

# Identifying High Resource Consumption Areas of Assembly-Centric Manufacturing in the United States

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## Abstract

This paper examines supply chain value added in the US for producing assembly-centric products, which includes machinery, computers, electronics, and transportation equipment, and determines whether costs are disproportionally distributed. The implication being that reductions in resource consumption in some cost areas can disproportionally reduce total resource consumption. Efforts to develop and disseminate innovative solutions to improve efficiency can, therefore, be targeted to these high cost areas, resulting in larger efficiency improvements than might otherwise be achieved. An input-output model is used for this examination and is combined with labor data and data on assets. The top 20 industries, occupations, and industry occupation combinations contributing to production are identified. A sensitivity analysis is conducted on the model using Monte Carlo simulation. The results confirm that costs are disproportionally distributed, having a Gini coefficient of 0.75 for value added and for compensation it is 0.86. *Wholesale trade, aircraft manufacturing, and the management of companies and enterprises* were the industries with the largest contribution to assembly-centric manufacturing, even when including imports. Energy in the form of electricity and natural gas were discussed separately, but would rank 8<sup>th</sup> if compared to the industry rankings. In terms of occupation activities, team assemblers, general and operations managers, and sales representatives were the largest occupations. Public entities might use this model and results to identify efficiency improvement efforts that will have the largest impact on industry per dollar of expenditure.

## Introduction

Public entities have a significant role in the US innovation system (Block and Keller 2016). The federal government has had a substantial impact in developing, supporting, and disseminating numerous innovations and industries, including the Internet, telecommunications, aerospace, semiconductors, computers, pharmaceuticals, and nuclear power among others, many of which may not have come to fruition without public support (Wessner and Wolff 2012). Although the Defense Advanced Research Projects Agency (DARPA), Small Business Innovation Research Program (SBIR), and Advanced Technology Program (ATP) have received attention in the scholarly community, there is generally limited awareness of the government's role in US innovation. The vastness and diversity of US federal research and development programs along with their changing nature make them difficult to categorize and appreciate (Block and Keller 2016), but even the origins of Google are rooted in a public grant through the National Science Foundation (National Science Foundation 2004; Block and Keller 2016). One objective of public innovation is to enhance economic security and improve our quality of life (National Institute of Standards and Technology 2017), which is achieved in part by advancing efficiency in which resources are consumed or impacted by production. For example, the National Institute of Standards and Technology (NIST) has expended resources in supporting the development of the International Standard for the Exchange of Product Model Data (STEP) (Robert D. Niehaus, inc 2014), which reduces

the need for duplicative efforts such as re-entering design data. Another effort to advance efficiency is the development of the Core Manufacturing Simulation Data (CMSD) specification, which enables data exchange for manufacturing simulations (Lee et al 2011). In addition to investing in the development of new innovations, public investments are also made in disseminating new processes and innovations. For example, NIST's Manufacturing Extension Partnership (MEP) has been involved in disseminating process improvement innovations. In one instance, MEP aided in reducing labor input for packing by 50 % and lead time by 30 % at a factory in Detroit, MI (Manufacturing Extension Partnership 2017). In other instances, MEP aided in the adoption of ISO standards, training programs, and safety standards to improve quality and reduce costs (Manufacturing Extension Partnership 2017). In many instances, it is the adoption of recently developed ideas and technologies that can have significant impact on efficiency rather than the development of new technologies and ideas.

There are three major impacts that public investment in developing and disseminating innovations has on manufacturing. The first is innovative solutions that produce an efficiency improvement in the production and delivery of functioning products. This amounts to a decrease in the resources needed to produce a particular product. The second impact is an innovative solution that provides an efficiency improvement in achieving end use purposes. Products are manufactured to achieve a purpose such as transportation, communication, or entertainment. In the process of achieving these purposes (i.e., the use of manufactured products), resources are consumed. Automobiles, for instance, consume fuel while televisions and computers consume electricity. Improving energy efficiency along with other characteristics of a product amounts to an efficiency improvement in achieving its end use purpose. Improving the longevity of an automobile, for example, might improve efficiency in achieving end use purpose, as less resources are expended on automobiles per mile traveled. The last impact is that of innovations that achieve new end use purposes, such as a new vaccine or space travel. Together, these three impacts – efficiency in production, efficiency in end use, and new end-use purposes – constitute the major impacts of innovation in manufacturing. This paper focuses on potential efficiency improvements in production, leaving issues in end use purposes for future research.

Public entities have scarce resources, therefore, they must prioritize their investments in developing and disseminating innovative solutions to improve efficiency in production by focusing on those cost areas that have a disproportional impact on resource consumption. Companies often do this naturally by examining their accounting books and concentrating on their largest costs rather than their smallest ones. It may seem apparent that those who seek to improve US manufacturing efficiency as a whole would apply similar methods; however, there is limited evidence that this is occurring. For public entities identifying large costs requires economy wide analysis and there is limited research and literature focusing on this topic.

A frequently invoked axiom posits that roughly 80 % of a problem is due to 20 % of the cause, a phenomenon referred to as the Pareto principle (Hopp and Spearman 2008). This paper examines whether costs are disproportionately distributed for assembly-centric products and measures the statistical dispersion using the Gini coefficient (Klein 2002). The paper further seeks to identify those costs that account for a disproportionately high level of resource consumption. Assembly-centric products include machinery, computers/electronics, and transportation equipment. These products were examined as they include what is commonly referred to as high-tech manufacturing. Additionally, they require similar production activities such as the mass transportation of intermediate parts, which may not be required in the production of other types of products. Industry value added and compensation by occupation is used as the measure of cost. From this value the top 20 costs are identified by industry, occupation, and industry/occupation combination. The robustness of these rankings are then examined

in a Monte Carlo analysis. The costs from 412 industries and 92 assembly-centric commodities are analyzed. This analysis facilitates prioritizing efficiency efforts in assembly-centric manufacturing by identifying the costs by industry, occupation, and industry/occupation combination. Another contribution is the breakout of energy costs and how energy is used in manufacturing. The purpose of this approach is to facilitate the identification of economy-wide opportunities for efficiency improvements per dollar of expenditure in assembly-centric manufacturing. Public entities, trade organizations, and other change agents that seek to have the largest efficiency improvement possible must prioritize their efforts to develop and disseminate innovations so that they can get the largest increase per expenditure dollar.

