A DYNAMIC RANKING OF U.S. MANUFACTURING SUBSECTOR COMPETITIVENESS INDICATORS

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INTRODUCTION

The capacity of innovation, supported by well-functioning supply chains, to produce strong job and wage growth is a compelling issue for the U.S. manufacturing sector and policy makers as manufacturing adjusts to rapid and volatile globalization as well as supply chain-altering technological transformation. Because manufacturing industry subsectors have notable differences in terms of industry structure, capital intensity, labor force characteristics, market dynamics, and degrees of global exposure, research on the innovation/supply chain/jobs dynamic must occur on the subsector level in order to generate results that are illuminating and useful for both business and public policy discussion.

This paper makes use of U.S. manufacturing subsector data and a dynamic ranking analysis, used by the author in a prior publication,* to consider the evolving picture of innovation, supply chain strength, and employment. The ranking exercise identifies subsectors that are showing relative strength in these metrics versus those that are lagging. The ranking results are analyzed in the context of a framework in which, consistent with recent literature, manufacturing employment change is modeled as the outcome of the sometimes competing forces of trade and domestic innovation.

In the next section, the relevant literature is reviewed. This literature is then used to develop the conceptual framework. The data and empirical method are then explained, after which the results of the ranking exercise are revealed. In the final section, the ranking results are discussed in the context of the conceptual framework to show the implications of the research.

LITERATURE REVIEW

Recent literature on the U.S. manufacturing sector focuses on the drivers of the significant employment decline suffered after 2000. Fort et al. (2018) noted the 25percent drop in U.S. manufacturing jobs from 2000 to 2012, more than twice the decline seen between the post-WWII peak in manufacturing employment, reached in 1979 and 2000. The authors assert that two primary factors in the employment decline, which are often discussed as competing explanations, are trade and technology. They argue that it is difficult to separate the impacts of trade from the impacts of technology as they often intersect. Certain technologies, for example, facilitate trade, and the impact of technology adaptation can be augmented by trade and global competition forces. Houseman (2018) sides with trade as being the chief explanation for the U.S. manufacturing employment decline.

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*Waldman, Cliff. 2016. "The Evolving Contours of Productivity Performance and Automation Investment in U.S. Manufacturing," *Business Economics*, 51(4): 213-238.

Technology is a component of an innovation ecosystem, which facilitates improved productivity growth. An important question: Is productivity growth an enemy of job gains in the manufacturing sector? Research conducted by Nordhaus (2005) provides important insights. In a paper that models a nexus between domestic productivity growth and global competition, he concludes that at the macroeconomic level the impact of productivity growth on employment is ambiguous. It depends upon the bias of technological change, the prices of competing goods, and the price elasticity of demand. On the whole, faster productivity growth leads to lower prices and expanding demand, thus increasing manufacturing employment. But the positive effects of rapid domestic productivity growth on domestic factory sector jobs is more than offset if there is rapid productivity growth and price in the economies of foreign competitors.

Garcia et al. (2005) in some ways extends the Nordhaus model by considering the innovation-jobs relationship. They model the relationship on the firm level where process innovations are expected to reduce the number of workers needed to produce output, creating a "displacement effect." But the increased production efficiency brought about by process innovation implementation will reduce the marginal cost of production. If lower marginal cost is passed into the price of the output it will increase demand and thus employment – a "compensation effect." The authors assert that the compensation effect is expected to overwhelm the displacement effect, creating a net positive for employment. The magnitude depends upon the elasticity of demand for the output.

Leonard and Waldman (2007) model the sources of innovation in U.S. manufacturing. In doing so, they estimate equations for both process and product innovation. For their process equation they choose growth of multifactor productivity in the U.S. manufacturing sector as their endogenous variable. The exogenous variables are the growth rate of investment in equipment and software in the economy, the growth rate of dollar expenditures on university and college-performed basic research, and the growth rate of full-time equivalent scientists and engineers in research and development (R&D) performing companies. For their product innovation equation, the endogenous variable is a four-year moving average of utility patent approvals, an accepted proxy for product innovation output. The exogenous variables, as in the process innovation equation, include the growth rate of full-time equivalent scientists and engineers in R&D performing companies and the growth rate of dollar expenditures on university and college performed basic research. Also included in the product innovation equation is R&D expenditures as a percent of sales in the manufacturing sector.

