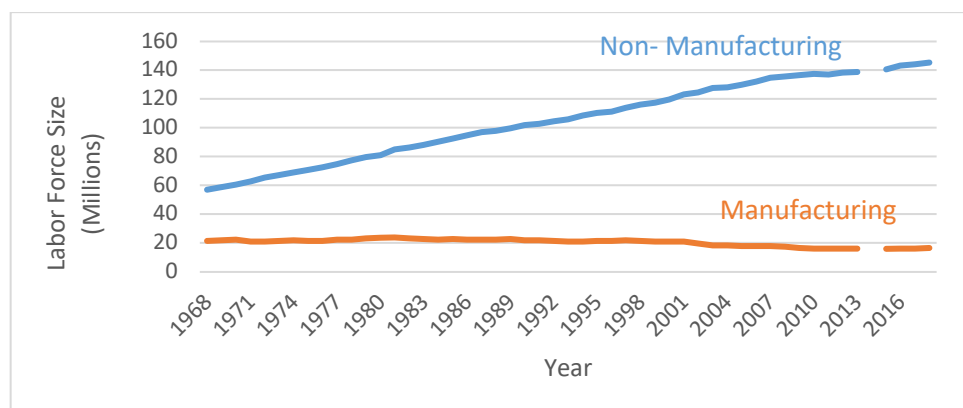


Figure 5 Absolute Magnitude of the U.S. Non-Manufacturing and Manufacturing Labor Force, IPUMS – CPS, ASEC microdata¹⁸

¹⁷ Each individual observation in the data is weighted by the ASEC population weight.

¹⁸ In Figure 5, 2014 is omitted to allow for use of consistent weighting by the ASEC population weight, as the CPS underwent an experimental redesign.

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 last five decades. Berman et al. (1994) argue that labor-saving technological change is the leading cause of this trend. Berman et al. (1998) find further international evidence of manufacturers increasing demand for skilled workers and increasing skill premiums, in line with 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 6, the manufacturing sector (bold orange line) consistently has a higher proportion of workers with a HS education or less relative to non-manufacturing sectors (bold blue line); each year the manufacturing labor force is comprised of 8-12 percentage points more of lower educated workers relative to the non-manufacturing sector.

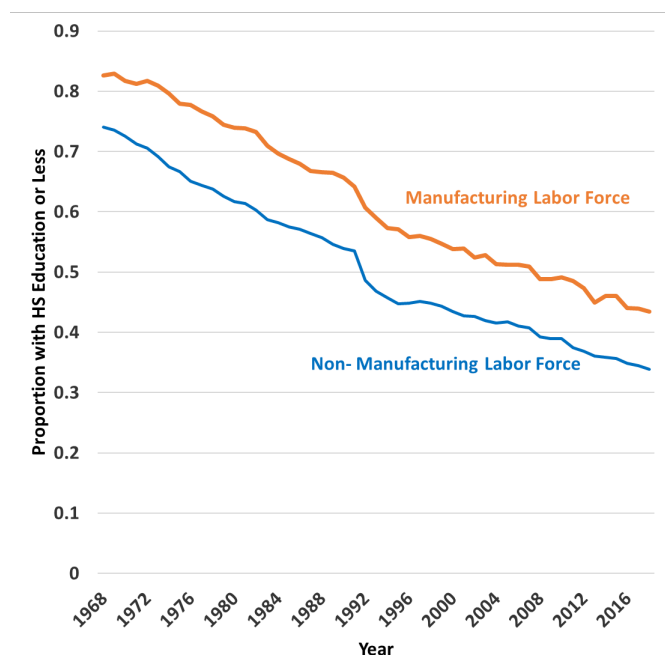


Figure 6 Manufacturing and Non-Manufacturing Labor Force Educational Attainment exhibiting a consistent difference. IPUMS- CPS ASEC microdata (1968- 2018)

The manufacturing industry's labor force has remained nearly completely private wage or salary workers: 98% in 1975 and 95% in 2015. The proportion of the manufacturing labor force earning less than \$10,000 (2017 dollars) remains less than the proportion of the non-manufacturing labor force (8% manufacturing, 19% non-manufacturing). The proportion of the manufacturing labor force whose earnings fall between \$10,000 and \$250,000 is also higher than the non-manufacturing labor force (91% manufacturing, 81% non-manufacturing).

5. Manufacturing Share of Value Added and Share of R&D Funding

5.1.1. Disproportionate R&D Funding from Manufacturing Relative to MVA

As described in Sections 1 and 3, manufacturing historically and currently makes up a disproportionate source of industrial R&D funding in the United States: about 96% in 1982, and about 66% in 2015. Though shrinking proportionally, R&D funds from manufacturing grew in real terms by 197% in the same period. Manufacturing represents a much smaller proportion of U.S. nongovernmental value added (14%), 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%. At that time, manufacturing share of industrial R&D spending was 76%. With a proportional decline in R&D share of 13% and a proportional decline of MVA share of 26% since 1997, the proportional difference between manufacturing subsector's contribution to U.S. R&D spending and to value added has been growing. As can be seen in Figure 7, this difference between a sector's contribution to U.S. industrial R&D spending versus a sector's contribution to U.S. value added, while most pronounced in manufacturing, is not unique to manufacturing [see Appendix N]. For example, the information sector comprises 22% of U.S. industrial R&D spending but 6% of U.S. value added. In contrast, professional, scientific and technical services comprise 7% of U.S. industrial R&D spending but a much larger percentage of U.S. value added. Uncovering the sources of these differences in other sectors is outside the scope of this paper but is an important broader phenomena to unpack in the U.S. economy.¹⁹

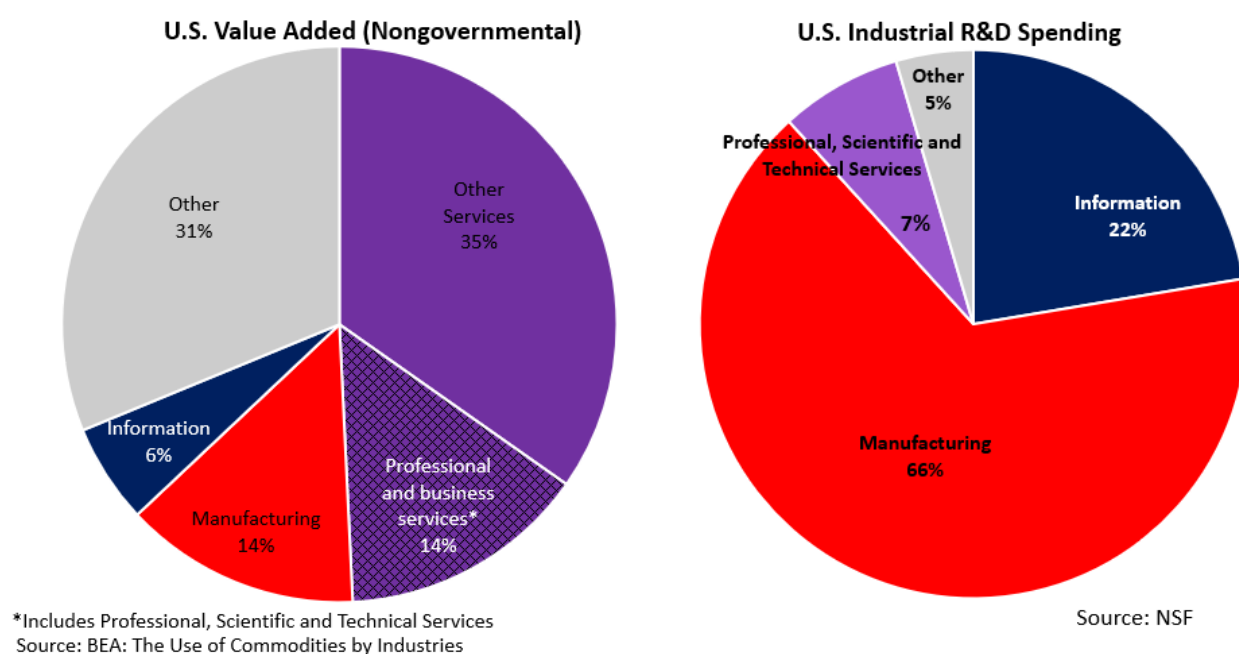


Figure 7 Share of Value Added and Industrial R&D Spending by Sector (2015)

5.2 Hypotheses, Evaluation, and a Partial Explanation

¹⁹ More recent work by NSF (NSF 19-324) has sought to reclassify R&D spending based on the dominant revenue source of a firm, rather than the dominant industry focus of its R&D. This approach suggests that about 40% of industrial R&D performance occurs within firms whose primary revenue source is manufacturing. This figure is less than the 66% of industrial R&D spending with a manufacturing focus but remains much greater than the share of manufacturing in U.S. 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.

We propose and evaluate three hypotheses for what might in part account for the disproportionate share of U.S. industrial R&D spending from manufacturing: (1) Other sectors of the economy underreport their R&D spending, possibly due to incentives in the R&D tax credits available under the U.S. 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 not reflected in value added statistics from U.S. manufacturing. Our ongoing 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 L. 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 U.S. 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 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 2016), 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 others.

Hypothesis 2 proposes that the disproportionate share of U.S. 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 L). Preliminary evidence based on the rudimentary regression rather 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 general purpose technology 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 improve 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 non-manufacturing 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, 2016).²⁰

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 Bureau of Economic Analysis (BEA) data from the US Direct Investment Abroad surveys (BEA 2019). Statistics on value added and R&D performed within 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 (NCSES)²¹ reports that US multinational companies performed seventy-nine percent of all R&D conducted by US-located businesses.

Figure 8 illustrates that concentrating attention on US MNCs – and including all of their global activity – significantly shrinks the gap between value added and R&D performed for manufacturing firms vs non-manufacturing firms. The left-hand side of the panel is a bar graph representation of the pie chart from Figure 7 in Section 5.1 and shows the original motivating puzzle: manufacturing firms contribute disproportionately to R&D and yet very little value added results from this. The right-hand side of the panel 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 VA and R&D for manufacturing firms as compared to non-manufacturing firms shrinks significantly.

²⁰ 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 U.S. 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.

²¹ Moris, Francisco. R&D Performance of US-Located Multinational companies: Results from Multiagency Survey Linking Project. February 2016. National Center for Science and Engineering Statistics. NSF 16-305. <https://www.nsf.gov/statistics/2016/nsf16305/nsf16305.pdf>

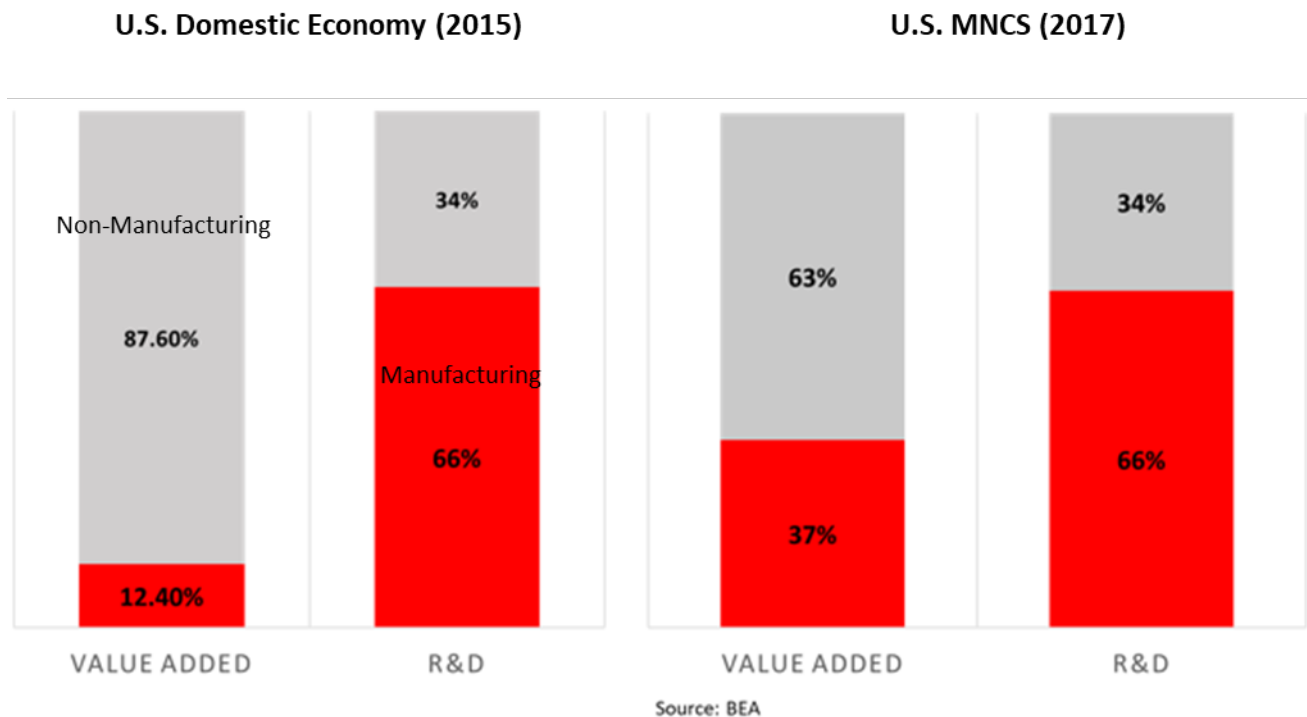


Figure 8 Share of Value Added and R&D Contributed to by Manufacturing vs Non-Manufacturing Firms

Figure 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 than R&D, which is highly concentrated in the US.

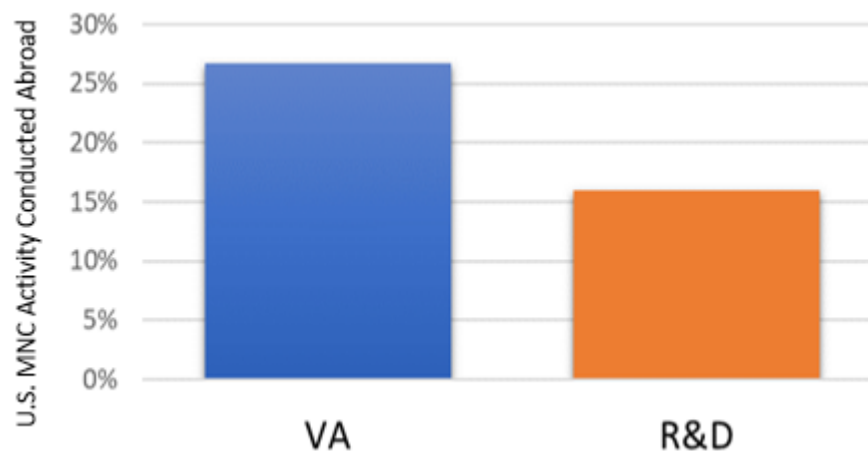


Figure 9 The percentage of US MNC Activity Conducted Abroad in 2017 (BEA)

The picture becomes even more clear when we take this one step more and consider how US MNCs in the manufacturing sector geographically distribute their value added and R&D activities relative to those in the non-manufacturing sector. Figure 10 illustrates this point: US MNCs in the manufacturing sector do only 14% of their R&D activities abroad, while those in

the non-manufacturing sector do 20% of their R&D activities abroad, as of 2017. In contrast, they are much likely to have value-added abroad; 31% of manufacturing value added is at their foreign affiliates, while only 24% of non-manufacturing value added is at their foreign affiliates.