The top 20 % of costs include more than 80 industries, 150 occupations, and more than 60 000 industry/occupation combinations, which is difficult to report out in a paper. For this reason, this paper discusses the top 20. Out of more than 400 industries, the top 20 represent 43 % of the costs from assembly-centric manufacturing, suggesting that a significant amount of the cost is concentrated within a small number of industries. Out of 800 occupations, the top 20 represent 21 % of the costs and Out of more than 300 000 industry/occupation combinations, the top 20 represent 5 % of the costs. These categories of cost have a disproportional impact on total cost, creating an opportunity for innovative solutions that have a large impact on cost.

## **Background**

To develop and disseminate publicly supported innovative solutions that provide economy-wide efficiency improvements, researchers have suggested that “the supply chain must become the focus of policy management, in contrast to the traditional emphasis on single technologies/industries” (Tassey 2010). A majority of costs are hidden in the supply chain. For example, 83 % of value added for automobile manufacturing is in the supply chain, occurring in establishments other than where the final assembly takes place.<sup>1</sup> The level of analysis in this paper can capture costs from system-level inefficiencies such as those that result from the “bullwhip effect” where variations in demand are magnified through a supply chain (Lee et al 1997; Bray and Mendelson 2012). Efficiency improvements in high cost supply chain entities can reduce unit cost, increase quality, and increase flexibility. These increases can spur growth in employment and value added as the domestic share of global markets expand (Tassey 2010). The McKinsey Global Institute also identifies industry sector level examinations as the key to understanding competitiveness and growth in an economy (McKinsey Global Institute 2010). Additionally, Bhatnagar and Sohal show that industry supply chains have a significant impact on operational competitiveness (Bhatnagar and Sohal 2005). Despite the importance of supply chains, there is limited research on economy-wide issues or costs. There are many individual supply chain studies, such as the RAND study on ammunition supplies for the US military (Butler et al. 2016) or a report by the Australian Logistics Council (2014) that investigates national logistics issues; however, these and other studies either focus on the supply chain of a specific product or a specific issue within the national supply chain.

The US federal government collects and distributes a wide range of manufacturing industry data, including the Annual Survey of Manufactures, economic census, and the National Compensation Survey; however, these datasets alone do not provide an analysis of the system-level supply chain for manufactured goods. For example, a major data source on national manufacturing, the Annual Survey of Manufactures, is an invaluable resource; however, by itself the insight it provides is limited, as it has a limited number of cost categories, has limited information about supply chain costs, and no information

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<sup>1</sup> Calculated using Input-Output analysis of the BEA Benchmark data.

about the types of labor in each industry. Assembly-centric products require raw materials, material refining, and intermediate components, which require buildings, machinery, and laborers. Data on manufacturing activity provides insight into the total production of raw materials, material refining, and intermediate components along with the total capital assets such as buildings and machinery; however, these items are used for multiple purposes. For example, metal is used in the construction of buildings and intermediate components are used in the maintenance and repair of old products. Additionally, raw materials, metal, and intermediate components might be produced for export rather than for domestic finished goods production. Moreover, domestic data alone provides limited insight into the resources required to produce assembly-centric products. Without an input-output model or similar analyses, there is limited understanding concerning the use and costs of resources for manufacturing at a national level and there is minimal understanding of the supply chain for such products.

Establishments look at performance across a variety of factor inputs, including transportation, worker skills, materials, components, and energy to remain competitive. In order for domestic manufacturing to remain vibrant, it can be argued that a nation must consider these issues as well, but at a larger scale (McKinsey & Company 2012). This analysis uses input-output analysis, a systems level approach, to identify economy wide opportunities for efficiency improvement in manufacturing, a matter that is lacking in the literature to date. The analysis crosses multiple industries, occupations, and supply chains. Input-output analysis reveals inter-industry relationships through a system of linear equations. It characterizes an industry's product throughout the economy, thus, revealing the supply chain. This effort might be analogous to a company estimating and examining its accounting books to identify high cost areas. For example, Dell identified significant cost increases in one of its intermediate production steps. It assembled a team to identify the root causes of these costs and was able to successfully reduce it (Simchi-Levi et al 2008). Companies such as Dell and others track and analyze their cost data to identify high cost areas where efficiency improvements might be made to remain a competitive business. Public efforts that seek to improve economy-wide efficiency and competitiveness in manufacturing would benefit from similar cost data; however, unlike a company, a representative cost breakdown is not readily available. Measuring assembly-centric production at the macro or economy wide level poses slightly different challenges than an individual company might face, as it requires tracking multiple products being produced by multiple companies each with their own supply chain. The result is that data are collected from sample surveys, takes years to assemble, and must be combined for analysis. The approach in this paper is consistent with calls for system-level productivity and examining supply chains to achieve efficiency improvements in manufacturing. The resulting economy-wide efficiency improvements may lead to increases in long term economic growth, per capita income (Weil 2005), employment, and innovation (Tassey 2010). Input-output analysis allows us to break apart a product into its costs by establishment, occupation, and industry/occupation combination. The results can aid in identifying innovative solutions that have a high impact on efficiency.

Although input-output analysis is, typically, used to examine the impact of changes in demand, there is some precedent for using these models for examining supply chains. Albino et al. (2002), for example, develop an input-output approach on production processes to investigate supply chain flows. Lu et al. (2007) provide a model to plan production, procurement, and distribution using input-output models. Each of these, however, focuses on the individual company or supply chain level, studying enterprise input-output accounts. Despite these applications, there seems to be limited use of input-output models to motivate efforts to develop and disseminate innovations.

This analysis uses data from previous years to estimate current industry activity, which results in some uncertainty. In order to account for this uncertainty, a probabilistic sensitivity analysis was conducted using Monte Carlo analysis (which can also be used for numerical integration and optimization

problems). Examinations of uncertainty in environmental Input-Output analysis have used both fuzzy set theory and stochastic models (Raina and Thomas 2012; Egilmez et al 2016; Beynon and Munday 2007; Beynon and Munday 2005; Temurshoev 2015); however, with there being limited in-depth examinations of uncertainty, there is not a consensus on a specific approach (Diaz and Morillas 2011). Monte Carlo analysis is based on works by McKay, Conover, and Beckman (1979) and by Harris (1984) that involves a method of model sampling. Monte Carlo simulation methods are superior to deterministic modeling for our purposes because deterministic modeling uses single-point estimates while Monte Carlo generates a probability distribution for every single variable of interest and allows for a comprehensive comparison of those probabilities.