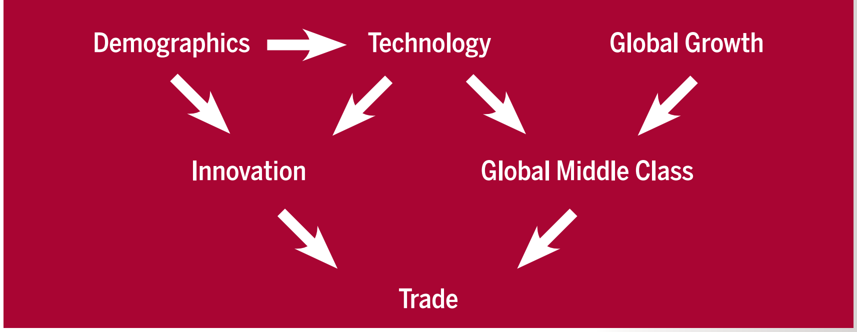
Waldman (2016) models productivity growth in the U.S. manufacturing sector on a three-digit North American Industry Classification System (NAICS) level. The explanatory variables in his multifactor productivity growth equations are a ten-year moving average of utility patent grants for the individual subsector and annual growth in equipment investment for the subsector. Two alternative specifications were estimated, with a four-year moving average of labor productivity growth as the endogenous variable. In the first, a four-year moving average of the growth in capital intensity was paired with the labor force participation rate of workers with a BA degree and higher as the exogenous variables. The second labor productivity equation uses a ten-year moving average of patents in the place of a four-year moving average of capital intensity. The analysis and results presented in Waldman's paper support the significant role of innovation and capital investment in driving multifactor productivity growth across a wide range of manufacturing subsectors. Also evident in his results is the definitive role played by the economy's supply of educated labor in driving labor productivity growth across a wide range of manufacturing subsectors. Waldman's statistical evidence raises the question of whether productivity outcomes are completely independent across manufacturing subsectors. The manufacturing sector is becoming integrated along a growing number of parameters, clearly affecting the impact of innovation investments.

CONCEPTUAL FRAMEWORK

A framework that models the sometimes competing forces of global competition and domestic innovation and considers their net impact on domestic U.S. manufacturing employment will be used for analyzing the dynamic ranking results presented in this paper. The above-discussed literature provides the context for such a framework. Consistent with this literature, the framework is drawn out in Figures 1, 2, and 3.

Figure 1 takes a 30,000 foot view of the relevant global macro-dynamics. Demographic change, primarily population aging, to a large extent catalyzes the application of new technologies into innovation as a result of the impact of demographic shifts on the supply of labor and the composition of goods demand. Demographic shifts and technology collectively and apart catalyze innovation activity in manufacturing. A key source of demand for manufacturing output worldwide is the emergence of a stable and geographically broad-based global middle class. The growth of the global middle class is assumed to largely be a function of long-term global economic growth aided by technology, the latter opening new markets, allowing for a smoother path to entrepreneurship, and empowering households with the benefits of various kinds of connectivity. The growth of global trade activity over the long-term is assumed to be a function of the growth of the global middle class and the pace of worldwide innovation, the latter creating new supply chains and markets for trade. Technology is key. It spurs innovation and impacts the growth of the global middle class, both of which impact trade.

FIGURE 1



As shown in Figure 2, trade is assumed to take the form of either import penetration or direct imports through a global supply network. Import penetration and an increase in foreign competitor productivity growth, which leads to lower foreign competitor prices, has a negative impact on U.S. domestic manufacturing employment. Consistent with recent literature, when trade takes the form of direct imports by manufacturing companies, the domestic U.S. manufacturing employment impact is either zero or positive (notably Fort et al. 2018). Counterbalancing the challenges from trade, Figure 3 models the benefits of manufacturing innovation in the U.S., as outlined in the literature. Innovation positively impacts U.S. domestic productivity growth in the manufacturing sector. Acceleration of domestic productivity growth lowers prices and expands