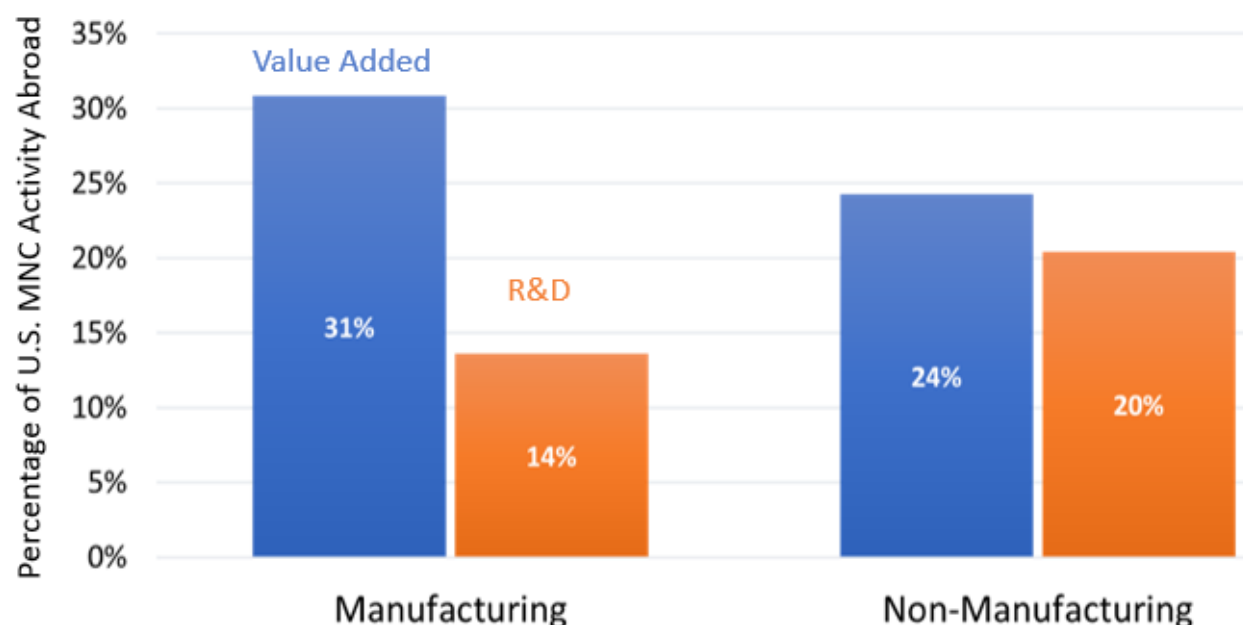


Figure 10 The percentage of US MNC Activity Conducted Abroad in 2017, by Sector BEA)

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.

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, explaining the differences in manufacturing's contribution to R&D vs VA within 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 below in Figure 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.

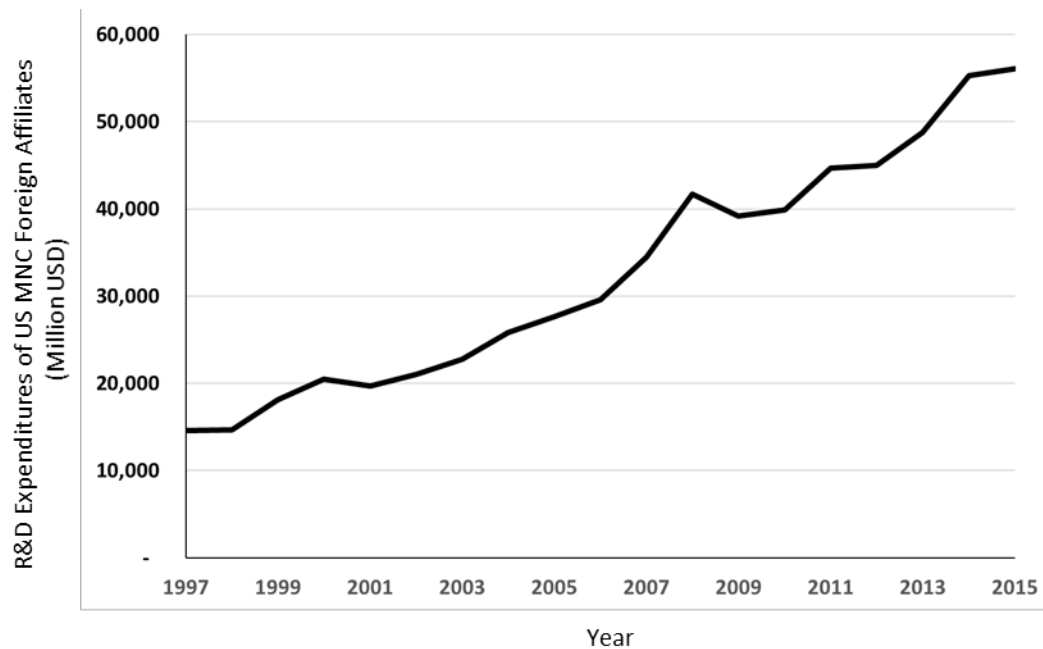


Figure 11 R&D expenditures of US MNC foreign affiliates, in millions USD (BEA)

Figure 12 and Figure 13 illustrate that the expansion abroad has largely been driven by non-manufacturing sectors. The services sector – and especially the professional, scientific, and technical services sector – in particular 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 their R&D at home.

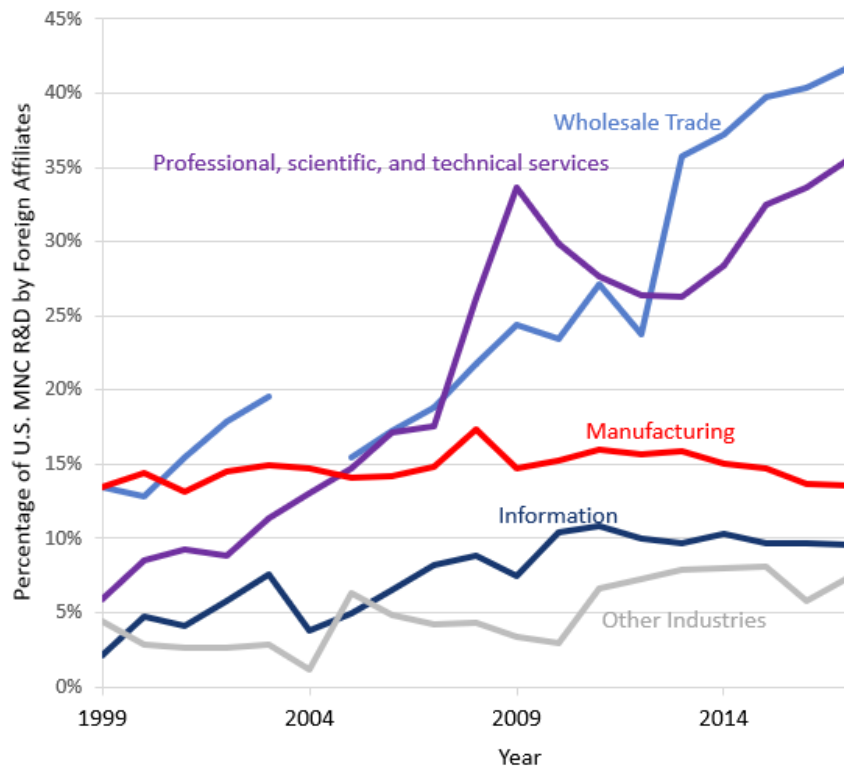


Figure 12 Percentage of R&D conducted at foreign affiliates, by sector (BEA)

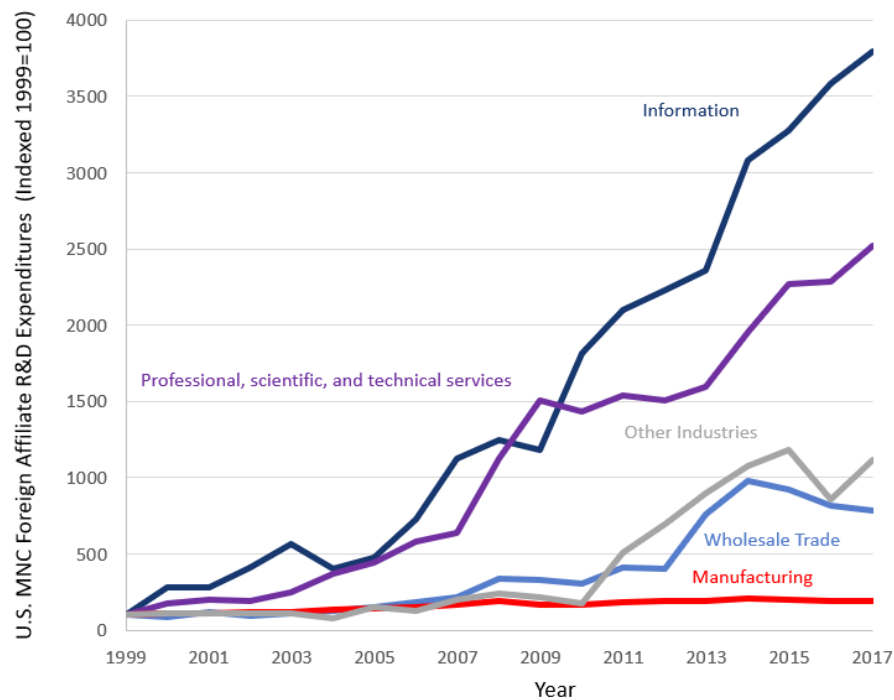


Figure 13 R&D Expenditures by US MNC Foreign Affiliates by Industry of Foreign Affiliate, Indexed (1999=100) (BEA)

6. Manufacturing Sub-Sectoral Variations in the Concentration of Value Added, R&D Funding, Employment and Revenue

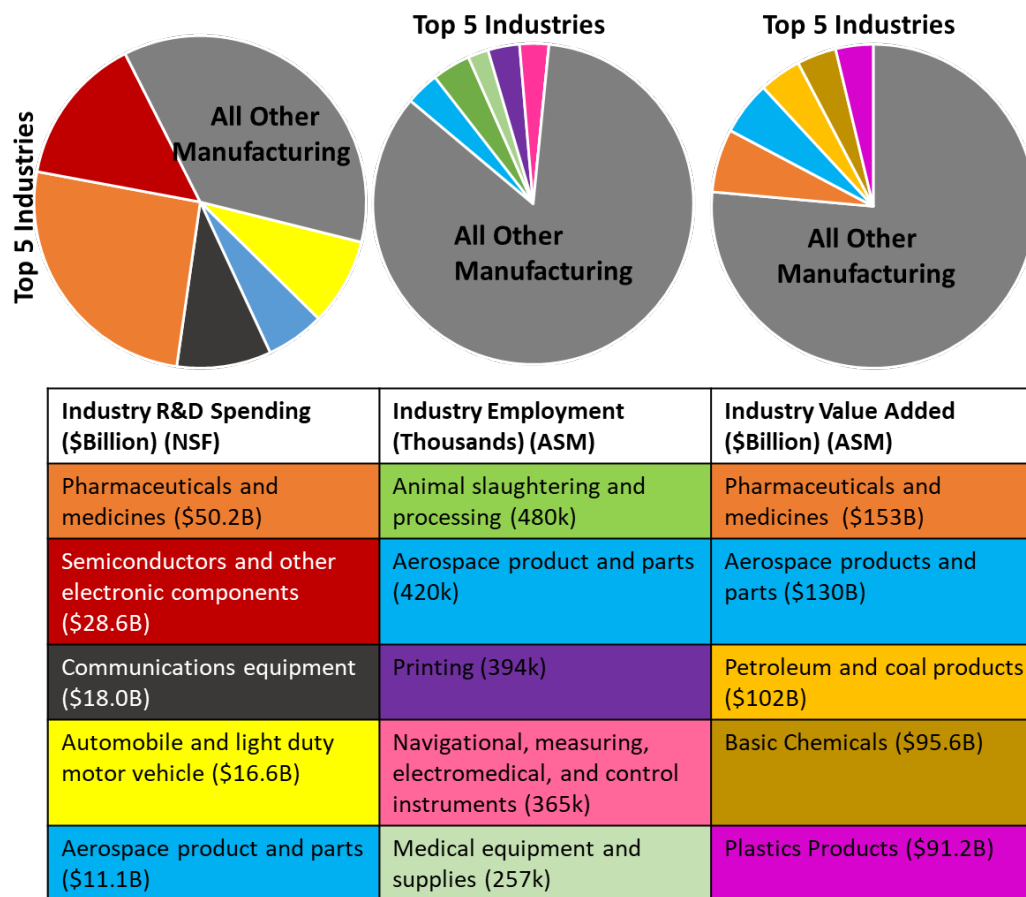
Today, the U.S. manufacturing sector is composed of industries that vary in the level of spending that they dedicate to research and development, with key industries representing dominant sources of current investment. The disproportionate role of manufacturing in R&D activity becomes starker when considering the top 5 manufacturing subsectors by R&D spending. These subsectors contributed 42% of U.S. industrial R&D Spending in 2015 (NSF 2018), despite representing only 18% of manufacturing value added and thus 2.1% of total value added in the economy (US Census Bureau 2018, BEA 2019). 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, manufacturing value added is not dominated by any core sector or sectors, nor are the top subsectors necessarily the largest by R&D spending. Appendix M shows the share of total manufacturing value added by the top 5 subsectors by MVA and by industrial R&D spending.

Table 1 illustrates the concentration of R&D spending, Employment and Value Added within the manufacturing sector by 4-digit NAICs subsector: the pie charts are color-coded to match the top 5 firms in each measure for 2015, listed directly below the charts. As the table illustrates, the industries that provide the most funding for industrial R&D are not necessarily the largest employers or sources of value 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 5 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% of the total, followed by semiconductors and electronic components with 15% of the total and communications, automobile and aerospace manufacturing contributing a cumulative 23%, for a total of 64% 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 industry. Thus, not only are the largest five sectors by R&D spending disproportionately dominant, but the concentration continues to scale within the top five.

Table 1 The Concentration of R&D Spending, Employment and Value Added within Manufacturing (2015)



Employment and value added show a wider dispersion across manufacturing industries. The five largest manufacturing industries by revenue make up 24% of total manufacturing revenue, while the five industries with the highest employment represent 15% 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% 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 1994²² to the latest NSF data by sector in 2015. Figure 14 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 4th 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

²² The NSF annual reports on “Research and Development in Industry” including annual data extending back to 1982, but classification shifts from the 1993 to 1994 reports limit comparisons before 1994: the composition of the top 5 sectors may have changed prior to 1994, but comparison is infeasible before and after the reclassifications.

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 period 2004-2015 period, with the bottom three industries remaining fairly close to each other in level of funding and a growing gap between both the top and bottom three and between pharmaceuticals and semiconductors.