## **Data and Methods**

This paper uses input-output analysis and Monte Carlo analysis to examine the costs of assembly-centric commodities. Input-output analysis is used to estimate the costs and Monte Carlo analysis is used to test the robustness of the results. These approaches build of Thomas and Kandaswamy (2015) are discussed below. A number of data sources are needed for tracking costs, including input-output data from the Bureau of Economic Analysis (BEA), energy use data from the Energy Information Administration (EIA), asset purchases from the Annual Survey of Manufactures (ASM), employment and wage data from the Bureau of Labor Statistics, and construction cost data from RS Means. As illustrated in Figure 2A, these datasets are mapped together based on the North American Industry Classification System (NAICS), which categorizes establishments based on their products and processes, and the Standard Occupation Classification system (SOC), which categorizes labor by occupation. As illustrated in Figure 2B, value added represents the total cost, which is broken into compensation, taxes, and gross operating surplus. Each of these and their subcategories can be calculated for each industry NAICS code, seen on the Y-axis to the left. Compensation can further be decomposed into Standard Occupation Classification System categories. Gross operating surplus can be decomposed into net operating surplus, a profit like measure, and depreciable assets such as buildings and machinery. All of the categories in the X-axis are calculated by the NAICS categories on the Y-axis. This paper primarily discusses value added, compensation, and depreciable assets (i.e., buildings and machinery) by NAICS code categories.

*Input-Output Analysis:* Within an input-output model, economies of scale are ignored; thus, the model operates under constant returns to scale. The model also assumes that a sector uses inputs in fixed proportions. These issues are, typically, relevant to analyses that examine the impact of a change in demand. This paper is not seeking to predict the impact of a change in demand, but rather seeks to track the resources used for the production of particular goods; therefore, ignoring economies of scale and assuming sectors use inputs in fixed proportions has limited impact on the underlying analysis. The input-output model provides the goods and services that are used up in the production process; thus, capital investments are excluded and will be examined separately. The analysis utilizes the BEA Benchmark input-output tables, which has data for over 350 industries (Bureau of Economic Analysis 2014). This data includes Make tables, which show the production of commodities (products) by industry, and Use tables, which show the components required for producing the output of each industry. The data is categorized by altered codes from the North American Industry Classification System (NAICS).

This paper uses an industry-by-commodity input-output format as outlined in Horowitz and Planting, which accounts for the fact that an industry may produce more than one commodity or product such as secondary and by-products (Horowitz and Planting 2006; Miller and Blair 2009; European Commission 2008). An input-output analysis develops a total requirements matrix that when multiplied by the vector

of final demands equals the output needed for production. The total requirements matrix is developed using the methods outlined in Horowitz and Planting (2006):

Equation 1

$$X = W(I - BW)^{-1} * Y$$

Where:

$X$  = Vector of output required to produce final demand

$Y$  = Vector of final demand

$$W = (I - \hat{p})V\hat{q}^{-1}$$

$$B = U\hat{g}^{-1}$$

$I$  = Identity matrix

$p$  = "A column vector in which each entry shows the ratio of the value of scrap produced in each industry to the industry's total output."

$U$  = "Intermediate portion of the use matrix in which the column shows for a given industry the amount of each commodity it uses—including noncomparable imports, scrap, and used and secondhand goods. This is a commodity-by-industry matrix."

$V$  = "Make matrix, in which the column shows for a given commodity the amount produced in each industry. This is an industry-by-commodity matrix.  $V$  has columns showing only zero entries for noncomparable imports and for scrap."

$g$  = "A column vector in which each entry shows the total amount of each industry's output, including its production of scrap. It is an industry-by-one vector."

$q$  = "A column vector in which each entry shows the total amount of the output of a commodity. It is a commodity-by-one vector."

$\hat{\phantom{x}}$  = "A symbol that when placed over a vector indicates a square matrix in

which the elements of the vector appear on the main diagonal and zeros elsewhere.”

The total requirements matrix  $W(I - BW)^{-1}$ , which shows the total output required to meet a given level of final demand, is multiplied by final demand in the input output data to estimate the total output. The output required to produce a particular level of final demand can be calculated by altering final demand to  $Y'$ . For this analysis,  $Y'$  has the total final demand for assembly-centric products and zero for other products.

Value Added Analysis: Value added is calculated by assuming the proportion of output needed to produce a commodity is the same proportion of value added, which is consistent with methods proposed by Miller (2009). The proportions calculated using the input-output analysis are then multiplied by the value added and scaled to 2014 dollars using the estimate of gross output for that year:

Equation 2

$$VA_{z,Y',2014} = \frac{x_{z,Y',2007}}{x_{z,2007}} * VA_{z,2007} * \left( \frac{x_{z,2014}}{x_{z,2007}} \right)$$

Where

$VA_{z,Y',2014}$  = Value added from industry  $z$  with final demand  $Y'$  in 2014

$x_{z,2007}$  = Total output for industry  $z$  in 2007

$x_{z,2014}$  = Total output for industry  $z$  in 2014

$x_{z,Y',2007}$  = Output for industry  $z$  with final demand  $Y'$  in 2007

$VA_{z,2007}$  = Total value added from industry  $z$  in 2007

Imports are calculated in a similar fashion, where the proportion of total output used from a particular industry is the same for imports.

Energy Analysis: The BEA input-output data provides estimates of energy use but not the requisite detail in how the energy is used, which is an important issue in tracking industry operations. In order to better understand energy use, the Manufacturing Energy Consumption Survey (MECS) was used to breakout the BEA data to show not only how much energy is used, but what it is used for. The Energy Information Administration collects energy data on a quadrennial basis and samples approximately 15 500 establishments drawn from a nationally representative sample frame that includes 97 % to 98 % of the manufacturing payroll (Energy Information Administration 2010). Energy data is categorized by the NAICS codes and end use. The U.S. Energy Information Administration (EIA) distinguishes between two types of energy usage in manufacturing – “energy consumed for fuel and energy consumed for feedstock” (Energy Information Administration 2010). Energy consumed for fuel is described aptly by its

title whereas energy used as feedstock is “energy used as a raw material for purposes other than for heat, power, and electricity generation” (Energy Information Administration 2010). For this analysis, the EIA energy data has been mapped to the 2007 Benchmark make and use tables in order to expand out the input-output analysis. In instances where the EIA NAICS codes did not match the BEA NAICS codes, the proportions of energy use at the next NAICS level of detail was used. The BEA benchmark code of *coal mining* was expanded to include seven categories:

212100	Coal mining
212100-A	Indirect Uses-Boiler Fuel
212100-B	Process Heating
212100-D	Machine Drive
212100-F	Other Process Use
212100-G	Facility HVAC (g)
212100-K	Conventional Electricity Generation

The BEA benchmark NAICS code for *electric power generation, transmission, and distribution* was expanded to thirteen categories:

221100	Electric power generation, transmission, and distribution
221100-A	Indirect Uses-Boiler Fuel
221100-B	Process Heating
221100-C	Process Cooling and Refrigeration
221100-D	Machine Drive
221100-E	Electro-Chemical Processes
221100-F	Other Process Use
221100-G	Facility HVAC (g)
221100-H	Facility Lighting
221100-I	Other Facility Support
221100-J	Onsite Transportation
221100-K	Other Nonprocess Use
221100-L	End Use Not Reported

*Natural gas distribution* was expanded into ten categories:

221200	Natural gas distribution
221200-A	Indirect Uses-Boiler Fuel
221200-B	Process Heating
221200-C	Process Cooling and Refrigeration
221200-D	Machine Drive
221200-F	Other Process Use
221200-G	Facility HVAC (g)
221200-I	Other Facility Support
221200-K	Conventional Electricity Generation
221200-L	Other Nonprocess Use

Energy consumed for purposes other than for heat, power, and electricity generation remained in the base category (e.g., *coal mining: NAICS 212100*). The result of expanding the make and use tables is that the energy consumed for similar purposes (e.g., process heating) is tracked through multiple industries



for a selected final product, which in this case is assembly-centric goods. For example, an analysis of automobile manufacturing would reveal not only the process heating in the automobile manufacturing industry, but also the process heating within the metal foundries for the metal that went into the automobiles produced.

An additional issue regarding energy involves the use of industry categorizations. Value added is generally the best metric for measuring industry activity; however, it can somewhat disguise energy costs in this case as the value added is broken up into different industries. For instance, the cost of purchased electricity is broken into the mining of coal, extraction of gas, and generation of electricity. The analysis in this paper also breaks energy up further into its end use. Due to these complications, it is useful to discuss energy separately. To estimate energy use, the value added from electric power generation, transmission, and distribution needs be calculated along with the value added that contributes to it. To address this issue, an estimate of the aggregated impacts of energy are examined. This is done by estimating the output for  $Y''$  with final demand for "*electric power generation, transmission, and distribution*" equal to 1 and demand for all other commodities in  $Y''$  set to zero. This allows us to calculate the value added from each industry to produce a unit of value added from assembly-centric manufacturing:

Equation 3

$$VA_E = \frac{[\sum_{i=1}^n VA_{i,Y''}] - VA_{E,Y''} - VA_{N,Y''}}{VA_{E,Y''}}$$

Where

$VA_E$  = Indirect value added per percentage point of direct value added from *electric power generation, transmission, and distribution*

$VA_{E,Y''}$  = Value added from the *electric power generation, transmission, and distribution* for final demand  $Y''$

$VA_{N,Y''}$  = Value added from the *natural gas distribution* industry for final demand  $Y''$

A similar calculation can be made for natural gas where final demand for  $Y''$  is set to 1 for *natural gas distribution* and zero for all other commodities:

Equation 4

$$VA_N = \frac{[\sum_{i=1}^n VA_{i,Y''}] - VA_{E,Y''} - VA_{N,Y''}}{VA_{N,Y''}}$$

Where

$VA_N$  = Indirect value added per percentage point of direct value added from natural gas

Once we have distinguished between the dual uses of energy in the manufacturing sector, we can note that the energy use categories provided include: indirect uses-boiler fuel, process heating, process cooling and refrigeration, machine drive, electro-chemical processes, other process use, facility HVAC, facility lighting, facility support, onsite transportation, other non-process use, and end use not reported. Electric power generation, transmission, and distribution from the BEA data is broken into these categories by portioning out coal mining, electricity generation, and natural gas distribution by proportions calculated from the EIA. Unfortunately, this does not fully account for the energy value *added*, as oil and gas extraction cannot be broken out using this method; therefore, gasoline, diesel, and other such fuels are not broken out.

It should be noted that there exists another method for measuring energy consumption in the manufacturing process. Borrowing from the field of chemical analysis, “pinch analysis” has been applied to manufacturing activities, particularly at the production planning stage (Mohr et al 2012). The demand for pinch analysis grew dramatically in the first decade of the twenty-first century among manufacturers as variable costs sharply increased and companies sought to minimize costs.

A McKinsey report titled “Manufacturing Resource Productivity” by Stephan Mohr, Ken Somers, Steven Swartz and Helga Vanthournout describes pinch analysis. Basically, the analysis consists of “calculat(ing) the thermodynamically minimum energy required and evaluat(ing) actual consumption relative to this theoretical limit” (Mohr et al. 2012). The McKinsey report situates pinch analysis in the broader context of “lean manufacturing” techniques but that is not the focus of this report. What is important to note in this context is that BEA data aggregation can conceal very important facets about underlying efficiencies in the manufacturing industry and that techniques like “pinch analysis” can be used to focus in more narrowly on important information that might be otherwise lost.

Occupation Analysis: In order to examine labor activity, Bureau of Labor Statistics employment data from the Occupational Employment Statistics (OES) is matched with the BEA IO NAICS categories. The OES is categorized by industry by occupation. It includes over 800 occupations categorized by the Standard Occupation Classification (SOC) system and over 450 industries classified by NAICS; however, archived data covers fewer industries (Bureau of Labor Statistics). The data is gathered through surveys and covers full-time and part-time wage and salary workers in nonfarm industries. For this analysis, the Bureau of Labor Statistics employment data has been mapped to the detail level found in the 2007 Benchmark Input-Output data. In instances where the NAICS codes for the occupation data did not match that of the input-output data, the values were estimated. When the BEA data had a NAICS code at a lower level of detail than the occupation data, the occupation data was aggregated up to the BEA level of detail. If the occupation data was at a lower level of detail, then the BEA levels were estimated by assuming the proportion of the cost of compensation in the BEA was the same as that for employment. This provides an estimate of occupational employment by industry at the NAICS level of detail. To estimate the hours of labor, these estimates are multiplied by the average hours per week for each occupation and, then, multiplied by the total weeks per year. These hours are then multiplied by wages per hour and adjusted to match the BEA estimates of compensation assuming the BEA proportions of labor are the same as that calculated using BLS data. When examining a specific product commodity such as automotive manufacturing, the input-output calculations are used to estimate the output from each industry required to produce the given product. The proportion of the total output needed from each industry is multiplied by the occupational employment for each industry to estimate the amount of labor, which is consistent with methods proposed in Miller (2009). The result is a matrix

of the amount of labor needed, categorized by NAICS by occupation, to produce the relevant commodity.