FIGURE 2

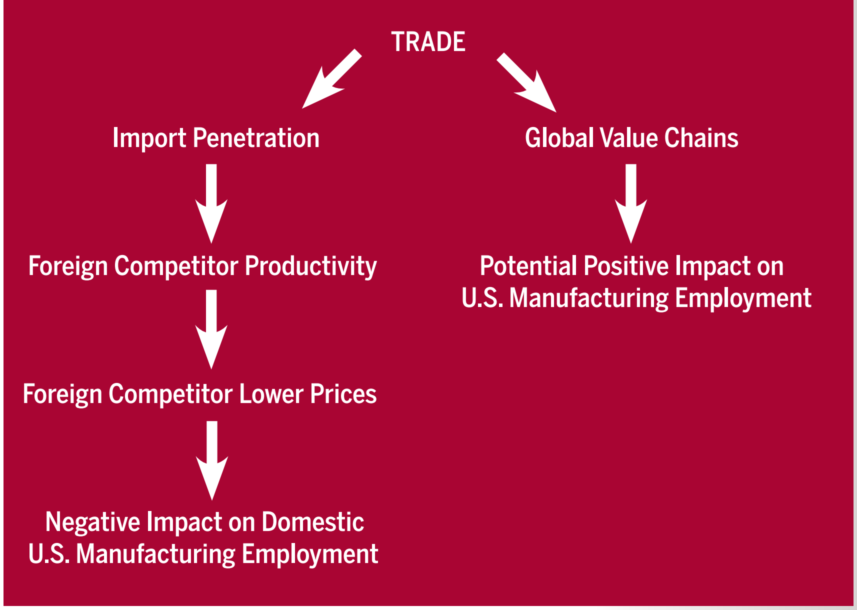
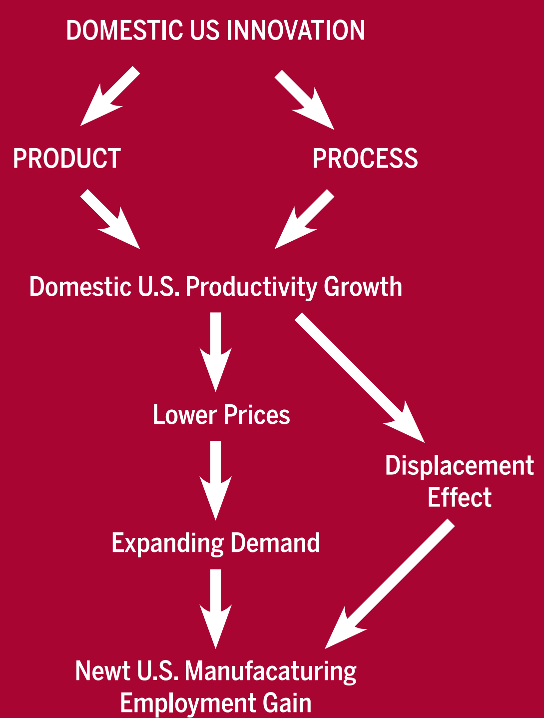


FIGURE 3



demand and thus domestic manufacturing employment, overwhelming the initial employment displacement impact of innovation. This all assumes no disruptive activity by market players such as efforts to capture innovation rents.

This framework casts innovation not just as an investment but as a crucial competitive tool in an increasingly integrated global manufacturing economy. The net impact of domestic U.S. manufacturing innovation versus trade (and, more broadly, global competition) governs U.S. manufacturing employment growth.

DATA

The fruits of U.S. manufacturing competitiveness are consistent, broad-based employment growth and robust wage growth. The framework described in the previous section suggests that domestic, productivity-enhancing innovation is a fundamental driver for sustained domestic employment and wage growth. Efficient, productive supply chains are needed to spread the benefits of innovation investment and give them job-creating value throughout the manufacturing sector. These inferences highlight the data that need to be examined on a subsector level to assess the degree of competitiveness in U.S. manufacturing and to examine how U.S. manufacturing competitive strength has been evolving over time.