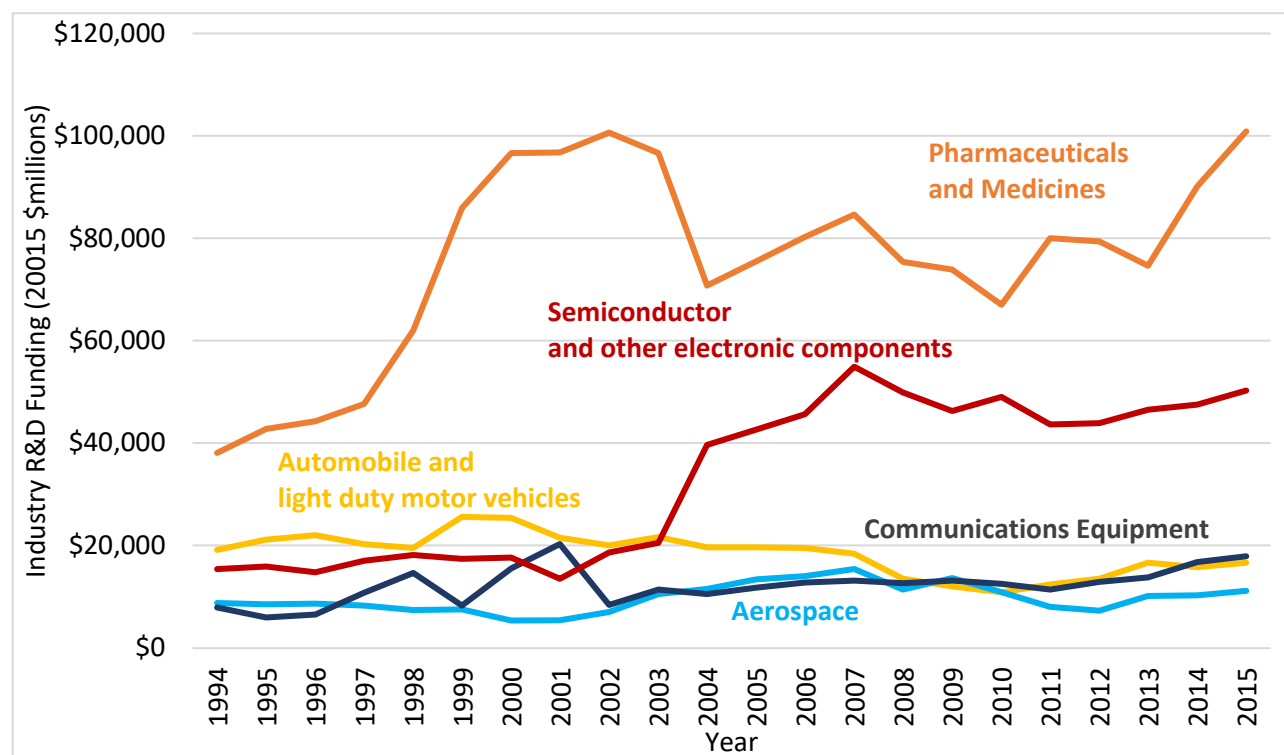


Figure 14 Industrial R&D Funding by Top 5 R&D Funders in Manufacturing, 1994-2015

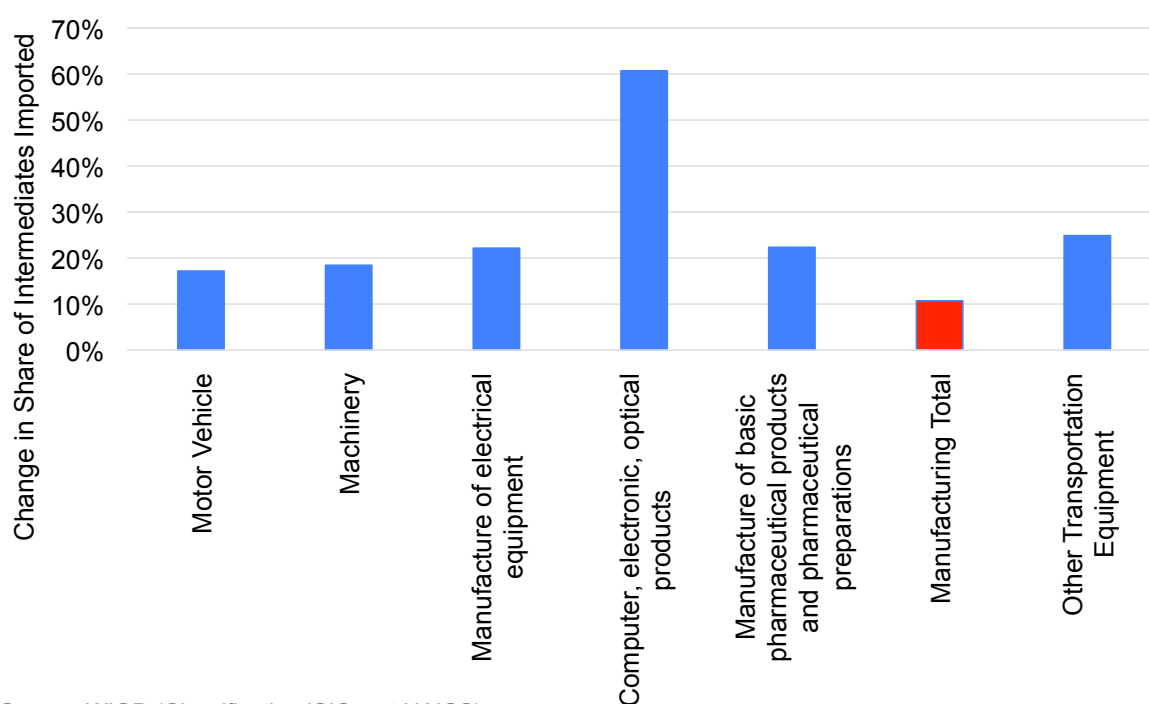
7. Sub-Sectoral Nuances in the Offshore Realization of Manufacturing R&D Returns

7.1 Globalization of MVA and R&D Subsector Story

To better understand the dichotomy between manufacturing value added and industrial R&D spending, we looked at the changes in share of intermediates imported for the subsectors in the ISIC classification which most closely correspond to the manufacturing subsectors under NAICS with the top industrial R&D spending.²³ While U.S. manufacturing overall saw a 10% 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

²³ While some research (c.f.e Los, Timmer and de Vries 2015) has imputed value added from the input-output data of the World Input Output Database (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.

greater shifts in their share of intermediate inputs imported than manufacturing overall (see Figure 15). Motor vehicles and machinery had nearly double an increase in their share of intermediates imported, at 17% and 18% respectively, compared to manufacturing on average. The largest industrial R&D spending subsector in manufacturing, pharmaceuticals, saw a 22% increase in its share of intermediate inputs imported between 2005 and 2014. Meanwhile, computer, electronic and optical products, saw a 61% 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 within these sectors was and was not shifted abroad and why.



Source: WIOD (Classification ISIC, not NAICS)

Figure 15 Manufacturing subsector differences in shifting inputs offshore (2005-2014)

Although on aggregate US MNCs in the manufacturing industry concentrate their R&D activity in the US, Figure 16 below 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.

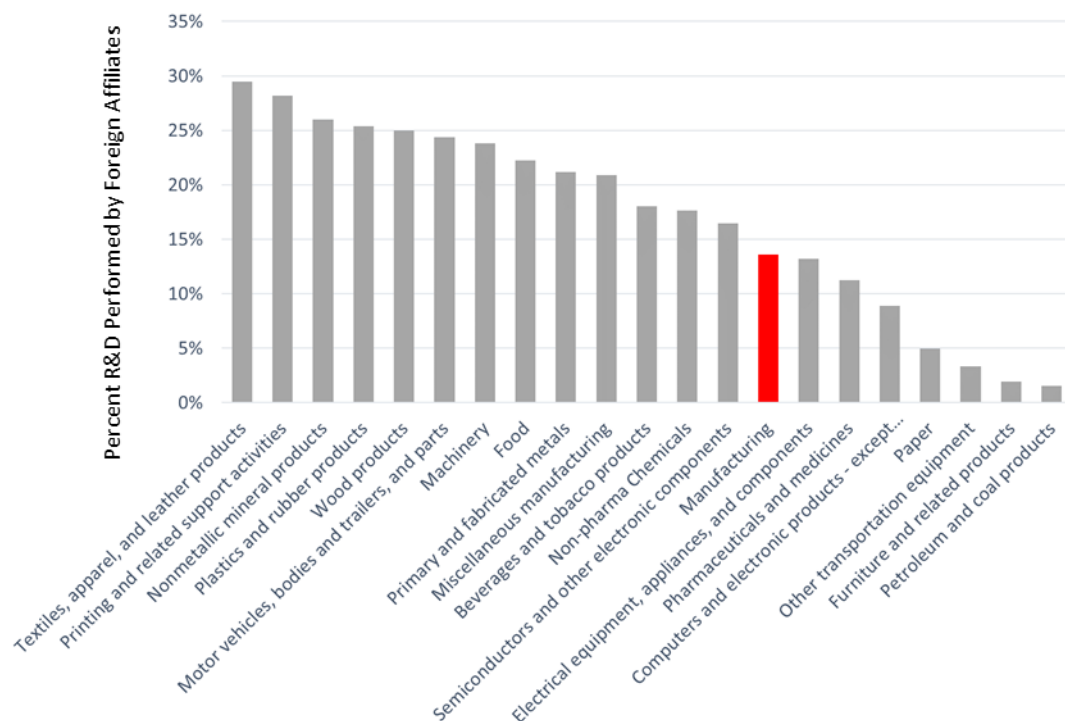


Figure 16 Percentage of R&D performed at US MNCs foreign affiliates in 2017 (BEA)

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

7.2 Globalization of MVA: Labor subsector story

The realization of MVA returns abroad by 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 4), we show in Figure 17 that the largest manufacturing subsectors by R&D spending (left) tend to skew less toward high school level employees than the largest subsectors by employment (right).²⁴

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 high-school intensive subsectors. Not only do the subsectors driving manufacturing R&D spending overall employ relatively fewer high school level employees, those subsectors which have offshored the most (e.g. electrical and communications equipment) appear to skew furthest away from high school level employment. The subsectors realizing MVA returns offshore have a more highly educated domestic

²⁴ 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).

employment profile than do subsectors with lower offshoring and either low R&D or high R&D spending.

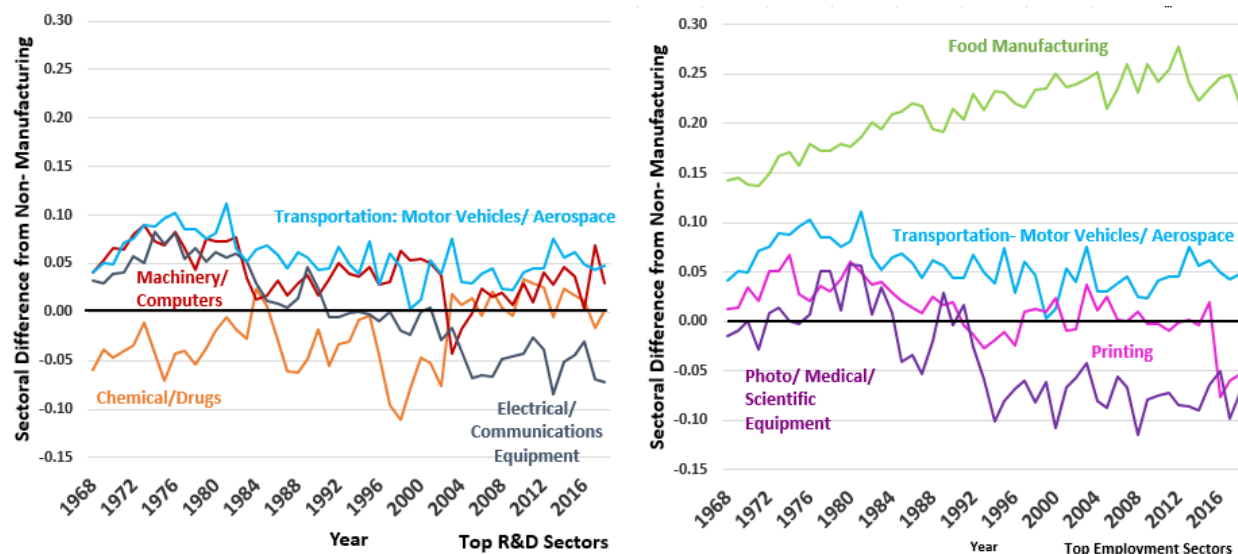


Figure 17 Manufacturing Sub-sectoral Differences from Share of High-School Level Employees in Non-Manufacturing 2015 [Top 5 R&D Spending Subsectors (left) and Top 5 Employment Subsectors (right)] (IPUMS – CPS ASEC microdata 1968- 2018)

8. Discussion: Potential Relationships between Manufacturing Location, Innovation, and Labor Outcomes – A need to technology differentiation

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 et al 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 U.S. firms shifted production to developing East Asia, differences in these production characteristics meant that products developed in the U.S. 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 of their locations overseas and in the United States (Fuchs and Kirchain 2010; Yang, Nugent, and Fuchs 2014).

Recent work has further underscored the potential negative relationship between overseas activities and innovation. Autor et al (2019) find that foreign competition (in the form of import substitution) reduces U.S. 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 U.S. multinationals in the manufacturing sector have increased their industrial R&D spending proportionally in the U.S. and at foreign locations, as of 2013, the most industrial R&D spending on manufacturing globally is occurring in China. Notably, Bransetter 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).²⁵ It is unclear whether it will just be a matter of time for levels of manufacturing patents in China to catch up to levels of manufacturing value added (China’s manufacturing value added superseded the U.S. 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 U.S.-based establishments and U.S. 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; Cummings, 2009). 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 (2014) find that offshoring by U.S. firms from the U.S. 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 related to general production. Branstetter et al (2020), 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 towards 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 towards the non-offshored parts.

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 (Lecuyer 2006), pharmaceuticals (Pisano 2000), and additive manufacturing (Bonnin-Roca 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 (Fuchs and Kirchain 2010, Bohn 2005, Bonnin-Roca 2017b). 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

²⁵ Branstetter et al 2018 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 represent 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.

separating design from production could potentially leverage location-based differences in production characteristics to diversify their product development portfolio, and potentially increase their innovation.

Further, 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 consumers in the U.S. 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 multinational or their Chinese joint venture counterparts to undertake electric vehicle production or innovation in China, leaving open – with 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).

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 U.S. 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). Industrial robots in particular 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 1997), shifting from line operators toward labor involved in equipment support. Some technology change 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 within that occupation constant; other technology change may shift skill requirements such as to shift 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. (2018) find that automation polarizes the demand for skill within manufacturing operator occupations, eliminating demand for middle-skilled tasks while shifting demand toward low and high skill tasks. Relatedly, Combemale et al (2018) 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 (2018) work finds that competing technologies with seemingly comparable production cost outcomes can be associated with different outcomes for labor and skill demand.

9. Conclusions, Potential Policy Implications, and Future Work

The manufacturing sector dominates industrial R&D spending in the U.S. as measured, however manufacturing's share of U.S. value added and share of U.S. domestic employment have been in decline. This disproportionate contribution of manufacturing firms to U.S.-based industrial R&D compared to total U.S. employment or U.S. gross value-added is in part driven by the offshoring of manufacturing facilities from the U.S. to other nations, and in particular China, without equivalent offshoring of U.S.-based manufacturing R&D. The U.S. 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 U.S.-based firms in motor vehicles increased intermediate inputs imported by 18%, pharmaceuticals increased intermediated imported by 22% (classification ISIC, not NAICS).

The manufacturing sector is not alone in disproportionately contributing to U.S.-based R&D compared to value-added: the information sector's fraction of U.S.-based R&D spending is also greater than its fraction of U.S.-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 U.S.-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 multinationals in the manufacturing sector (the latter whose R&D spending has risen equally in the U.S. and at foreign affiliates.) Further 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 research and development activities. In contrast, the proportion of deals by count (2%) and monetary volume (3%) aimed at manufacturing industries is comparatively quite small. This lower investment in manufacturing is perhaps surprising given that Lerner and Kortum (2000) find that VC in manufacturing is more productive (measured by patents per dollar) than corporate R&D. However, the capital intensity of manufacturing (Levinson 2013; 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 (Levin et al. 1987, Cohen et al. 2000, Arora et al. 2015). 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 et al 2010; Fuchs et al 2011). Likewise, Autor et al (2019) find that foreign competition (in the form of import substitution) reduces U.S. innovation (measured in patents). Branstetter et al 2018 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 U.S., 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 U.S. 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 U.S. economy.

While the size of the U.S. manufacturing labor force has remained relatively constant in the last half a century, growth in U.S. jobs outside manufacturing has led to manufacturing being a small fraction of today's overall U.S. labor force. That said, in those U.S. jobs that remain, manufacturing is an outsized employer of non-college educated workers, and generally has better-paying jobs than non-manufacturing. 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. 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. 2019).

REFERENCES (in alphabetical order):

- Acemoglu, Daron, and Pascual Restrepo. "Robots and jobs: Evidence from US labor markets." *NBER working paper* w23285 (2017).
- Achillas, C., Aidonis, D., Iakovou, E., Thymianidis, M., & Tzetzis, D. "A methodological framework for the inclusion of modern additive manufacturing into the production portfolio of a focused factory." *Journal of Manufacturing Systems* 37 (2015): 328-339.
- Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin, and John Van Reenen. 2016. "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry." *Journal of Political Economy* 124 (1) (February): 1– 51. doi:10.1086/684581. <https://dash.harvard.edu/bitstream/handle/1/27759048/SSRN-id2186325.pdf>
- Aghion, Philippe, Peter Howitt, and Giovanni L. Violante. "General purpose technology and wage inequality." *Journal of Economic Growth* 7.4 (2002): 315-345.