Equation 5

$$C_{z,s,Y'} = \frac{x_{z,Y'}}{x_z} * C_{z,s} * \left( \frac{E_{z,s} * LH_s * W_{z,s}}{\sum_{i=1}^n E_{z,i} * LH_s * W_{z,i}} \right) * \left( \frac{x_{z,2014}}{x_{z,2007}} \right)$$

Where

$C_{z,s,Y'}$  = Compensation for occupation s in industry z with final demand  $Y'$

$C_{z,s}$  = Total compensation for occupation s in industry z

$x_z$  = Total output for industry z

$x_{z,Y'}$  = Output for industry z with final demand  $Y'$

$E_{z,s}$  = Employment for industry z and occupation s

$LH_s$  = Labor hours per employee for occupation s

$W_{z,s}$  = Hourly wages per employee for industry z and occupation s

Buildings and Machinery: Depreciable assets are measured in a similar fashion to that of labor. The proportion of output estimated from the input-output calculations is multiplied by the total depreciable assets for that industry, resulting in an estimate of depreciable assets utilized for the production of the commodity being examined. The data for depreciable assets is taken from the Economic Census, which is classified by NAICS codes. An estimate for buildings and machinery/equipment is made by utilizing RS Means data. The total square footage of manufacturing space from the Manufacturing Energy Consumption survey is multiplied by the average construction cost per square foot from RS Means (RS Means 2005). This is assumed to be the buildings share of depreciable assets with the remaining amount assumed to be machinery/equipment:

Equation 6

$$DB_{z,Y'} = \frac{x_{z,Y',2007}}{x_{z,T,2007}} * (SF_z * RM)$$

Equation 7

$$DM_{z,Y'} = \left[ \frac{x_{z,Y',2007}}{x_{z,T,2007}} * DA_z \right] - DB_{z,Y'}$$

Where

$DB_{z,Y',MB}$  = Depreciable building assets from industry  $z$  associated with final demand  $Y'$  in 2014

$DM_{z,Y'}$  = Depreciable machinery assets from industry  $z$  associated with final demand  $Y'$  in 2014

$x_{z,T,2007}$  = Total output for industry  $z$  in 2007

$x_{z,Y',2007}$  = Output for industry  $z$  with final demand  $Y'$  in 2007

$SF_z$  = Estimated square feet of manufacturing floor space for industry  $z$

$RM$  = RS Means estimated construction cost per square foot of manufacturing floor space

$DA_z$  = Gross value of depreciable assets (end of year) from the annual survey of manufactures

A similar calculation is made for the purchase of new and used capital assets, where the proportion of output estimated from the input-output calculations is multiplied by the value of new and used capital assets purchased.

Equation 8

$$CE_{z,Y',MB} = \frac{x_{z,Y',2007}}{x_{z,T,2007}} * CE_{MB}$$

Where

$CE_{z,Y',MB}$  = Capital expenditures by industry  $z$  with final demand  $Y'$  on MB, where MB is either machinery or buildings

$x_{z,T,2007}$  = Total output for industry  $z$  in 2007

$x_{z,Y',2007}$  = Output for industry  $z$  with final demand  $Y'$  in 2007

$CE_{z,MB}$  = Total capital expenditures by industry  $z$  on MB, where MB is either machinery or buildings

One challenge of examining depreciable assets is that they are long term investments; thus, it is difficult to compare them directly to the cost of those items that are used up in production. In accounting, the cost of depreciable assets is spread out over years. The annual estimates depend on the method of depreciation and the estimated useful life of the assets. A simple method would be to use straight-line depreciation and divide the acquisition cost by a selected useful life (e.g., 10 years for machinery and 30 years for buildings). This paper discusses the acquisition cost of assets, leaving the topic of estimating annual depreciation for future research.

*Monte Carlo Analysis:* As mentioned previously, this analysis uses data from previous years to estimate current industry activity, which results in some uncertainty. In order to account for this uncertainty, a probabilistic sensitivity analysis was conducted using Monte Carlo analysis. This technique is based on works by McKay, Conover, and Beckman (1979) and by Harris (1984) that involves a method of model sampling. It was implemented using the Crystal Ball software product (Oracle 2013), an add-on for spreadsheets. Specification involves defining which variables are to be simulated, the distribution of

each of these variables, and the number of iterations performed. The software then randomly samples from the probabilities for each input variable of interest.

Monte Carlo methods use repeated random sampling to draw insights into some phenomena of interest. The important thing to note about Monte Carlo is that the simulation methods do not require true randomness to draw conclusions. A bounded or constrained domain of values that approximate pseudo-randomness can be, and in practice often are, used with Monte Carlo simulations. This method is particularly useful for sensitivity analysis because it can trace variations to a particular input. By moving away from deterministic sampling, Monte Carlo provides a more accurate probabilistic picture. The avoidance of deterministic modeling also means that instead of doing simulations with a single point, a range of probabilities covering all scenarios can be incorporated.

For this analysis, the largest 30 industries, as measured by value added contributing to assembly-centric manufacturing, is varied using a triangular distribution (see Table 1). The top 30 are varied so that the identification of the top 20 has significant robustness. The lower bound is 25 % below the calculated value while the upper bound is 25 % above it. These 30 industries represent 54 % of the value added for assembly-centric manufacturing. The most likely value is the calculated base case value. The remaining industries are varied together by +/- 10 %. These distributions apply to the industry, occupation, industry-occupation, and depreciable assets examinations. For the industry occupation combination, the top 20 industry occupation combinations were varied by +/- 25 %, which tests the results under significant error with wide boundaries. Although different levels of variation could be selected, it has been shown that this level of error is reasonable (European Science and Technology Observatory 2006; Temurshoev 2015). The industries included in the Monte Carlo analysis are listed in Table 1. This simulation contained 10 000 iterations.