Patent data, sourced from the U.S. Patent and Trademark Office, will be used to proxy product innovation, as cited in the literature review section. While patents are not a full empirical representation of innovation (since not all innovations are patented), patent data are known to track innovation activity. Many would argue for the use of R&D expenditure data for innovation analysis. Some may suggest using measures such as the private fixed investment in intellectual property products component of the national income and product accounts (NIPA). The challenge is that the use of any innovation investment measure disregards what could be significant differences among industry subsectors in the productivity of R&D, a key issue for innovation output. For the purposes of empirical tractability, data quality, and analytical correctness, patents is a better choice than R&D for the current study as the conceptual model postulates a link from innovation output to jobs and wages. As has been done in prior research by the author of this study, share of total manufacturing patents for each subsector will be used for ranking analysis.

Similarly, the share of total manufacturing jobs for each manufacturing subsector will be considered. To further flesh out the employment picture, average hourly earnings of production and non-supervisory employees in each manufacturing subsector will be used. Employment and wage data are sourced from the U.S. Bureau of Labor Statistics.

Economists have produced minimal work on modeling supply chains and incorporating supply chain models into macro models. Partially as a consequence, there is no harmonized metric for supply chain strength. A recent paper by Delgado and Mills (2017) did discuss the innovation benefits of a supply chain. They note that because suppliers produce specialized inputs, they can generate learning spillovers, which can improve the efficiency of the innovation process. They also note that suppliers and customers can benefit from co-location and generate a cluster, which is known to support innovation-generating activities. Thus, a supply chain strength measure is important for empirical analysis in the current study as supply chain strength supports innovation strength which the framework of the previous section suggests is of critical importance for domestic manufacturing employment strength.

In many ways a supply chain is a production system that favors dispersion over agglomeration. Many locations are seen as being efficient for the production of the final product rather than a geographically proximate cluster of companies and suppliers. The reasons vary by industry and are largely dependent upon the complexity of the product and the nature of the production process. A strong supply chain should validate the dispersion decision and should use inputs with minimal waste to produce the product with maximum output per unit of time. Thus, we evaluate the strength of a supply chain in much the same way we would evaluate the production efficiency of a single company. The author will use two variables for the current study. The first is the inventory-sales (IS) ratio, which, in effect, is a measure of lean efficiency, a critical element for a well-functioning supply chain. The second variable is total factor productivity growth, which is arguably a proxy for the effectiveness of the production structure of the supply chain, as it would be for a single enterprise. These data series, sourced from the U.S. Bureau of Economic Analysis and the U.S. Bureau of Labor Statistics, are measures of U.S.-based inventory ratios and U.S.-based productivity growth.

All variable rankings will make use of three-digit level NAICS manufacturing data. At a more granular four-digit NAICS level, it is difficult to get a meaningful ranking. It is likely that groups of four-digit industries will congregate around a value (for each of the variables) and thus a ranking. A higher level of aggregation-creates a more differentiated result. In evaluating a ranking of four-digit NAICS industries, we would naturally be seeking to evaluate the three-digit patterns, making the use of four-digit NAICS data inefficient and unnecessary for ranking analysis.

Three-digit NAICS analysis does mask micro-level employment issues, such as employment generated by globally competitive food prices and falling natural gas prices. It's important to keep in mind, however, that the current study is not analyzing manufacturing subsectors in an absolute sense, but in a comparative sense. As will be seen, one of the values of a ranking analysis is the capacity it generates to assess the degree of concentration of various measures of competitive strength within the manufacturing sector. A four-digit analysis would diminish the clarity of such results without adding insight.

EMPIRICAL METHOD

All of the variables discussed in the prior section are ranked through time. (Raw data are also provided for each subsector.) For most variables, the chosen years for rankings are 1993, 1999, 2005, 2014, and 2017. These years are consistent with the author's prior research. They are chosen to avoid the distorting influence of recession and recovery years. By avoiding 2018 and 2019, the potentially distorting influence of the U.S.-China trade war is also eliminated from the results. The series on utility patents by three-digit NAICS subsectors stops at 2012. And there is an issue with the continuity of the 1990s inventory-sales data. Thus, 2005, 2014 and 2017 are ranked for inventory-sales.