- American Association for the Advancement of Science. Historical Trends in Federal R&D. AAAS 2019.
- Amirapu and Gechter, "Labor Regulations and the Cost of Corruption: Evidence from the Indian Firm Size Distribution," February 2017. Working Paper.
- Arora, Ashish, Sharon Belenzon, and Andrea Pataconi. *Killing the golden goose? The decline of science in corporate R&D*. No. w20902. National Bureau of Economic Research, 2015.
- Arora, Ceccagnoli, and Cohen, "R&D and the Patent Premium" (2003) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=368187
- Arora, Cohen, and Walsh, "The Acquisition and Commercialization of Invention in American Manufacturing: Incidence and Impact" (2015) <https://www.nber.org/papers/w20264>
- Atack, Jeremy, Robert A. Margo, and Paul W. Rhode. "'Automation' of Manufacturing in the Late Nineteenth Century: The Hand and Machine Labor Study." *Journal of Economic Perspectives* 33.2 (2019): 51-70.
- Atzeni, Eleonora, and Alessandro Salmi. "Economics of additive manufacturing for end-usable metal parts." *The International Journal of Advanced Manufacturing Technology* 62.9-12 (2012): 1147-1155.
- Autor, David and Dorn, David. "The growth of low-skill service jobs and the polarization of the US labor market." *The American Economic Review* 103.5 (2013): 1553-1597.
- Autor, David H. David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu. Foreign Competition and Domestic Innovation: Evidence from U.S. Patents *American Economic Review: Insights*, forthcoming
- Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song. "Trade adjustment: Worker-level evidence." *The Quarterly Journal of Economics* 129, no. 4 (2014): 1799-1860.
- Autor, David H., Frank Levy, and Richard J. Murnane. "The skill content of recent technological change: An empirical exploration." *The Quarterly journal of economics* 118.4 (2003): 1279-1333.
- Baldwin, Carliss Y., and Kim B. Clark. "Managing in an age of modularity." *Managing in the modular age: Architectures, networks, and organizations* 149 (2003): 84-93.
- Baldwin, Carliss Young, and Kim B. Clark. *Design rules: The power of modularity*. Vol. 1. MIT press, 2000.
- Bartel, Ann P. "Productivity gains from the implementation of employee training programs." *Industrial relations: a journal of economy and society* 33.4 (1994): 411-425.
- Bartel, Ann, Casey Ichniowski, and Kathryn Shaw. "How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills." *The quarterly journal of Economics* 122.4 (2007): 1721-1758.
- Berman, Eli, John Bound, and Stephen Machin. "Implications of skill-biased technological change: international evidence." *The quarterly journal of economics* 113, no. 4 (1998): 1245-1279.
- Berman, Eli, John Bound, and Zvi Griliches. "Changes in the demand for skilled labor within US manufacturing: evidence from the annual survey of manufactures." *The Quarterly Journal of Economics* 109, no. 2 (1994): 367-397.
- Bernard, Andrew B., and Charles I. Jones. "Comparing apples to oranges: productivity convergence and measurement across industries and countries." *The American Economic Review* (1996): 1216-1238.

- Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum. "Plants and productivity in international trade." *American economic review* 93, no. 4 (2003): 1268-1290.
- Bohn, R. From Art to Science in Manufacturing: The Evolution of Technical Knowledge. Foundations and Trends in Technology, Information, and Operations Management. Vol 1.2 (2005): 1-82.
- Bollinger, John G., and Neil A. Duffie. *Computer control of machines and processes*. New York: Addison-Wesley, 1988.
- Bonin-Roca, Jaime, Vaishnav, P., Morgan, M. G., Mendonça, J., & Fuchs, E. "When risks cannot be seen: Regulating uncertainty in emerging technologies." *Research Policy* 46.7 (2017): 1215-1233.
- Bonnín-Roca, Jaime, Parth Vaishnav, Joana Mendonça, and Millett Granger Morgan, "Getting past the hype about 3-D printing." *MIT Sloan Management Review* 58.3 (2017): 57.
- Branstetter, Chen, Glennon, Zolas (2018), "Does offshoring manufacturing impact innovation in the home country? New evidence from Taiwan and China"
- Branstetter, Drev, Kwon (2015) "Get with the Program: Software- Driven Innovation in Traditional Manufacturing" NBER Working Paper 21752. November 2015.
- Branstetter, Glennon, Jenson (2018a), "Knowledge Transfer Abroad: The Role of U.S. Inventors within Global R&D Networks," NBER Working Paper 24453. March 2018.
- Branstetter, Glennon, Jenson (2018b), "The IT Revolution and the Globalization of R&D," NBER Working Paper 24707. June 2018.
- Branstetter, Lee G., Britta Glennon, and J. Bradford Jensen. "The IT Revolution and the Globalization of R&D." *Innovation Policy and the Economy* 19.1 (2019): 1-37.
- Branstetter, Lee, Guangwei Li, and Francisco Veloso. "The rise of international coinvention." *The changing frontier: Rethinking science and innovation policy*. University of Chicago Press, 2014. 135-168.
- Branstetter, Li, and Veloso (2014) "The Globalization of R&D: China, India, and the Rise of International Co-invention" April 2014
- Bresnahan, Timothy F., and Manuel Trajtenberg. "General purpose technologies 'Engines of growth'?" *Journal of econometrics* 65.1 (1995): 83-108.
- Browne, Jim, Didier Dubois, Keith Rathmill, Suresh P. Sethi, and Kathryn E. Steckle, "Classification of flexible manufacturing systems." *The FMS magazine* 2.2 (1984): 114-117.
- Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin. "Finance and development: A tale of two sectors." *American economic review* 101, no. 5 (2011): 1964-2002.
- Bureau of Economic Analysis, "U.S. Direct Investment Abroad (USDIA)." Retrieved November 2019.
- Bureau of Economic Analysis. *The Use of Commodities by Industries*. 2019.
- Bureau of Labor Statistics (2019), "Manufacturing: NAICS 31-33" Industries at a Glance. Updated April 11th 2019. <https://www.bls.gov/iag/tgs/iag31-33.htm>
- Buzacott, John A., and David D. Yao. "Flexible manufacturing systems: a review of analytical models." *Management science* 32.7 (1986): 890-905.
- Card, David, and John E. DiNardo. "Skill-biased technological change and rising wage inequality: Some problems and puzzles." *Journal of labor economics* 20.4 (2002): 733-783.

- Caro, Felipe, and Jérémie Gallien. "Inventory management of a fast-fashion retail network." *Operations Research* 58.2 (2010): 257-273.
- Caro, Felipe, and Jérémie Gallien. "Inventory management of a fast-fashion retail network." *Operations Research* 58.2 (2010): 257-273.
- CB Insights, Private Equity and Venture Capital Data. Retrieved June 2019.
<https://www.cbinsights.com/industries>
- Chandler, Alfred Dupont. *Scale and scope: The dynamics of industrial capitalism*. Harvard University Press, 1990.
- Charles, Hurst, Schwartz. "The transformation of manufacturing and the decline in U.S. Employment," NBER Working Paper, March 2018.
- Cheng, T. C., and Susan Podolsky. *Just-in-time manufacturing: an introduction*. Springer Science & Business Media, 1996.
- Cherubini, Andrea, Robin Passama, André Crosnier, Antoine Lasnier, and Philippe Fraisse. "Collaborative manufacturing with physical human–robot interaction." *Robotics and Computer-Integrated Manufacturing* 40 (2016): 1-13.
- Chesbrough, Henry. "Towards a dynamics of modularity: a cyclical model of technical advance." *The business of systems integration* 174 (2003): 181.
- Cohen, L., and Noll, R. (1991). "The Technology pork barrel." Washington, D.C: Brookings Institution.
- Cohen, Nelson, Walsh. "Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not)," NBER Working Paper. February 2000.
- Cohen, Wesley M., and Steven Klepper. "Firm size and the nature of innovation within industries: the case of process and product R&D." *Review of Economics and Statistics* 78.2 (1996): 232-243.
- Colfer, Lyra J., and Carliss Y. Baldwin. "The mirroring hypothesis: theory, evidence, and exceptions." *Industrial and Corporate Change* 25.5 (2016): 709-738.
- Combemale, Christophe, Kate S. Whitefoot, Laurence Ales and Erica R.H. Fuchs. "Not All Technological Change is Equal: Disentangling Labor Demand Effects of Automation and Parts Consolidation." *Available at SSRN 3291686* (2018).
- Crafts, Nicholas FR. "The first industrial revolution: A guided tour for growth economists." *The American Economic Review* (1996): 197-201.
- David, H., and David Dorn. "The growth of low-skill service jobs and the polarization of the US labor market." *American Economic Review* 103.5 (2013): 1553-97.
- David, H., David Dorn, and Gordon H. Hanson. "The China syndrome: Local labor market effects of import competition in the United States." *American Economic Review* 103, no. 6 (2013): 2121-68.
- Davis, Steven J., and John Haltiwanger. "Gross job creation, gross job destruction, and employment reallocation." *The Quarterly Journal of Economics* 107, no. 3 (1992): 819-863.
- Doeringer, Peter B., Edward Lorenz, and David G. Terkla. "The adoption and diffusion of high-performance management: lessons from Japanese multinationals in the West." *Cambridge Journal of Economics* 27.2 (2003): 265-286.
- Dunne, Timothy, Mark J. Roberts, and Larry Samuelson. "The growth and failure of US manufacturing plants." *The Quarterly Journal of Economics* 104, no. 4 (1989): 671-698.
- Ford, Robert C. "The Springfield Armory's role in developing interchangeable parts." *Management Decision* 43.2 (2005): 265-277.

- Fralix, Michael T. "From mass production to mass customization." *Journal of Textile and Apparel, Technology and Management* 1.2 (2001): 1-7.
- Fuchs, Erica RH, et al. "Plastic cars in China? The significance of production location over markets for technology competitiveness in the United States versus the People's Republic of China." *International Journal of Production Economics* 132.1 (2011): 79-92.
- Fuchs, Erica RH. "Global manufacturing and the future of technology." *Science* 345.6196 (2014): 519-520.
- Fuchs, Erica, and Randolph Kirchain. "Design for location? The impact of manufacturing offshore on technology competitiveness in the optoelectronics industry." *Management Science* 56.12 (2010): 2323-2349.
- Gallien, Jérémie, Yann Le Tallec, and Tor Schoenmeyr. "A model for make-to-order revenue management." *Sloan School of Management, Massachusetts Institute of Technology* (2004).
- Gertler, Mark, and Simon Gilchrist. "Monetary policy, business cycles, and the behavior of small manufacturing firms." *The Quarterly Journal of Economics* 109, no. 2 (1994): 309-340.
- Goldin, Claudia, and Lawrence F. Katz. "The origins of technology-skill complementarity." *The Quarterly journal of economics* 113, no. 3 (1998): 693-732.
- Gordon, Bart. "US competitiveness: The education imperative." *Issues in Science and Technology* 23.3 (2007): 31-36.
- Greenwood, Jeremy. *The third industrial revolution: Technology, productivity, and income inequality*. No. 435. American Enterprise Institute, 1997.
- Hall, B. H., and Ziedonis, R. H. 2001. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. *Rand Journal of Economics*, 32(1): 101-128.
- Hall, B., A. Jaffe, M. Trajtenberg (2001), "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools", NBER Working Paper 8498 (<http://www.nber.org/papers/w8498>)
- Hayes, Bradley, and Brian Scassellati. "Challenges in shared-environment human-robot collaboration." *learning* 8.9 (2013).
- Heidi Williams, "How do Patents Affect Research Investments?" 2017 <https://www.nber.org/papers/w23088>
- Helper, Susan R., and Mari Sako. "Supplier relations in Japan and the United States: are they converging?." *MIT Sloan Management Review* 36.3 (1995): 77.
- Helveston, John P., Yanmin Wang, Valerie J. Karplus, and Erica RH Fuchs. "Institutional complementarities: The origins of experimentation in China's plug-in electric vehicle industry." *Research Policy* 48.1 (2019): 206-222.
- Helveston, John Paul, Yimin Liu, Elea McDonnell Feit, Erica Fuchs, Erica Klampf, and Jeremy J. Michalek. "Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the US and China." *Transportation Research Part A: Policy and Practice* 73 (2015): 96-112.
- Herrigel, Gary. *Manufacturing possibilities. Creative action and industrial recomposition in the United States, Germany, and Japan*. New York: Oxford, 2010.
- Hounshell, David. From the American system to mass production, 1800-1932: The development of manufacturing technology in the United States. No. 4. JHU Press, 1985.
- Hu, Albert Guangzhou, and Gary H. Jefferson. "A great wall of patents: What is behind China's recent patent explosion?." *Journal of Development Economics* 90.1 (2009): 57-68.

- Hu, S. Jack. "Evolving paradigms of manufacturing: from mass production to mass customization and personalization." *Procedia CIRP* 7 (2013): 3-8.
- Hulten, Charles R., and Robert M. Schwab. "Regional productivity growth in US manufacturing: 1951-78." *The American Economic Review* 74, no. 1 (1984): 152-162.
- Ichniowski, Casey, Kathryn Shaw, and Giovanna Prennushi. *The effects of human resource management practices on productivity*. No. w5333. National bureau of economic research, 1995.
- Jorgenson, Dale W. "Information technology and the US economy." *American Economic Review* 91.1 (2001): 1-32.
- Jorgenson, Dale W., Frank M. Gollop, and Barbara Fraumeni. *Productivity and US economic growth*. Vol. 169. Elsevier, 2016.
- Kaber, David B., and Mica R. Endsley. "The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task." *Theoretical Issues in Ergonomics Science* 5.2 (2004): 113-153.
- Katz, Lawrence F., and Kevin M. Murphy. "Changes in relative wages, 1963–1987: supply and demand factors." *The quarterly journal of economics* 107.1 (1992): 35-78.
- Klepper, Steven, and Kenneth L. Simons. "The making of an oligopoly: firm survival and technological change in the evolution of the US tire industry." *Journal of Political economy* 108, no. 4 (2000): 728-760.
- Kortum, Samuel, and Josh Lerner. "Assessing the Impact of Venture Capital to Innovation." *RAND Journal of Economics* 31, no. 4 (winter 2000): 674–692.
- Kortum, Samuel, and Josh Lerner. "Does venture capital spur innovation?." *Entrepreneurial inputs and outcomes: New studies of entrepreneurship in the United States*. Emerald Group Publishing Limited, 2001. 1-44.
- Kumar, Mukul, and Yoshinori Ando. "Chemical vapor deposition of carbon nanotubes: a review on growth mechanism and mass production." *Journal of nanoscience and nanotechnology* 10.6 (2010): 3739-3758.
- Lafortune, Jeanne, Ethan Lewis, and José Tessada. "People and Machines: A Look at the Evolving Relationship between Capital and Skill in Manufacturing, 1860–1930, Using Immigration Shocks." *Review of Economics and Statistics* 101, no. 1 (2019): 30-43.
- Lerner and Paul Gompers, "The Venture Capital Cycle" (MIT Press) Introduction. ISBN-13: 978-0262572385. 1999.
- Lerner, Josh, Amit Seru, Nicholas Short, and Yuan Sun. "21st Century: Evidence from U.S. Patenting." *Working Paper*, 2020.
- Lerner, Josh, and Kristle Romero-Cortes. "Bridging the Gap? Government Subsidized Lending and Access to Capital ." *Review of Corporate Finance Studies* 2, no. 1 (March 2013): 98–128.
- Lerner, Josh. "The Government as Venture Capitalist: The Long-Run Effects of the SBIR Program." *Journal of Business* 72 (July 1999): 285–318.
- Levin, Klevorick, Nelson, and Winter, "Appropriating the Returns from Industrial Research and Development," *Brookings Papers on Economic Activity* 3:1987
- Levinson, Marc. "US manufacturing in international perspective." (2013).
- Liu, Jifeng, Xiaochen Sun, Dong Pan, Xiaoxin Wang, Lionel C. Kimerling, Thomas L. Koch, and Jurgen Michel, "Tensile-strained, n-type Ge as a gain medium for monolithic laser integration on Si." *Optics express* 15.18 (2007): 11272-11277.