## Results

This paper examines supply chain value added in the U.S. for producing assembly-centric products. An input-output model is used for this examination and is combined with labor data and data on assets. A sensitivity analysis is conducted on the model using Monte Carlo simulation. Figure 3 illustrates the data and the value added for assembly-centric manufacturing. On the left of the figure are the assembly-centric commodities, including machinery, transportation equipment, and computers/electronics. The dollars associated with these products flows from the purchase of the commodities on the left to the industries that contributed to the commodity. From the industries it flows to owners/investors in the form of gross operating surplus, to employees in the form of compensation, and to the government in the form of taxes (note that only taxes on production are represented). Figure 3 is a summary of the data, as there are over 350 industries and 800 occupations. The model facilitates estimating value added for industry and occupation combinations for each commodity examined. That is, an estimation of the value added of a particular occupation from a particular industry can be estimated for a selected commodity. A breakout of the largest 20 resource areas by industry, occupation, and industry occupation combination is discussed below. Also discussed is the top 20 depreciable assets broken out into building assets and machinery assets. As discussed previously, Figure 2B illustrates the data categorization. The tables discussed below follow this categorization.

As seen in Figure 4, the distribution of industry cost is consistent with Pareto's principle where 80 % of the cost is due to 20 % of the cause (80<sup>th</sup> percentile). The x-axis in the line graph is the percentile of industry cost while the y-axis is the cumulative percent cost; therefore, the far left of the line graph represents those industries where the highest cost occurs while the right side represents those with the least impact. As one moves from left to right, the line represents the cumulative cost of industries, ranked from highest to lowest, aggregated together. If you move to the 80<sup>th</sup> percentile on the x-axis,

which accounts for the top 20 % of industries by cost, one can see that the line graph corresponds with nearly 80 % of the total cost from assembly-centric products. For occupations, the 80<sup>th</sup> percentile accounts for over 90 % of the occupation costs. The Gini coefficient for the industry line (i.e., value added) in this figure is 0.75 and for the occupations (i.e., compensation) it is 0.86, suggesting very unequal distribution.

*Industry:* For each iteration of the Monte Carlo analysis, the largest 20 industries (4.9 %) out of the 405 contributing to assembly-centric products, are identified. These 20 industries represent 46 % of the total value added associated with assembly-centric products. The number of times an industry was identified as being in each rank (i.e., rank 1 through 20) is shown in Table 2. *Wholesale trade* (NAICS 420000) was identified as the largest contributor to value added for 9985 iterations or 99.9 %, meaning that wholesale trade contributes more to assembly-centric products than each of the assembly-centric industries. In addition to *wholesale trade*, a number of other non-manufacturing industries appear in the top 20, including *management of companies and enterprises* (NAICS 550000), *oil and gas extraction* (NAICS 211000), *truck transportation* (NAICS 484000), *legal services* (NAICS 541100), *monetary authorities and depository credit intermediation* (NAICS 52A000), and *employment services* (NAICS 561300). It is important to remember that oil and gas extraction includes more than energy, it is also the raw material for other items such as plastic. *Aircraft manufacturing* (NAICS 336411), which includes the final assembly of an aircraft, was the second largest contributor to assembly-centric manufacturing for 8828 iterations (88.3 %), more than any other industry. Management of companies and enterprises was the third largest for 8085 iterations (80.9 %). On the right of the table is the baseline estimate of value added for the industry. The top three had a value added of \$73.5 billion, \$49.2 billion, and \$41.2 billion. The Monte Carlo analysis had 30 industries being identified as being among the top 20 with 21 of them being manufacturing industries.

One issue with measuring only US value added is that the cost of imported intermediate goods and services is not measured. Table 3 provides the frequency of each industry's contribution to assembly-centric products, similar to Table 2, except that imports are included. The boundaries of this analysis is to examine US activity; therefore, imports are treated as an external cost. That is, the supply chain of imported goods is not broken out, but rather treated as a unit cost. As seen in Table 3, wholesale trade remains the largest, followed by aircraft manufacturing and the management of companies and enterprises.

Table 4 provides value added estimates for assembly-centric products by industry groupings with and without imports. Transportation equipment is the largest contributor, but it is important to remember that this includes the manufacture of airplanes, automobiles, and trains. Figure 5 provides a cumulative probability graph for value added and value added with imports from the Monte Carlo analysis results.

*Occupation:* For each iteration of the Monte Carlo analysis, the largest 20 occupations (2.4 %) out of 820 total contributing to assembly-centric products, was identified. The top 20 occupations from the base case represent 22 % of valued added and 40 % of compensation associated with these products. Note that total compensation accounts for 56 % of the value added for assembly-centric products. The remaining 44 % is gross operating surplus, which goes to the owners and investors, and taxes on production. *Team assemblers* was identified as the largest occupation in all of the Monte Carlo iterations and accounted for \$27.24 billion of the base case value added, as seen in Table 5. *General and operations managers* was identified as being the second largest for all iterations and accounted for \$23.23 billion of the base case value added. *Wholesale and manufacturing sales representatives* was third for 6086 iterations (60.9 %). A number of occupations in the top 20 are non-production, including sales, engineers, accountants, software developers, material movers, and truck drivers to name a few. A

summary of total compensation by broad compensation categories is provided in Table 6A. *Production, management, and architecture and engineering occupations* account for the three largest categories. Industry groups often have particular interest in production occupations that contribute to assembly-centric goods; therefore, the top 25 for the base case are listed in Table 6B. Additionally, Table 6C shows the top 25 occupations when including the associated taxes and gross operating surplus. For example, we can see that team assemblers accounts for \$27.24 billion, as seen in Table 6B. When including taxes on production and gross operating surplus, team assemblers accounts for \$52.96 billion. This is estimated by assuming that the proportion of gross operating surplus and taxes to compensation are constant within an industry; thus, gross operating surplus and taxes are being proportionately associated with labor, as these items correlate with each other. When including the gross operating surplus and taxes, the top 20 account for 39 % of value added compared to the previously discussed 22 %.

*Occupation by Industry:* The largest 20 out of 332 100 occupation industry combinations contributing to assembly-centric products are identified for each iteration of the Monte Carlo analysis. These account for 5 % of the value added in the base case. As seen in Table 7, *sales representatives from wholesale trade* was identified as the largest industry/occupation combination for 7423 (74.2 %) of the iterations and accounted for \$7.3 billion of the base case value added. *Team assemblers* from the automobile manufacturing industry was identified as the second largest for 7422 of the iterations (74.2 %). These two occupation by industry categories have by far the greatest value added. The next 6 top categories are relatively similar in value added, with baseline value added of 2.3 billion to 3.2 billion. *Truck drivers for truck transportation* was identified as the third largest for 4324 of the iterations (43.2 %). A number of non-manufacturing industries and activities were among the top 20. For example, financial managers in the management of companies and enterprises were identified as being the 10<sup>th</sup> largest in 2789 of the iterations (27.9 %) and industrial engineers in aircraft manufacturing were identified as being the seventeenth largest in 1485 of the iterations (14.9 %). In total, the Monte Carlo analysis has 33 occupation industry combinations appearing in the top 20 with 20 of them being in non-manufacturing industries and 11 being in manufacturing industries.