RESULTS

Table 1 shows the absolute number of jobs for the selected years. The dramatic fall in manufacturing employment between 1999 and 2005 is evident as is the further employment decline into 2014 in the wake of the Great Recession and slow recovery. As the manufacturing jobs picture stabilized into 2017, there were employment gains in 12 of the 20 subsectors.

Table 1: Manufacturing Jobs (Thousands)	1993	1999	2005	2014	2017
Textile Mills	479	397	218	117	112
Textile Products Mills	233	232	176	115	116
Apparel	857	541	251	140	119
Wood	527	623	561	372	397
Paper and Paper Products	640	616	484	373	366
Printing and Related Support	785	815	646	454	440
Petroleum and Coal Products	146	128	112	112	115
Chemicals	1025	983	872	803	824
Plastics and Rubber Products	848	947	802	674	717
Nonmetallic Mineral Products	491	541	505	384	410
Primary Metals	619	625	466	399	371
Fabricated Metal Products	1510	1728	1522	1454	1424
Machinery	1331	1468	1164	1127	1079
Computer and Electronic Products	1656	1781	1316	1049	1039
Electrical Equipment and Appliances	576	588	434	378	386
Transportation Equipment	1915	2088	1772	1559	1643
Furniture and Related Products	576	665	567	370	395
Misc. Durable Goods MFG	703	724	647	582	594
Misc. Non-Durable Goods MFG	325	283	231	239	291
Total MFG	16776	17323	14226	12185	12439

Source: Bureau of Labor Statistics

Table 2 shows that the U.S. manufacturing employment share is fairly concentrated. In 2017, double-digit employment shares are seen in food manufacturing, fabricated metal products, and transportation equipment. Those three subsectors alone accounted for nearly 38 percent of total U.S. manufacturing employment in 2017. Subsectors with employment shares below one percent in 2017 were either very labor intensive, such as apparel, or very capital intensive, such as petroleum. The data in Table 2 and Table 3 show that manufacturing employment and wages are sometimes correlated and sometimes not. In spite of its small share of employment, in 2017 average hourly earnings in petroleum and coal was $39.95, approaching twice the $20.89 average for total manufacturing.

Table 4 shows that only a few of the three-digit industry subsectors experienced dramatic fluctuations in their employment share rankings. Apparel, for example, experienced a drop from a ranking of 7 in 1993 to 16 in 1999, clearly catalyzed by the general dwindling of domestic U.S.

Table 2: Manufacturing Employment Share (%)	1993	1999	2005	2014	2017
Food MFG	9.15	8.95	10.39	12.18	12.85
Textile Mills	2.85	2.29	1.53	0.96	0.90
Textile Products Mills	1.39	1.34	1.24	0.94	0.93
Apparel	5.11	3.12	1.76	1.15	0.96
Wood	3.14	3.60	3.94	3.05	3.19
Paper and Paper Products	3.81	3.55	3.40	3.07	2.94
Printing and Related Support	4.68	4.70	4.54	3.72	3.54
Petroleum and Coal Products	0.87	0.74	0.79	0.92	0.92
Chemicals	6.11	5.67	6.13	6.59	6.62
Plastics and Rubber Products	5.05	5.47	5.64	5.53	5.76
Nonmetallic Mineral Products	2.93	3.12	3.55	3.15	3.29
Primary Metals	3.69	3.61	3.28	3.27	2.98
Fabricated Metal Products	9.00	9.98	10.70	11.94	11.45
Machinery	7.93	8.48	8.19	9.25	8.67
Computer and Electronic Products	9.87	10.28	9.25	8.61	8.35
Electrical Equipment and Appliances	3.43	3.39	3.05	3.10	3.11
Transportation Equipment	11.42	12.06	12.46	12.79	13.21
Furniture and Related Products	3.43	3.84	3.98	3.04	3.17
Misc. Durable Goods MFG	4.19	4.18	4.55	4.78	4.78
Misc. Non-Durable Goods MFG	1.94	1.63	1.63	1.96	2.34