- Locke, Richard M., and Rachel L. Wellhausen, eds. *Production in the innovation economy*. MIT Press, 2014.
- Los, Bart, Marcel P. Timmer, and Gaaitzen J. de Vries. "How global are global value chains? A new approach to measure international fragmentation." *Journal of regional science* 55.1 (2015): 66-92.
- Malone, Patrick M. "Little kinks and devices at Springfield Armory, 1892-1918." *IA. The Journal of the Society for Industrial Archeology* (1988): 59-76.
- Mansfield, Edwin. "The diffusion of flexible manufacturing systems in Japan, Europe and the United States." *Management Science* 39.2 (1993): 149-159.
- Mehri, Darius. "The darker side of lean: an insider's perspective on the realities of the Toyota production system." *Academy of Management Perspectives* 20.2 (2006): 21-42.
- Mellor, Stephen, Liang Hao, and David Zhang. "Additive manufacturing: A framework for implementation." *International Journal of Production Economics* 149 (2014): 194-201.
- Mindell, David A. *Our robots, ourselves: Robotics and the myths of autonomy*. Viking Adult, 2015.
- Mindell, David A. *Our robots, ourselves: Robotics and the myths of autonomy*. Viking Adult, 2015.
- Mokyr, Joel. "The second industrial revolution, 1870-1914." *Storia dell'economia Mondiale* (1998): 219-45.
- Moore, Gordon E. "Cramming more components onto integrated circuits." (1965): 114-117.
- Moore, Gordon E. "The microprocessor: engine of the technology revolution." *Communications of the ACM* 40.2 (1997): 112-115.
- Mowery, David C. "Plus ça change: Industrial R&D in the "third industrial revolution"." *Industrial and corporate change* 18.1 (2009): 1-50.
- Mowery, David C. "Plus ça change: Industrial R&D in the "third industrial revolution"." *Industrial and corporate change* 18.1 (2009): 1-50.
- Mowery, David C., and Nathan Rosenberg. *Paths of innovation: Technological change in 20th-century America*. Cambridge University Press, 1999.
- Nadiri, M. Ishaq, and Theofanis P. Mamuneas. The effects of public infrastructure and R&D capital on the cost structure and performance of US manufacturing industries. No. w3887. National Bureau of Economic Research, 1991.
- Nadiri, M. Ishaq, and Theofanis P. Mamuneas. *The effects of public infrastructure and R&D capital on the cost structure and performance of US manufacturing industries*. No. w3887. National Bureau of Economic Research, 1991.
- National Academy of Engineering. Committee on Foundational Best Practices for Making Value for America. *Making value for America: Embracing the future of manufacturing, technology, and work*. National Academies Press, 2015.
- National Science Foundation.
- National Science Foundation. Business Research and Development and Innovation: 1991-2015. Retrieved May 2019.
- National Science Foundation. Examining Different Industry Classification Methods for Business R&D. NSF 19-324. 2019.
- Neumark, David, Brandon Wall, and Junfu Zhang. "Do small businesses create more jobs? New evidence for the United States from the National Establishment Time Series." *The Review of Economics and Statistics* 93, no. 1 (2011): 16-29.

- Nichols, A. J. "An overview of microprocessor applications." *Proceedings of the IEEE* 64.6 (1976): 951-953.
- OECD. *Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development*. 2015.
- Ohno, Taiichi. *Toyota production system: beyond large-scale production*. CRC Press, 1988.
- Orr- 16
- Pierce, Justin R., and Peter K. Schott. "The surprisingly swift decline of US manufacturing employment." *American Economic Review* 106.7 (2016): 1632-62.
- Pierce, Justin R., and Peter K. Schott. "The surprisingly swift decline of US manufacturing employment." *American Economic Review* 106, no. 7 (2016): 1632-62.
- PricewaterhouseCoopers. *Global Innovation 1000*. 2019.
- Relihan, Tom. "Setting the record straight on lean." *MIT Sloan Management Review* (2019).
- Revenge, Ana L. "Exporting jobs? The impact of import competition on employment and wages in US manufacturing." *The Quarterly Journal of Economics* 107, no. 1 (1992): 255-284.
- Rodrik, Dani. "Unconditional convergence in manufacturing." *The Quarterly Journal of Economics* 128, no. 1 (2012): 165-204.
- Rosenberg, Nathan, and Manuel Trajtenberg. "A general-purpose technology at work: The Corliss steam engine in the late-nineteenth-century United States." *The Journal of Economic History* 64.1 (2004): 61-99.
- Sakakibara, Sadao, Barbara B. Flynn, Roger G. Schroeder, and William T. Morrism. "The impact of just-in-time manufacturing and its infrastructure on manufacturing performance." *Management Science* 43.9 (1997): 1246-1257.
- Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0[dataset]. Minneapolis, MN: IPUMS, 2018.
- SBIR.gov, "Award Information" SBIR*STTR America's Seed Fund Powered by SBA. <https://www.sbir.gov/analytics-dashboard>, data retrieved July 2019.
- SBIR.gov, "About SBIR" SBIR*STTR America's Seed Fund Powered by SBA. <https://www.sbir.gov/about/about-sbir>, 2019.
- Shah, Rachna, and Peter T. Ward. "Lean manufacturing: context, practice bundles, and performance." *Journal of operations management* 21.2 (2003): 129-149.
- Shepherd, James F., and Samuel H. Williamson. "The coastal trade of the British North American colonies, 1768–1772." *The Journal of Economic History* 32.4 (1972): 783-810.
- Shu, Pian, and Claudia Steinwender. "The impact of trade liberalization on firm productivity and innovation." *Innovation Policy and the Economy* 19.1 (2019): 39-68.
- Smith, Merritt Roe, ed. *Military enterprise and technological change: Perspectives on the American experience*. MIT Press, 1985.
- Smith, Merritt Roe. *Harpers Ferry armory and the new technology: The challenge of change*. Cornell University Press, 1980.
- Soderbom and Teal, "Size and Efficiency in African Manufacturing Firms: Evidence from Firm-Level Panel Data," February 2003. *Journal of Development Economics*. 73 (2003) 369-394.
- Swamidass, Paul M. "The effect of TPS on US manufacturing during 1981–1998: inventory increased or decreased as a function of plant performance." *International Journal of Production Research* 45.16 (2007): 3763-3778.
- The CPA Journal. *U.S. Research and Development Tax Credit*. 2017.

- Troske, Kenneth R. "Evidence on the employer size-wage premium from worker-establishment matched data." *Review of Economics and Statistics* 81, no. 1 (1999): 15-26.
- Tyson, Thomas. "Accounting for labor in the early 19th century: The US arms making experience." *Accounting Historians Journal* 17.1 (1990): 47-59.
- U.S. Census Bureau. *Annual Survey of Manufactures*. 2018.
- U.S. Internal Revenue Service. *About Form 6765m Credit for Increasing Research Activities*. 2019.
- United States Census Bureau "2017 North American Industry Classification System Manual." 2017
- USPTO, PatentsView, Data Query. Retrieved May 2019.
<http://www.patentsview.org/query/#step/selectCriteria>
- Womack, James P., Daniel T. Jones and Daniel Roos. *The Machine that changed the world*. Simon and Schuster, 1990.
- Yang, Chia-Hsuan, Rebecca Nugent, and Erica RH Fuchs. "Gains from others' losses: Technology trajectories and the global division of firms." *Research Policy* 45.3 (2016): 724-745.
- Yossi Sheffi. "Will 3-D Printing Kill the Supply Chain?" *World Economic Forum* (2013).
- Zoltan Acs, David B Audretsch, *Kyklos* 42 (2), 171-180, 1989. <https://onlinelibrary-wiley-com.proxy.library.cmu.edu/doi/epdf/10.1111/j.1467-6435.1989.tb00186.x>

Appendices:

Appendix A: The Share of Manufacturing in U.S. Gross Value Added and the Share of the U.S. in Global Manufacturing and Gross Value Added

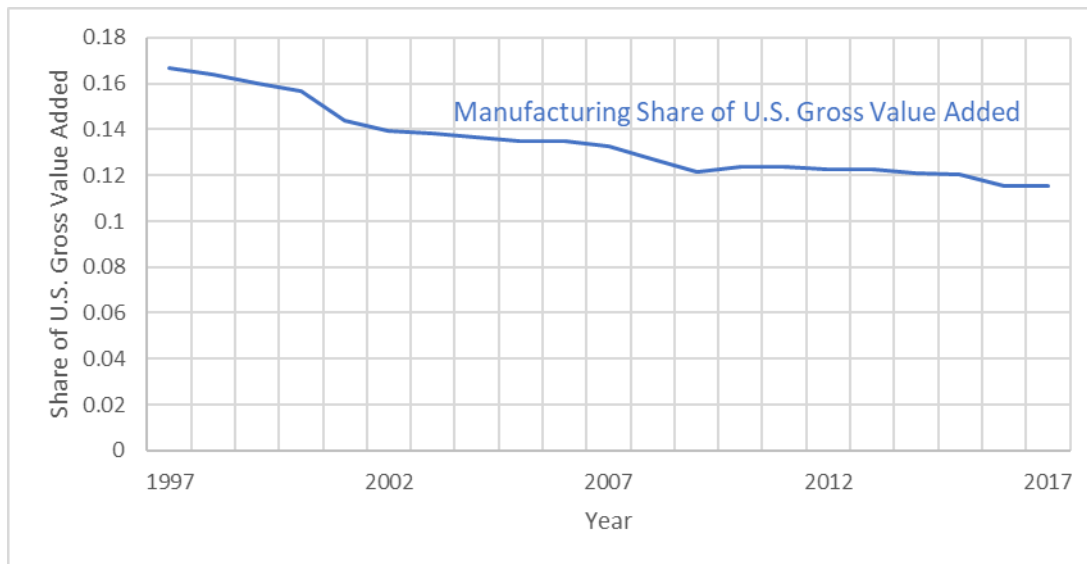


Figure A.1 Manufacturing Share of U.S. Gross Value Added 1997-2017

Figure A.1 illustrates the continually declining share of U.S. gross value added from manufacturing over the twenty years from 1997 to 2017. While U.S. MVA rose in real terms over the same period, its relative contribution to the economy shrank. The U.S. share of global MVA and Gross Value Added both declined from 1997 to 2017: the decline of manufacturing as a share of the U.S. economy is mirrored in the steeper decline of the U.S. share of global MVA, relative to world GVA.

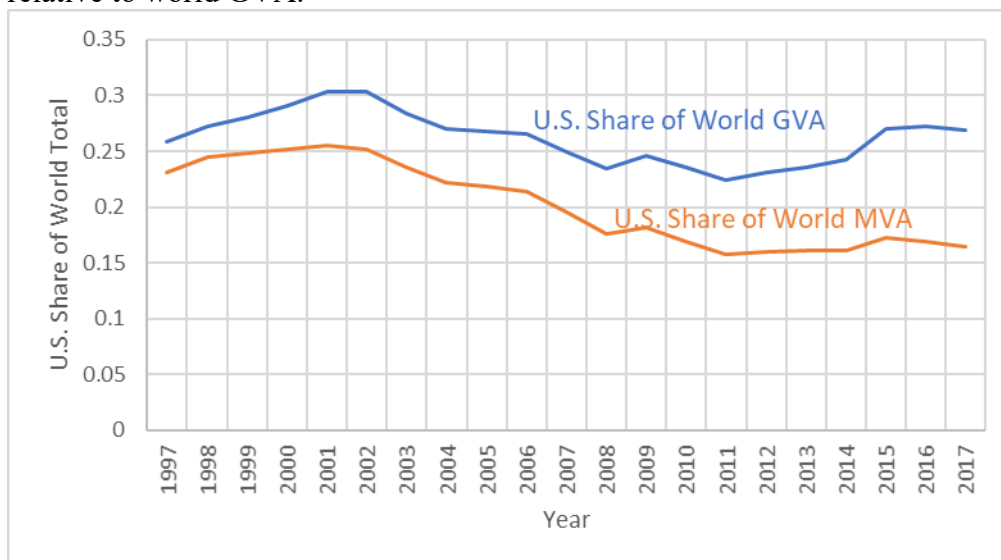


Figure A.2 U.S. Share of World MVA and GVA 1997-2017

Appendix B: Additional Visualizations of the Manufacturing Labor Force

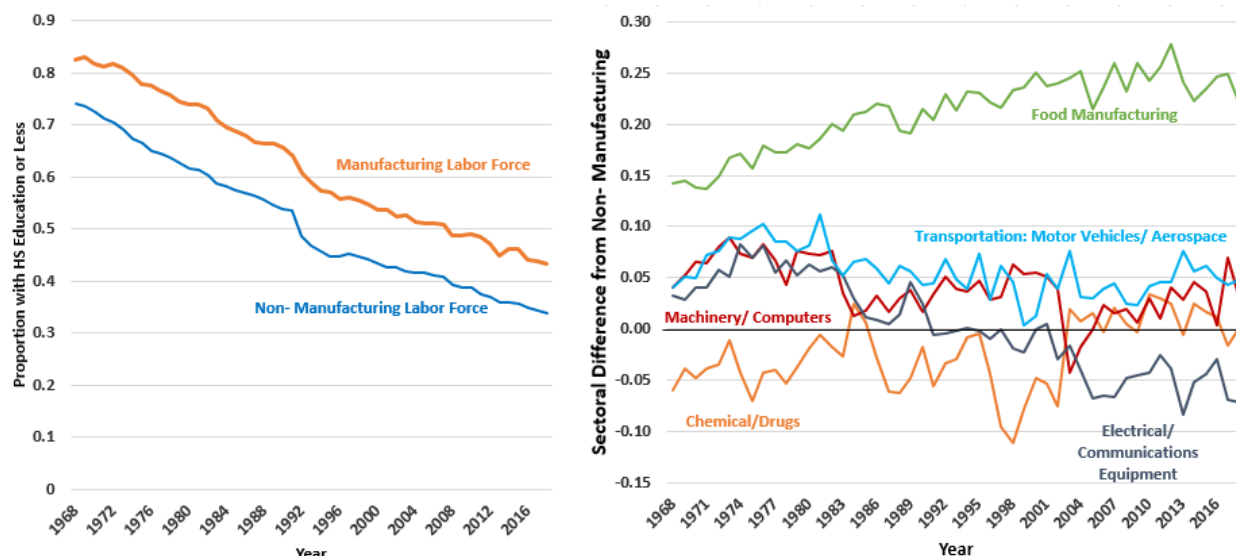


Figure B.1 Select manufacturing subsectors difference from non-manufacturing's educational attainment IPUMS- CPS ASEC microdata (1968- 2018) IPUMS – CPS ASEC microdata 1968-2018²⁶

Subsector analysis reveals heterogeneity among leading R&D and employment subsectors. Figure B.1 displays the difference in educational attainment of a few selected subsectors relative to the non-manufacturing sector. These subsectors include the top 5 subsectors by private R&D spending and the top 2 subsectors by employment in 2015. As can be seen, the manufacturing subsector that contributes the most to employment – the food manufacturing subsector (green line) – has on average a ten percent higher proportion of employees with HS education or less than non-manufacturing sectors. It also had an approximately 12 percentage higher proportion of employees 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. Other subsectors with a relatively large proportion of HS educated or less workers include apparel, textile, furniture, leather, and lumber manufacturing. In contrast, the top R&D spending manufacturing sub-sectors have larger proportions of their labor force who are higher educated: consider the chemical/drug subsector and the communications subsector, both contain a larger proportion of higher educated workers than non-manufacturing sectors.

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% in 1975 and 95% in 2015. In the non-manufacturing sector, private wage and salary workers have increased over time: 67% in 1975 and 74% in 2015. Figure B.2 shows annual individual wage and salary income, CPI adjusted to 2017 dollars, between 1968 and 2018 (as shown in **Error! Reference source not found.**). While the proportion of non-manufacturing workers with earnings less than \$10,000 declines over time, the proportion of the manufacturing labor force earning less than \$10,000 (2017 dollars) remains less than the proportion of the non-

²⁶ 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

manufacturing 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 the non- manufacturing labor force.