*Depreciable Assets:* In addition to value added and compensation, the depreciable assets contributing to assembly-centric production was also examined by industry. Two types of assets were examined: buildings and machinery/equipment within the manufacturing industry. Depreciable assets outside of the manufacturing industry are excluded due to data limitations. For each iteration of the Monte Carlo analysis, the 20 industries with the largest value of depreciable building assets were identified as well as the 20 industries with the largest value of depreciable machinery/equipment assets. The results are shown in Table 8 and Table 9. As might be expected, industries that produce large items such as aircraft and automobiles tend to have a higher level of depreciable building assets. *Semiconductor manufacturing* (NAICS 334413), which is known for requiring large levels of investment, was identified as having the largest level of machinery/equipment assets for 9595 iterations (96.0 %). The total depreciable assets, retirements, and capital expenditures for manufacturing buildings and machinery is shown in Table 12. Over the period of one year, new and replaced machinery/equipment represents approximately 5.8 % of the total machinery/equipment assets at the end of the year; therefore, assuming this rate continues unchanged, it would take a little over 17 years to completely replace all the machinery/equipment with its new or improved replacements machinery/equipment.

In addition to considering the depreciable machinery/equipment assets, it is also important to consider the machinery/equipment that was purchased during the study period. Recall that capital purchases are not part of the costs calculated in Table 2 through Table 7, as they include goods and services that are

used up in the production process.<sup>2</sup> The results of the Monte Carlo analysis on building capital purchased and machinery capital purchased by industry for assembly-centric products are provided in Table 10 and Table 11. Semiconductor and related device *manufacturing* (NAICS 334413) had the highest building capital cost at \$1.97 billion. This cost would be below the top 20 rankings in the industry rankings in Table 2; that is, the \$1.97 billion is too small to rank in Table 2. The same sector, NAICS 334413, also had the largest purchase of machinery at \$4.29 billion. This value would also be below the top 20 rankings in Table 2. The total capital purchases of buildings for all manufacturing associated with assembly-centric products was \$10.14 billion and for machinery it was \$41.99 billion. For buildings this would rank around 13<sup>th</sup> in the industry rankings in Table 2. For machinery, this would rank 3<sup>rd</sup>.

*Energy:* For electricity, there is an additional \$1.26 of value added and \$0.39 of imports per dollar of value added of electricity generation and distribution. For natural gas distribution, there is an additional \$2.63 of value added and \$1.34 of imports per dollar of value added. Table 13 provides the value added of electricity and natural gas that contributes to assembly-centric manufacturing. Also included is the estimate of other industries contributing to electricity and natural gas. The table is broken into the end use of the energy. Process heating constituted \$6775 million (calculated as the sum of electricity and natural gas) of the total \$27 830 million. Process cooling and refrigeration was \$508 million, machine drive was \$3443 million. Facility heating and cooling constituted \$2637 million and lighting was \$658 million. Among value added baseline rankings (Table 2), the total \$13 914 in value added energy would rank 12<sup>th</sup> while the total \$27 830 in value added and imports would rank 8<sup>th</sup> in the value added and imports table (Table 3).

Another source of energy is gasoline and diesel for the transportation of goods. Unfortunately, these fuels cannot be explicitly broken out, as the data categorization does not facilitate it. The NAICS code 324110 for Petroleum refineries is the closest match and accounts for \$39.98 billion in value added and imports when including associated industry activity. This estimate would then rank 3<sup>rd</sup> in the value added with imports table (Table 3). Petroleum refineries, however, make products other than gasoline and diesel, including benzene, jet fuel, asphalt, petroleum waxes, and oils among others. Also, the price of oil fluctuates significantly; therefore, an estimate might change rapidly.

## Summary and Discussion

Public entities have a significant role in the US innovation system (Block and Keller 2016). One objective of public innovation is to enhance economic security and improve our quality of life (National Institute of Standards and Technology 2017), which is achieved in part by advancing efficiency in which resources are consumed or impacted by production. Without an input-output model or similar analyses, there is limited understanding concerning the use and costs of resources for manufacturing at a national level. This paper examined, in dollar terms, the resources consumed in the production of assembly-centric commodities in the United States. The analysis identified the top 20 industries, occupations, and industry occupation combinations contributing to production. This paper also discussed purchased electricity and natural gas by end use along with depreciable assets associated with assembly-centric commodities. A Monte Carlo sensitivity analysis confirms that the rankings remain relatively stable in the face of significant error; therefore, the results from this analysis can be used with some confidence to prioritize efforts in the US to advance efficiency in assembly-centric manufacturing.

The results show that costs for assembly-centric manufacturing are disproportionally distributed, as illustrated in Figure 4. The Gini coefficient for the industry line (i.e., value added) in this figure is 0.75

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<sup>2</sup> It is important to note that the capital purchases and the goods and services used up in production cannot be added together as it would be double counting some values.



and for the occupations (i.e., compensation) it is 0.86, suggesting very unequal distribution. The Gini coefficient is a measure of statistical dispersion where 0 represents equal distribution (i.e., each cost category represents the same proportion of total cost) and 1 represents total unequal distribution (Klein 2002). The implication of costs being unequally distributed is that reductions in resource consumption in some cost areas can disproportionately reduce total resource consumption. Efforts to develop and disseminate innovative solutions can, therefore, be targeted to these areas, resulting in larger efficiency improvements than might otherwise be achieved. This paper identifies those high resource consumption areas for assembly-centric manufacturing, as discussed below.

Compensation as a whole accounted for 42.1 % of costs with imports, taxes, and gross operating surplus accounting for the remaining portion. Approximately 26.4 % of the cost of compensation for assembly-centric manufacturing was attributed to *production occupations*, the largest category. *Management* was the second largest labor category, accounting for 15.9 % of labor and *architecture and engineering occupations* were the third largest with 11.3 %. *Business and financial operations* (9.1 %); *office and administrative support* (8.4 %); *computer and mathematics* (6.3 %); *sales and related* (6.1 %), *transportation and material moving operations* (5.3 %); and *installation, maintenance, and repair occupations* (5.1 %) were ranked 4<sup>th</sup> through 9<sup>th</sup>. The remaining occupations were each less than 5 %. Moreover, production is a major labor cost, but it accounts for less than a third of the total labor cost. Office work, including engineering, business, administrative, mathematical, sales, and legal related activities, account for a significant portion (42.0 %) of the labor cost. Efficiency efforts that reduce the office burden, such as software interoperability standards or utilizing information technology, has the potential to have a significant impact on labor cost. The management burden, which is the second largest cost, might be reduced by having fewer layers of management and, thus, expanding the average span of manager control (Economist 2008). Public entities can facilitate reduced layers by providing research into the impact of expanding manager control.