Source: Bureau of Labor Statistics and *New World Economics*

Table 3: Average Hourly Earnings (Current $)	1993	1999	2005	2014	2017
Food MFG	9.82	11.40	13.04	15.55	16.92
Textile Mills	9.12	10.90	12.38	14.15	15.97
Textile Products Mills	8.10	10.04	11.61	13.35	14.80
Apparel	6.75	8.35	10.26	13.51	14.35
Wood	9.40	11.18	13.16	15.57	17.47
Paper and Paper Products	13.13	15.58	17.99	20.35	21.75
Printing and Related Support	11.67	13.67	15.74	18.01	18.61
Petroleum and Coal Products	19.43	22.22	24.47	35.39	39.95
Chemicals	13.97	16.40	19.67	21.49	24.29
Plastics and Rubber Products	10.56	12.25	14.80	16.51	17.63
Nonmetallic Mineral Products	11.83	13.97	16.61	19.16	20.34
Primary Metals	14.08	16.00	18.94	22.41	23.10
Fabricated Metal Products	11.40	13.34	15.80	18.68	20.15
Machinery	12.72	14.77	17.02	21.00	22.41
Computer and Electronic Products	11.95	14.37	18.39	23.36	24.58
Electrical Equipment and Appliances	10.65	12.90	15.24	18.28	19.72
Transportation Equipment	16.21	18.24	22.09	24.96	25.36
Furniture and Related Products	9.25	11.28	13.45	15.67	17.52
Misc. Durable Goods MFG	9.64	11.55	14.07	17.31	19.04
Total Manufacturing	11.69	13.85	16.55	19.56	20.89

Source: Bureau of Labor Statistics

Table 4: Employment Share Ranking	1993	1999	2005	2014	2017
Food MFG	3	4	3	2	2
Textile Mills	17	17	18	18	20
Textile Products Mills	19	19	19	19	18
Apparel	7	16	16	17	17
Wood	15	12	11	14	11
Paper and Paper Products	11	13	13	13	15
Printing and Related Support	9	8	9	9	9
Petroleum and Coal Products	20	20	20	20	19
Chemicals	6	6	6	6	6
Plastics and Rubber Products	8	7	7	7	7
Nonmetallic Mineral Products	16	15	12	11	10
Primary Metals	12	11	14	10	14
Fabricated Metals	4	3	2	3	3
Machinery	5	5	5	4	4
Computer and Electronic Products	2	2	4	5	5
Electrical Equipment	13	14	15	12	13
Transportation Equipment	1	1	1	1	1
Furniture	14	10	10	15	12
Misc. Durable Goods MFG	10	9	8	8	8
Misc. Non-Durable Goods MFG	18	18	17	16	16

Source: *New World Economics*

labor-intensive manufacturing. By contrast, the employment share ranking of nonmetallic mineral products rose from 16 in 1993 to 10 in 2017.

Overall, the dominating subsector is transportation equipment. Transportation equipment manufacturing ranked first in employment share in every measured year between and including 1993 and 2017. Other high-ranked subsectors for employment share include computers and electronic products, fabricated metals, machinery, and food manufacturing.

Table 5 shows minimal volatility in the earnings rankings, even less so than for employment share. The big winner for earnings is petroleum and coal which ranked first in every measured year of the sample. Other relatively high earnings industry subsectors include chemicals, primary metals, and transportation equipment.

Chemicals, computers and electronic products, and transportation equipment were the three industry subsectors that had generally high rankings for both employment share and earnings. Transportation ranked first in employment share throughout the observation period and second in earnings throughout the observation period.

Table 6 shows that the absolute number of utility patents has grown fairly dramatically in the U.S. manufacturing sector since the mid-1990s, more than doubling between 1994 and 2012. As with employment, patent activity is concentrated. In 2012 chemicals, machinery, and computers and electronic products accounted for 73 percent of total U.S. manufacturing utility patents. Computers and electronic products alone accounted for 54 percent of manufacturing patents in

Table 5: Earnings Ranking	1993	1999	2005	2014	2017
Food MFG	13	14	16	16	16
Textile Mills	17	17	17	17	17
Textile Products Mills	18	18	18	19	18
Apparel	19	19	19	18	19
Wood	15	16	15	15	15
Paper and Paper Products	5	5	6	7	7
Printing and Related Support	9	9	10	11	12
Petroleum and Coal Products	1	1	1	1	1
Chemicals	4	3	3	5	4
Plastics and Rubber Products	12	12	12	13	13
Nonmetallic Mineral Products	8	8	8	8	8
Primary Metals	3	4	4	4	5
Fabricated Metals	10	10	9	9	9
Machinery	6	6	7	6	6
Computer and Electronic Products	7	7	5	3	3
Electrical Equipment	11	11	11	10	10
Transportation Equipment	2	2	2	2	2
Furniture	16	15	14	14	14
Misc. Durable Goods MFG	14	13	13	12	11