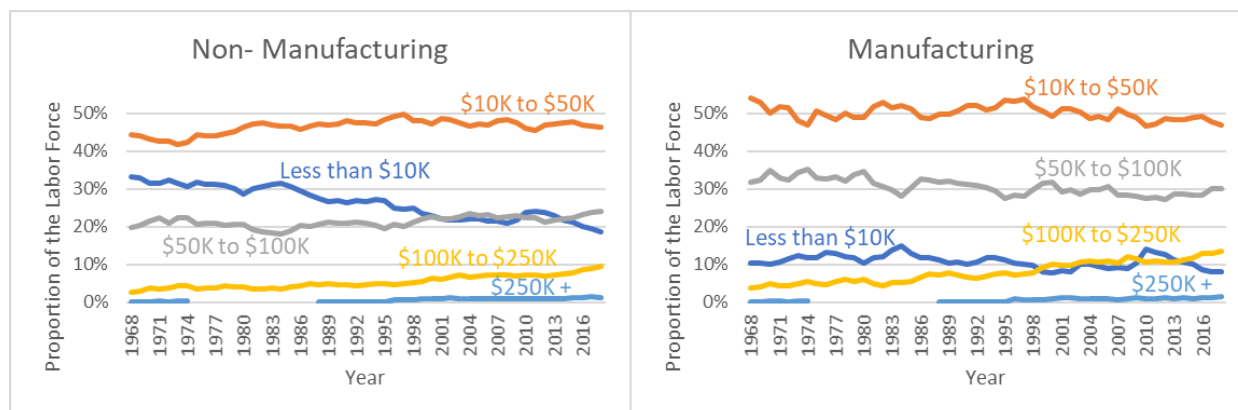


Figure B.2 Individual Wage and Salary Income Categories, CPS Microdata (1968 to 2018)

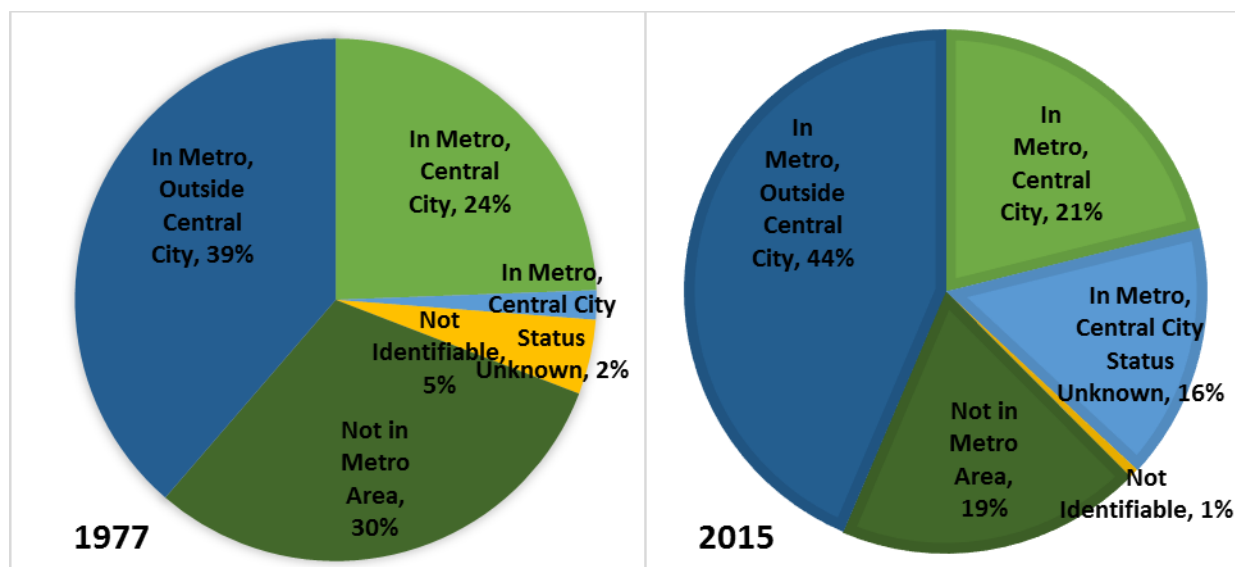


Figure B.3: Geographic location of the manufacturing labor force, IPUMS- CPS ASEC Microdata (1977 and 2015)

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 B.3 exhibits the manufacturing labor force's geographic location.

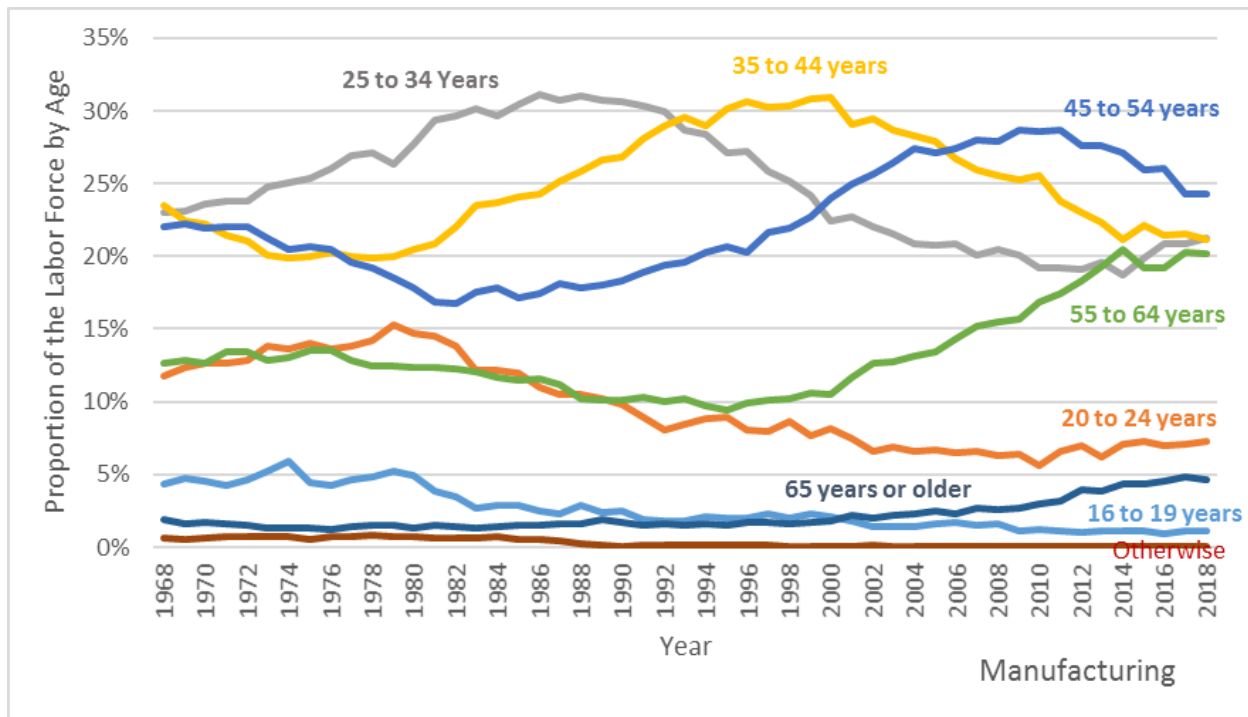


Figure B.4 Manufacturing Labor Force Age Distributions, IPUMS- CPS ASEC microdata (1968- 2018)

The age distribution of the manufacturing labor force is quite similar to the non-manufacturing workforce for prime aged workers (ages 25 to 64). Across time, the manufacturing labor force consistently has a lower proportion of participants age 16-19 and 20-24 and consistently has a larger proportion of participants age 25-64 relative to the non-manufacturing labor force. As can be seen in Figure B.3, within manufacturing, the proportion of labor force participants aged 16-19 and 20-24 have fallen across time. Meanwhile, the largest mass of the labor force has been increasing in age across time: the largest proportions of workers are aged 25-34 in the 1980s, aged 35-44 in 1990s, and aged 45-54 in the mid-2000s. Finally, the proportion of participants aged 65 and above in manufacturing is consistently lower relative to the non-manufacturing labor force although it has increased slightly over the last four decades.

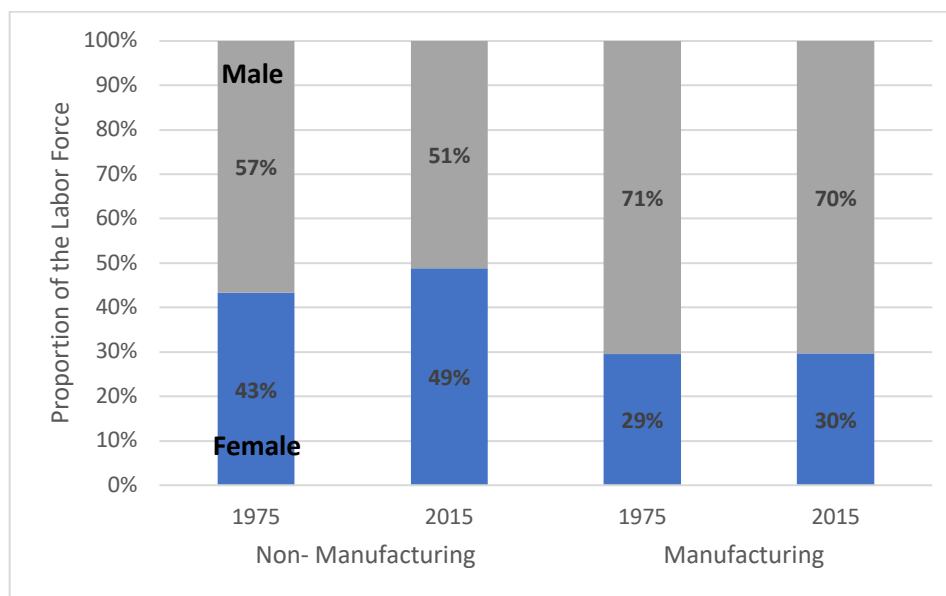


Figure B.5 Gender Composition of the Non- Manufacturing and Manufacturing Labor Force, IPUMS- CPS ASEC Microdata (snapshots of 1975 and 2015)

Figure B.5 shows the gender composition of the manufacturing and non-manufacturing labor force in 1975 and 2015. Across both non-manufacturing and manufacturing sectors, the majority of the labor force is comprised 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 non-manufacturing subsectors have made progress toward parity.

Appendix C: Additional Private Equity/ Venture Capital Data Visualizations

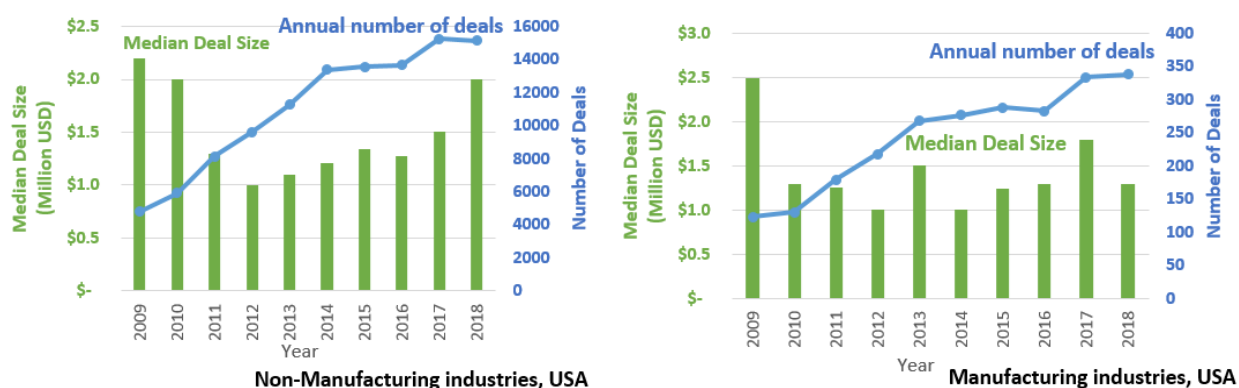


Figure C.1 PE/ VC in Non-Manufacturing Industries (left) and PE/VC in Manufacturing Industries (right), each with median deal size, data retrieved from CB Insights June 2019

As seen in Figure C.2, the U.S.'s percentage of global VC/PE 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 C.3 features a similar visualization

of the global distribution of non-manufacturing deals. Note that the global geographic dispersion of PE/ VC deals is quite similar between both manufacturing and non-manufacturing industries.

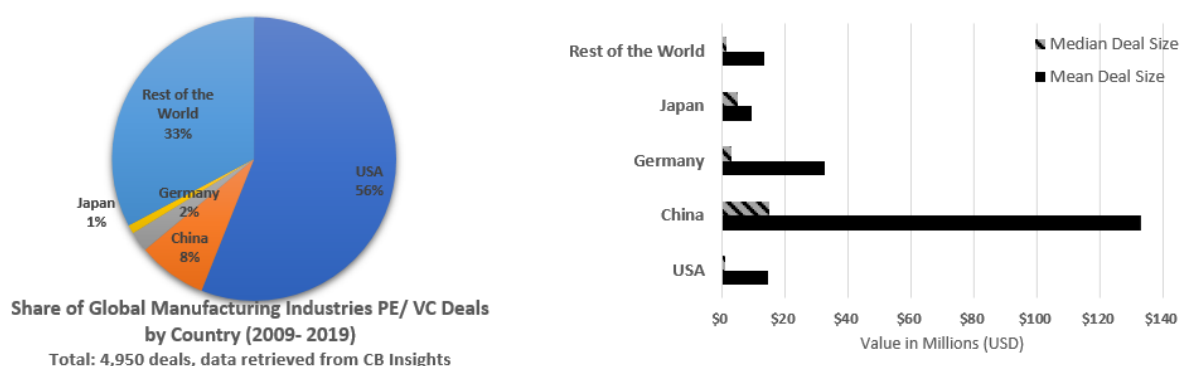


Figure C.2 Comparison of Global Manufacturing Industries PE/ VC, Inclusive of Top Four Countries by MVA; share of total manufacturing deals (left), median and mean deal size by geography (right). Data retrieved from CB Insights June 2019.

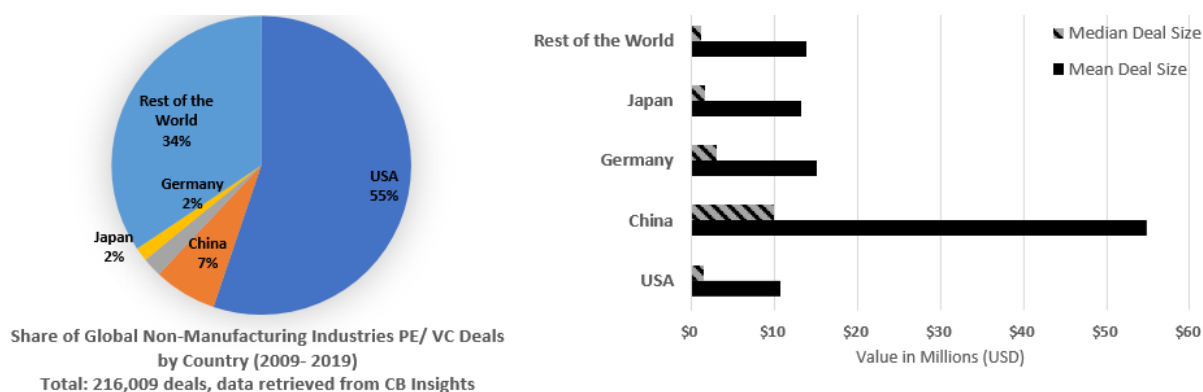


Figure C.3 Comparison of Global Non-Manufacturing Industries PE/ VC, Inclusive of Top Four Countries by MVA; country share of total non-manufacturing deals (left), median and mean deal size by geography (right). Data retrieved from CB Insights June 2019

Appendix D: “Public VC:” Data Visualization of SBIR and STTR Awards

The combined SBIR and STTR award counts, annual total award amounts, and distribution of awards by funding agency are exhibited in Figure D.1 (data from SBIR.gov)²⁷. Interestingly a majority of the awards have been given by two agencies: the Department of Defense and Health and Human Services.