Source: *New World Economics*

2012. The rankings in Table 7 reinforce the importance of computers and electronic products, machinery, and chemicals in manufacturing innovation activity.

Table 6: Number of U.S. Patents	1994	2004	2012
Food	304	239	225
Beverage and Tobacco	75	82	75
Textiles, Apparel and Leather	758	923	986
Wood	183	213	290
Paper, Printing, and Support	553	436	405
Chemicals	7177	8335	11659
Plastics and Rubber Products	2805	2702	2689
Nonmetallic Mineral Products	1068	1178	1176
Primary Metal	375	280	291
Fabricated Metal Products	4780	4520	4894
Machinery	9473	10407	11064
Computer and Electronic Products	16037	38353	65057
Electrical Equipment and Appliances	3449	5742	5983
Transportation Equipment	2414	3377	4042
Furniture and Related Products	314	426	370
Misc. MFG	6301	7057	11818
Total MFG	56066	84270	121024

Source: U.S. Patent and Trademark Office

Table 8 shows a four-year moving average of multi-factor productivity growth in total U.S. manufacturing and three-digit NAICS subsectors. Some might question the sensitivity of the ranking results to the choice of moving average specification. Using a moving average of a smaller number of years would fail to recognize the known pro-cyclical volatility of productivity measures. Of note is the high volatility in these data even with the moving average construction. Using a moving average of a greater number of years would remove meaningful volatility that would be desirable to capture. On the whole, there is some judgment in this moving average specification. But with the results reported over a 24-year span, a meaningful ranking on average is captured.

Table 7: Utility Patent Ranking (Ranking by Share of Total Manufacturing Patents)	1994	2004	2012
Food	15	15	15
Beverage and Tobacco	16	16	16
Textiles, Apparel and Leather	10	10	10
Wood	12	12	11
Paper, Printing, and Support	11	11	12
Chemicals	3	3	3
Plastics and Rubber Products	6	7	8
Nonmetallic Mineral Products	9	9	9
Primary Metal	13	14	14
Fabricated Metal Products	4	5	6
Machinery	2	2	2
Computer and Electronic Products	1	1	1
Electrical Equipment and Appliances	7	6	5
Transportation Equipment	8	8	7
Furniture and Related Products	14	13	13
Misc. MFG	5	4	4

Source: New World Economics

After 1999, when U.S. manufacturing jobs experienced a dramatic decline, multifactor productivity growth was accelerating, reflecting stratospheric and unsustainable productivity gains in the computers and electronic products subsector. With the productivity bubble in the computer subsector having burst, the question of catalysts for U.S. manufacturing productivity acceleration is certainly one of the most important issues for U.S. manufacturing competitiveness, as discussed by Waldman (2016).

As shown in Table 9, of all the metrics that were ranked for the current study, multifactor productivity growth (MFP) has the greatest volatility in terms of ranking through time for most industry subsectors. This creates a foggy picture of strength and weakness outside of computers and electronic products. In ranking the inventory-sales ratio (shown in Table 10), I calculated one divided by the inventory-sales ratio so a higher number signals a leaner supply chain on average. Petroleum, food, printing, and paper show the relatively leanest inventory picture.

Table 8: 4-Year Moving Average of MFP Growth (%)	1993	1999	2005	2014	2017
Food MFG	0.03	-1.43	0.23	-0.28	-1.18
Textile Mills and Textile Product Mills	0.10	1.43	1.50	1.13	-0.38
Apparel	0.73	-0.38	-0.55	2.25	-8.83
Wood	-2.03	-0.93	0.65	0.03	-0.45
Paper and Paper Products	0.73	0.33	2.35	0.25	-0.40
Printing and Related Support	-0.25	0.60	2.93	1.63	0.30
Petroleum and Coal Products	2.55	2.78	1.53	0.00	0.33
Chemicals	-1.50	-0.65	1.50	-3.55	-1.70
Plastics and Rubber Products	0.13	1.35	1.65	-1.00	0.60
Nonmetallic Mineral Products	0.00	0.43	1.88	1.68	-1.20
Primary Metals	0.95	0.38	1.73	1.00	0.23
Fabricated Metal Products	-0.65	-0.70	1.53	-0.48	-1.55
Machinery	-3.00	-1.60	2.45	-0.35	-2.13
Computer and Electronic Products	5.38	12.40	8.95	0.60	1.18
Electrical Equipment and Appliances	-1.53	-3.83	1.90	-0.50	-1.40
Transportation Equipment	-0.98	0.85	2.55	1.08	-2.43
Furniture and Related Products	0.50	0.80	1.60	-0.20	0.60
Misc. MFG	-1.15	2.23	1.08	-1.30	-0.80
Total Manufacturing	-0.10	1.48	2.73	-0.53	-1.20

Source: Bureau of Labor Statistics and New World Economics

Table 9: Multi-factor Productivity Growth Ranking	1993	1999	2005	2014	2017
Food MFG	9	17	18	12	11
Textile Mills and Textile Product Mills	8	5	14	4	7
Apparel	4	13	19	1	19
Wood	18	16	17	9	9
Paper and Paper Products	5	12	6	8	8
Printing and Related Support	12	9	2	3	5
Petroleum and Coal Products	2	2	13	10	4
Chemicals	16	14	15	19	16
Plastics and Rubber Products	7	6	10	17	3
Nonmetallic Mineral Products	10	10	8	2	12
Primary Metals	3	11	9	6	6
Fabricated Metals	13	15	12	14	15
Machinery	19	18	5	13	17
Computer and Electronic Products	1	1	1	7	1
Electrical Equipment and Appliances	17	19	7	15	14
Transportation Equipment	14	7	4	5	18
Furniture	6	8	11	11	2
Misc. MFG	15	3	16	18	10

Source: New World Economics

ANALYSIS AND IMPLICATIONS

The analytical framework developed for this study conceptualizes trade and domestic U.S. innovation as elements of a single dynamic which governs U.S. manufacturing employment growth. In this framework, innovation is not just a domestic investment but a competitive investment. An essential component of the prescription for strong domestic U.S. manufacturing employment gain is adequate innovation for the generation of globally competitive productivity growth. Strong, well-functioning supply chains are needed to spread the benefits of innovation and thus create the desired return on innovation investment, which takes the form of robust manufacturing job and wage growth.

The empirical picture presented in this paper is weak-to-mixed. There are pockets of strength, notably transportation equipment, chemicals, computers and electronic products, and machinery. But in looking at the U.S. manufacturing sector by subsectors it is clear that weakness is more widespread than

Table 10: Inventory-Sales Ranking (1/[I/S])	2005	2014	2017
Food MFG	3	3	2
Beverage and Tobacco	9	10	11
Textile Mills	13	17	17
Textile Product Mills	5	16	15
Apparel	20	21	21
Leather	21	20	20
Wood	8	8	5
Paper and Paper Products	7	4	4
Printing and Related Support	2	2	3
Petroleum and Coal Products	1	1	1
Chemicals	12	6	10
Plastics and Rubber Products	6	7	7
Nonmetallic Mineral Products	10	9	8
Primary Metals	14	11	12
Fabricated Metals	15	14	16
Machinery	18	13	14
Computer and Electronic Products	19	18	18
Electrical Equipment and Appliances	16	15	13
Transportation Equipment	11	12	9
Furniture	4	5	6
Misc. Durable MFG	17	19	19

Source: U.S. Department of Commerce and New World Economics strength. In the wake of the bursting of the computer and electronic products productivity bubble, productivity performance in U.S. manufacturing has been troublesome. This, in turn, is of concern for the health of supply chains and for realizing the full benefits of what had been strong innovation output. It is thus not a surprise that manufacturing employment is so concentrated and that only a few manufacturing subsectors show strength in both employment and wages.

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