²⁷ “Other” agencies include DHS, ED, EPA, DOT, DOI, and NRC

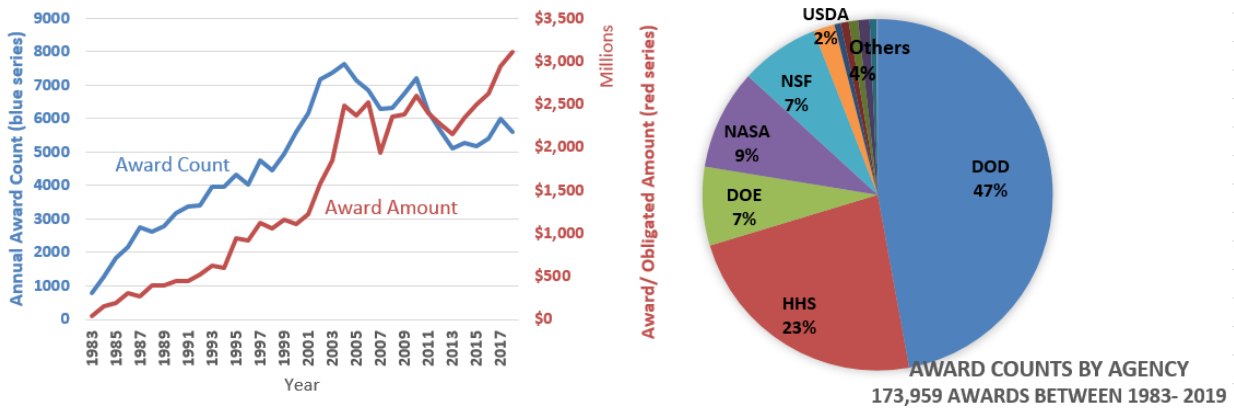


Figure D.1 Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) Programs Award Counts and Total Award Value by Year (left) and Distribution of Awards Given From Federal Agencies (right), 1983-2019, data retrieved from SBIR.Gov July 2019

Appendix E: Patenting Figure Reproductions

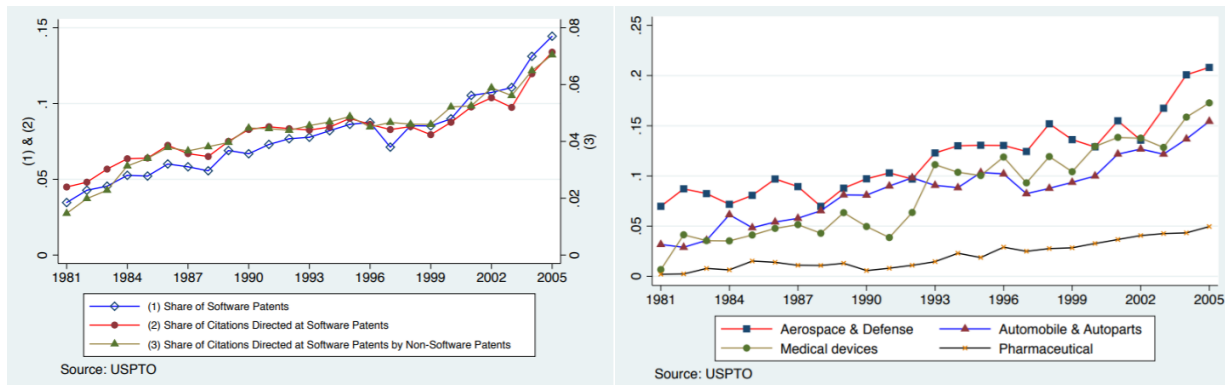
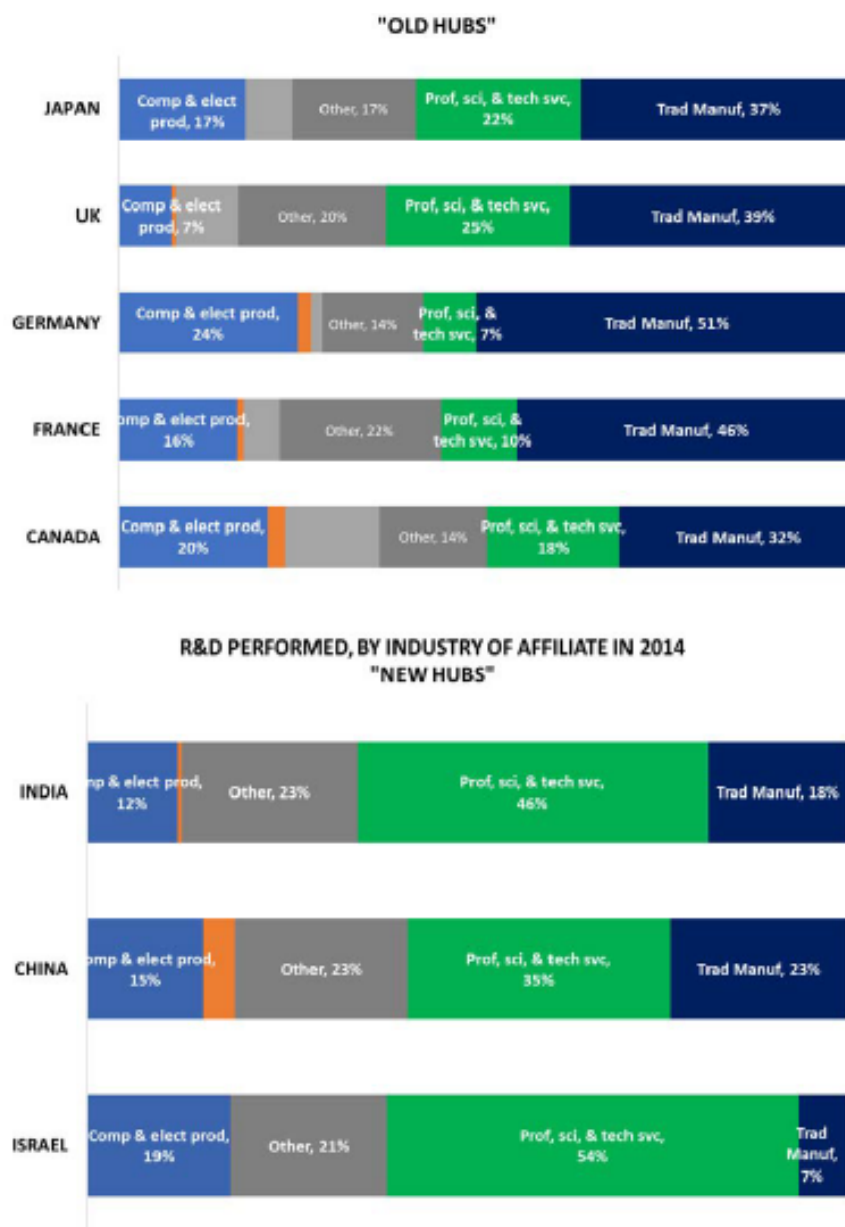


Figure E.1 Reproductions of Figure 1: Software Intensity of Patent Portfolios of Firms Active in Four Manufacturing Industries, (left) and Figure E.1: Share of Software Patents by Industry (Grant years 1981-2005) (right) Source: Branstetter et al. (2016) In both cases data is from the USPTO.



Notes: "Trad Manuf" refers to Chemical, Food, Machinery, Primary & Fabricated Metals, Transportation Equipment. Other includes mining, trade, and other. "Prof, Sci, & tech svc" is Professional, scientific, and technical services. "Comp & elect prod" is computer and electronics products manufacturing. The orange shade is for electrical equipment, appliances, and components manufacturing. The light grey is for information. The graphs illustrate that the specialization of "new hubs" like India, China, and Israel look very different from the specialization of "old hubs" like Japan, the UK, Canada, France, and Germany. Source is BEA public data.

Figure E.2 Old and New Research & Development Hubs, as Characterized by Branstetter, Glennon, and Jensen (2018b)'s Figure 3, reproduced here

Appendix F: Firm Counts and Firm Size Distribution

The total number of firms (irrespective of industry) in the U.S. have 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 (U.S. Census Bureau's Statistics U.S. Businesses Survey (2007 to 2016), see Figure F.1. The proportion of manufacturing firms relative to the total number of firms' averages ~4.5% 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 non-manufacturing firm counts following the Great Recession. The proportion of information sector firms of all firms has been relatively stable at ~1.2% over the same time period.

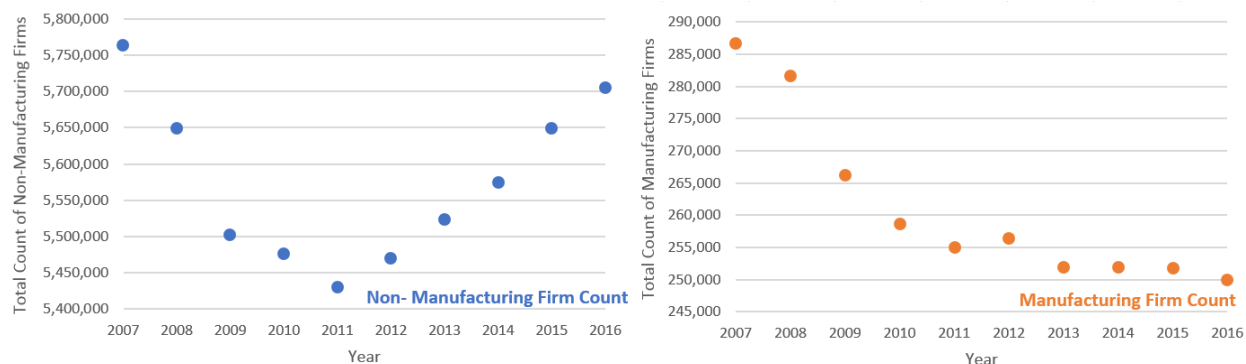


Figure F.1 Total Firm Counts 2007-2015: Non- Manufacturing Industries²⁸ (left) and Manufacturing (right), data retrieved from Census Statistics of U.S. Businesses (SUSB)

Notice that non-manufacturing industries feature a trough in the total number of firms coincident with the timing of the Great Recession, however, while manufacturing industries firm counts feature a similar decline, they do not see a subsequent recovery/ sustained uptick in the total count of manufacturing firms between 2013 and 2016.

²⁸ Non- Manufacturing Industries calculated by subtracting manufacturing firm counts (NAICS codes 31-33) from the total firm counts using the 2015 Census Statistics of U.S. Businesses (SUSB)

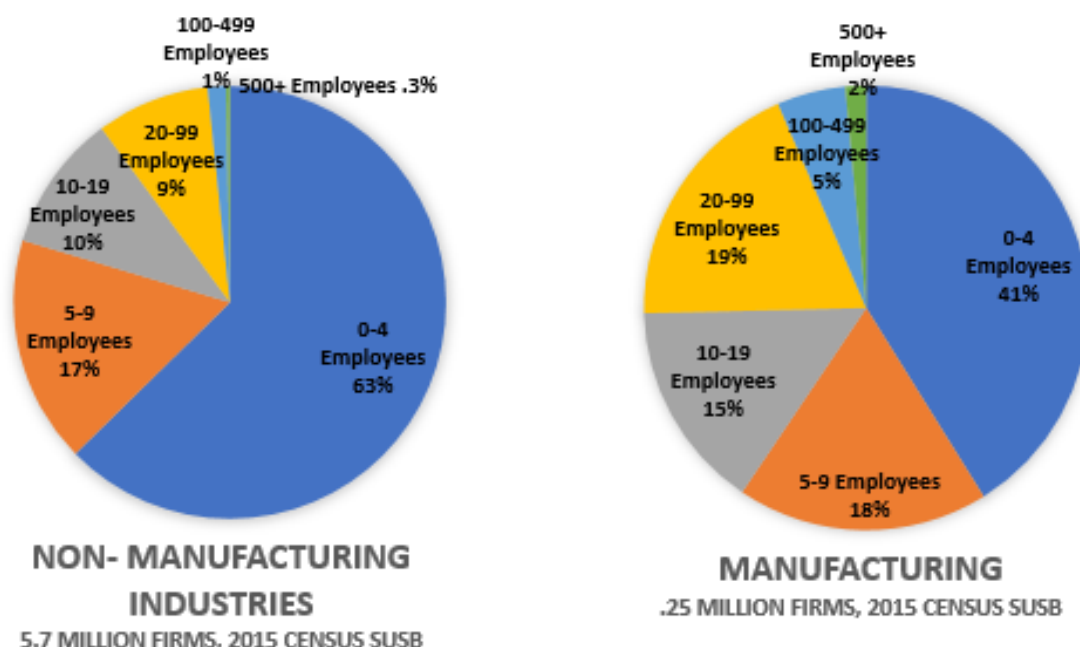


Figure F.2 Firm Size Distributions 2015: Non- Manufacturing Industries²⁹ (left) and Manufacturing (right), data retrieved from Census Statistics of U.S. Businesses (SUSB)

There are several differences between the firm size distribution of U.S. firms in non-manufacturing versus those in manufacturing (see Figure F.2.). The firm size distribution across non-manufacturing firms is monotonic, that is the density of firms in each category declines as the firm size grows (from 63% to 17% to 10% to 9% to 1%). In contrast, manufacturing proceeds from 41% of firms with 0- 4 employees, to 18% with 5- 9 employees, to 15% with 10- 19 employees, then a larger proportion 19% with 20- 99 employees and 5% with 100- 499 employees. These results may be suggestive that given manufacturing's capital intensity in many sectors, fewer firms find a 10-19 employee sized firm to be an efficient scale. In contrast, the 0-4 employees may reflect machining shops and similar undertakings.

Buera et al. (2011) argue that manufacturing, with larger scales of operation, is relatively more exposed to financial frictions than 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 et al (1992) document the countercyclical nature of the job reallocation rate³⁰, 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% of all non-manufacturing firms, however in manufacturing large firms comprise 1.5% of all manufacturing firms. That is, the manufacturing firm size distribution has proportionally 5 times as many large firms than the overall distribution, put another way, large (500+ employees) manufacturing firms comprised 20% of all large (500+ employees) firms in the U.S. in 2015. The relatively larger proportion of large manufacturing firms is consistent

²⁹ Non- Manufacturing Industries calculated by subtracting manufacturing firm counts (NAICS codes 31-33) from the total firm counts using the 2015 Census Statistics of U.S. Businesses (SUSB)

³⁰ Davis et al. (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- 1986, and finds they are 11.3% and 9.2% respectively.

with Nuemark et al. (2011), which documents the importance of large firms in manufacturing to job creation. Dunne et al. (1989) provide one explanation for the presence of more large firms, arguing 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 U.S. 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 the literature has documented a wage premium paid to workers of large U.S. manufacturing employers which can only be partially explained by observable characteristics of the workers and establishments (Troske 2006). It has also been documented that larger firms proportionally face higher relative prices of labor than their smaller competitors (Soderbom and Teal 2003 in the case of African manufacturing firms).

Appendix G: STEM Employees by Sector

Manufacturing represents 14.5% of employment for engineers, mathematical and computer science and scientific occupations, compared with 7.3% employment share for information and 4.3% share for R&D service companies.

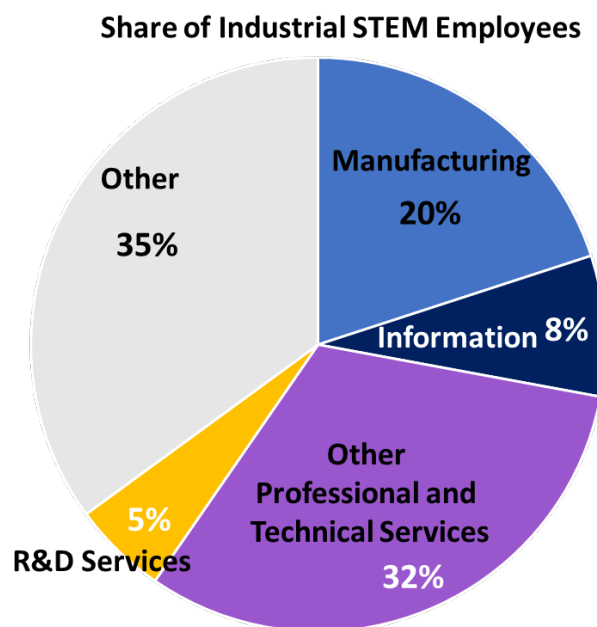


Figure G.1 Share of Industrial STEM Employees by Sector (Bureau of Labor Statistics 2019)

Appendix H: Example of Data Format

Table H.1 BEA Input-Output Sub-Sector Data Format Example

IOCode	Commodities/Industries	111CA	113FF	...	T019
	Name	Farms	Forestry, fishing, and related activities		Total use of products
111CA	Farms	71893	901		577472
113FF	Forestry, fishing, and related activities	23901	9627		101028
211	Oil and gas extraction		570365
212	Mining, except oil and gas	2771	2		128163
213	Support activities for mining		157109
22	Utilities	4500	139		656119
23	Construction	1782	44		1701712
321	Wood products	409	53		184489
...					
T005	Total Intermediate	259647	20529		39432054
V001	Compensation of employees	32707	26767	...	
V003	Gross operating surplus	98676	8273	...	
T00TOP	Other taxes on production	10256	1253	...	
VABAS	Value Added (basic prices)	141640	36293	...	
T018	Total industry output (basic prices)	401286	56822	...	
T00TOP	Taxes on products and imports	...	599	...	
T00SUB	Less: Subsidies	-12068	
VAPRO	Value Added (producer prices)	129572	36892	...	

Appendix I: 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 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.

Table I.1 Regression Outputs for Change in Value Added Over Output (annual) (BEA,NSF 2019)

Change in Subsector Value Added/Output ($R^2 = .274$)			
	Coefficients	Standard Error	P-value
Intercept	1.70E-03	1.23E-03	0.17
Change in Gross Value Added (U.S. Economy Wide)	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 3 year Adjust R&D	3.06E-12	2.69E-12	0.26
Motor vehicles, bodies and trailers, and parts Intensity 3 year Adjust R&D	-5.39E-12	5.66E-12	0.34
Publishing industries, except internet (includes software) Intensity 3 year Adjust R&D	1.18E-10	7.10E-11	0.10
Computer systems design and related services Intensity 3 year Adjust R&D	-3.34E-10	6.40E-10	0.60
Miscellaneous professional, scientific, and technical services Intensity 3 year Adjust R&D	9.84E-12	8.46E-12	0.24

Appendix J: Regression Outputs for Estimation of Sub-Sector Output with Time Fixed Effects

In order to account for possible exogenous factors in each year of our timeseries (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 in an estimation of the regression model in Table 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.

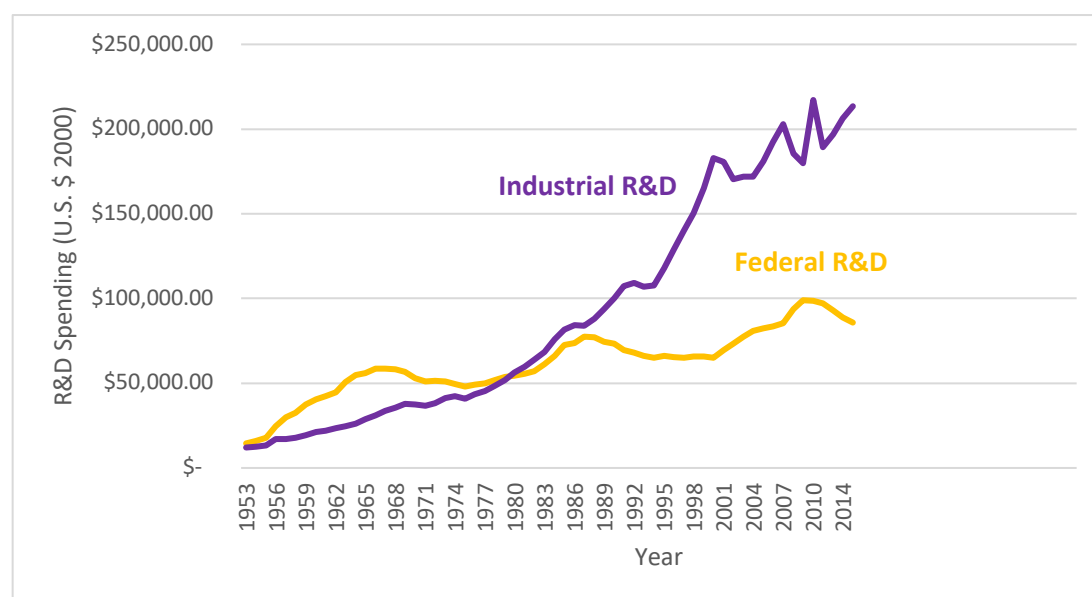
Table J.1 Regression Outputs for Estimation of Sub-Sector Output with Time Fixed Effects (BEA, NSF 2019)

Dependent Variable: ln(Output) ($R^2 = .86$)			
Independent Variables	Coefficients	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

Appendix K. U.S. R&D Funding by Federal Government and Industry

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



K.1. Industrial and Federal R&D (1953-2015) (NSF, AAAS)

Appendix L: Exploration of Alternative Hypotheses

L.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."³¹ R&D returns manifest outside of manufacturing, 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

³¹ 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 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; prospecting or exploration for natural resources.

the dominance of manufacturing industrial R&D spending (NSF 2018), 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 which 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 over the period 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% of VC/PE spending went to manufacturing, manufacturing would still represent at least 52% of nominal combined industrial and venture capital 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%).

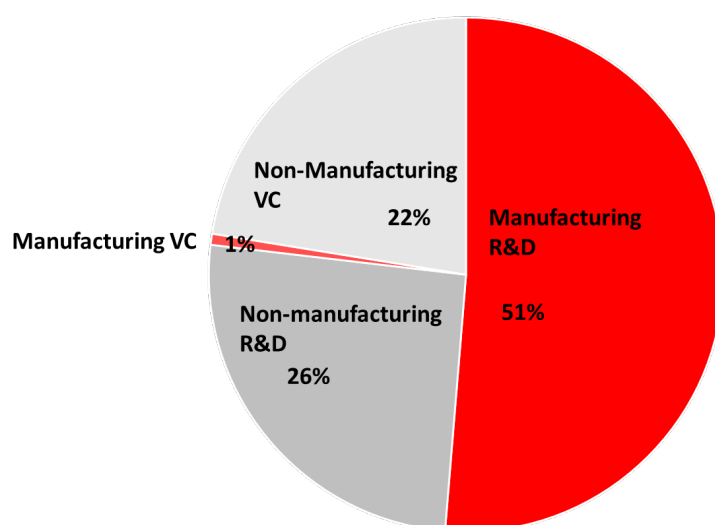


Figure L.1 Manufacturing and Nonmanufacturing Shares of R&D and Venture Capital Spending (2009-2015)

The third possible source of error that we examine is differences by sector in the incentives to report R&D spending. U.S. 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 (CPAJournal 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 2019). Qualified applications 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, not more. The credit notably excludes fixed capital, while wages, contracts and supplies are creditable (IRS 2019). 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 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, U.S. firms with fewer than 100 employees accounted for 6.3% of U.S. 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 L.2 that among the largest publicly traded U.S. firms by R&D spending (Price Waterhouse Coopers 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 U.S. firms used by PWC.

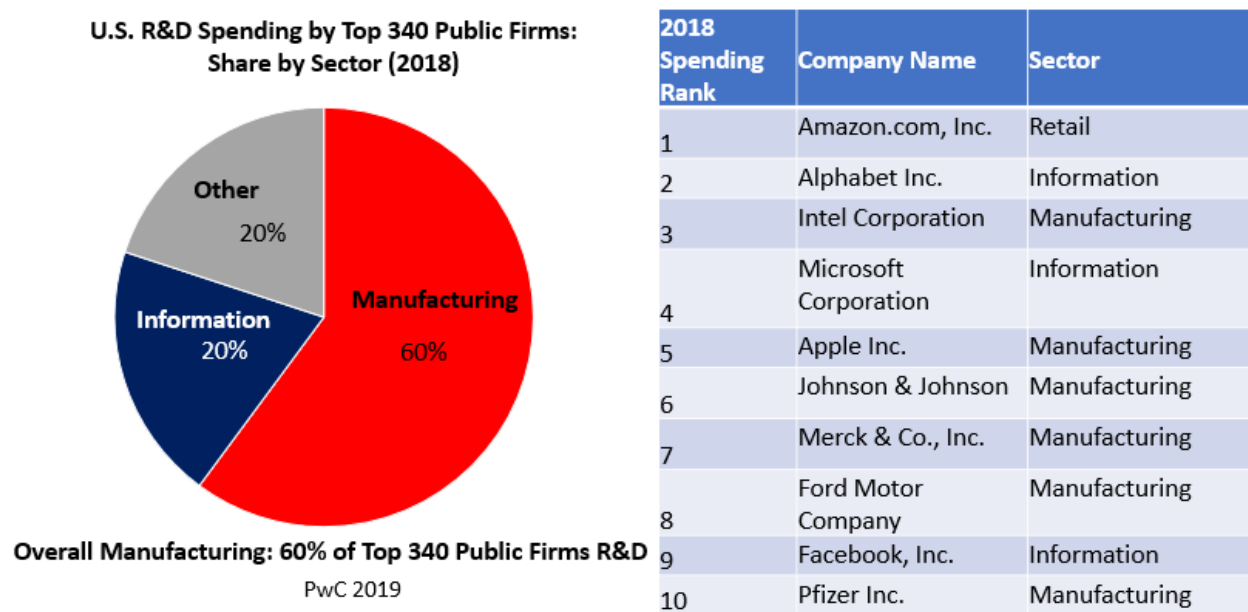


Figure L.2 R&D Spending by Sector, Top 340 Public U.S. Firms (Left); Top 10 U.S. Firms by R&D Spending (2018)

L.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 U.S. economy, is motivated by the literature on General Purpose Technologies (Helpman and Tratjenberg 1996; Aghion and Howitt 2002). Under this framework, manufacturing could generate R&D returns that are not accounted for until they are sold within other sectors, for example as would be the case. 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 (cfe Aghion and Howitt 2002). We evaluate this subcase of the GPT hypothesis using input-output accounts data by subsector from the Bureau of Economic Analysis (BEA 2019). This dataset, collected at the annual level, relates the inputs from individual subsectors of the U.S. economy to other U.S. subsectors and reports the output and value added of each subsector, with subsectors reported at 4 and 5 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 which 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 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 three year running average from sub-sector spending in $t - 2$ to spending in t , as measured by NSF (thus limiting the upper bound of our time series to 2015).³²

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:

³² We also test alternate formulations for our intensity measure $\frac{I_{j,i,t}}{\sum_{k=1}^{66} I_{j,k,t}}$, including three and five year averages to reflect accumulation of R&D-embodying stock, with no improvement of fit.

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

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 $\sum_{i \in V} S_{j,i,t}$ 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 we report the results of our regression estimating sub-sectoral output from inputs and intensity-adjusted R&D stock from manufacturing and from service and information (see appendix J 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).

Table L.1 Regression Outputs for Estimation of Sub-Sectoral Output (BEA, NSF 2019)³³

Dependent Variable: $\ln(\text{Output})$ ($R^2 = .86$)			
Independent Variables	Coefficients	Standard Error	P-value
Intercept	0.394	0.186	0.034

³³ 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.

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	1E-25

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. GPTs not being an explanation for all manufacturing subsectors, however, does not rule out it being an explanatory factor for some subsectors, such as, for example, innovation in microprocessors enabling innovation in other sectors throughout the economy (Jorgenson 2001, 2016).

The second subcase is that manufacturing is a source of GPTs which 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 which 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, 2016) finds that up to half of U.S. 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 construct technology-specific factor productivity analysis (cfe Jorgenson in 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 which are not generalist in their function (e.g. pharmaceuticals) or which 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 M:

Figure M.1 displays the share of overall manufacturing value added from both the top 5 manufacturing subsectors by value added and the top 5 manufacturing subsectors by R&D spending. We see that the top 5 manufacturing subsectors by R&D have a total value added about a third lower than the top 5 subsectors by value added. Two subsectors, aerospace and pharmaceuticals, are both among the top 5 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.

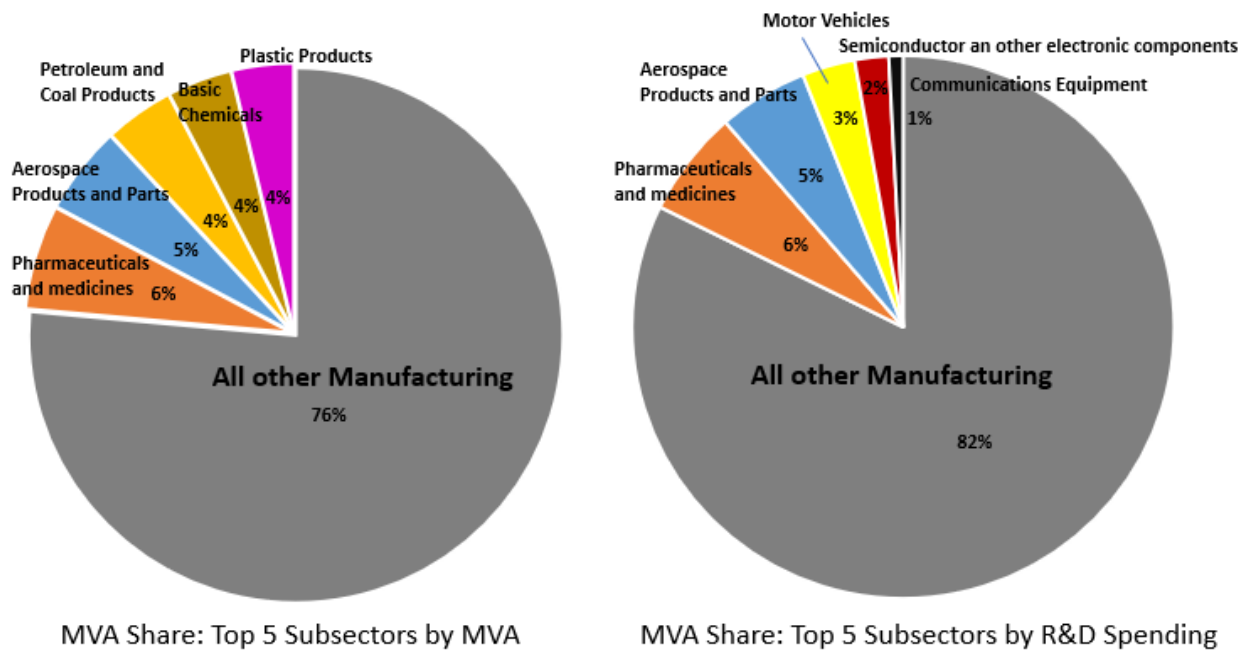
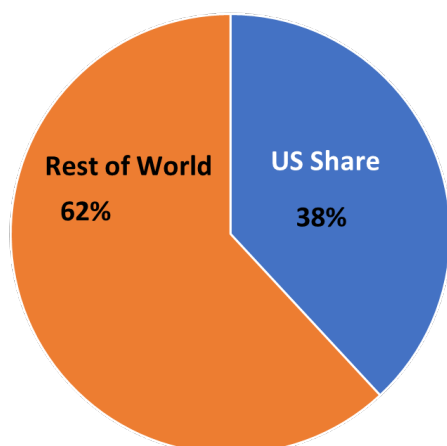


Figure M.1 Share of Total Manufacturing Value Added by Subsector, 2015 (ASM)

Appendix N: U.S. Share of R&D Spending by Top 1000 Firms by R&D Spending Worldwide

US Share of Manufacturing R&D Spending From Top 1000 World Firms by R&D Spending



US Share of Nonmanufacturing R&D Spending From Top 1000 World Firms by R&D Spending

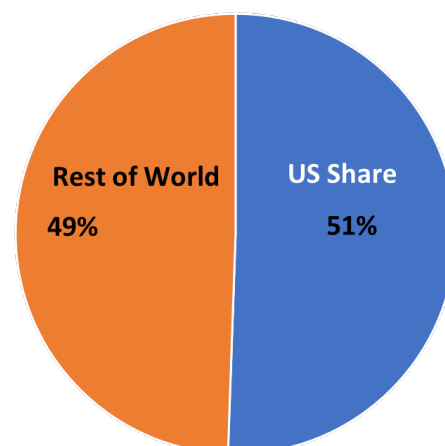


Figure N.1 U.S. Share of Manufacturing and Non-Manufacturing R&D Spending from Top 1000 World's Firms by R&D Spending