The largest industry category (i.e., broad category level) was *Transportation equipment*, accounting for 24.8 % of the value added with imports. *Machinery* and *Computer and electronics* were the second and third largest with 12.5 % and 12.2 % of the value added with imports, respectively. It is not surprising that the assembly-centric industries appear in the top cost categories, as it is common for the industry being examined to have the largest costs rather than its suppliers. The fourth largest, is the refining and forming of metal with 11.7 % of the costs. There may be an opportunity for efficiency improvement in this category, as the USGS estimates that 15 % of steel mill products end up as scrap in the manufacturing process (Fenton 2001). Other sources cite that at least 25 % of liquid steel and 40 % of liquid aluminum does not make it into a finished product due primarily to metal quality (25 % of steel loss and 40 % of aluminum loss), the shape produced<sup>3</sup> (10 % to 15 % of loss), and defects in the manufacturing processes (5 % of loss) (Allwood and Cullen 2012). This means that as much as 1.25 % of the machinery used to produce assembly-centric products, or \$6.9 billion in machinery assets, is being used to produce defective products that contain steel. Material losses mean there is the possibility of producing the same goods using less material, which could have rippling effects up and down the supply chain. There would be reductions in the burden of transportation, material handling, machinery, inventory costs, and energy use along with many other activities associated with handling and altering materials.

At the more detailed NAICS code level, *Wholesale trade, aircraft manufacturing* (i.e., the final assembly of aircraft), and the *management of companies and enterprises* were the industries with the largest

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<sup>3</sup> The steel and aluminum industry often produce standard shapes rather than customized shapes tailored to specific products. This results in needing to cut away some portion of material, which ends up as scrap.

contribution to assembly-centric manufacturing, even when including imports; therefore, public efficiency improvement efforts in these areas are likely to have bigger impact than efficiency improvement efforts in other areas. *Wholesale trade*, for example, is an activity that distributes intermediate goods and services to producers. There may be opportunities for efficiency improvement in connecting intermediate goods with producers through Information technology similar to the impact that it has had on retail trade. The appearance of *management of companies and enterprises*, which is largely company headquarters, in the top three industry rankings reiterates the cost impact of management and other non-manufacturing activities. A number of other non-manufacturing industries were in the top 20 contributing to assembly-centric products with two being in the top five. This suggests that non-manufacturing activities are a significant portion of the value added for these products.

In terms of occupation activities at the detailed level, *team assemblers*, *general and operations managers*, and *sales representatives* were the largest occupations; therefore, efficiency improvements in these areas are likely to have bigger impacts than efficiency improvements in other areas. A number of occupations were non-production activities, further supporting the significant role that non-manufacturing activities play in assembly-centric goods. Among them were *sales representatives*, *supervisors*, *engineers*, *accountants*, *software developers*, *managers*, *material movers*, and *truck drivers*. In terms of industry occupation combinations, *sales representatives* from *wholesale trade* and *team assemblers* from the *automobile manufacturing* industry represented the top two combinations. The appearance of sales in both the top occupation costs and top industry/occupation costs reiterates that a significant amount of resources are consumed in connecting intermediate goods with the producers in the next step of the supply chain.

Energy in the form of electricity and natural gas were discussed separately, but would rank 8<sup>th</sup> in the value added and imports table (Table 3). Process heating, such as the heating that occurs in metal refining and forming, is a significant consumer of electricity and natural gas along with machine drive, making these end use categories an opportunity for efficiency improvement efforts. Petroleum refineries, which includes fuel among other things, would rank 3<sup>rd</sup>. Electricity, natural gas, and petroleum refineries together (including all associated industries and imports) would rank 2<sup>nd</sup> in the value added and imports table (Table 3). It is important to note that there are some limitations of this modeling approach in measuring energy consumption during the different stages of the manufacturing process.

*Truck transportation* was within the top 20 industries contributing to assembly-centric products and appeared in the top 20 industry occupation categories. *Laborers and material movers* along with *truck drivers* was among the top 20 occupation components and both appeared in the list of industry occupation combination categories. The appearance of these suggests that the movement of goods is a significant cost and these estimates don't even include the energy for onsite transportation or fuel for trucks. The total of the transportation industries, their associated costs (e.g., fuel and repairs), *laborers and material movers* in other industries, and associated costs (i.e., gross operating surplus and taxes) accounts for \$70.2 billion or 5.9 % of the value added with imports, which would rank second in the value added with imports seen in Table 3. There might be opportunities for efficiency improvement in truck transportation, as approximately 20 % of truck miles are driven with no product being transported (Bureau of Transportation Statistics 2015). Reducing these empty miles would decrease labor, capital expenditures, and traffic. Several methods are being considered across the global economy to reduce these excess miles. In Germany, a new auction platform aims to improve truck space utilization (Science Daily 2011). Other efforts to co-load or ride-share have also received some attention. Efforts to develop

and disseminate Innovative solutions like these might reduce the resources consumed in the transport of goods.

*Sales representatives* and, as previously mentioned, *wholesale trade* appear as top costs, suggesting that the logistics of storing and distributing intermediate goods consumes significant resources. Advancing the dissemination of information on intermediate products might reduce the sales burden needed for distributing intermediate parts and components to producers. In addition to sales activity, wholesalers function as a warehouse to store inventory. Note that additional warehousing costs are categorized as “warehousing and storage” (NAICS 493000). Warehousing is needed to buffer for unpredictable fluctuations in demand. Thus, improved forecasting in demand might lessen the need for inventory/warehousing and in turn reduce wholesale trade costs.

Multiple types of engineers are included in both the occupation and industry occupation combination lists. Reducing redundancy such as data re-entry might reduce the amount of engineering needed for production. Accountants and lawyers appear among the top 20 occupations as well.

Public entities have a significant role in the US innovation system, including developing, disseminating, and nurturing numerous innovations and industries. One implicit objective of public innovation is to improve the efficiency in which resources are consumed or impacted by production. Public entities and other change agents might use this model and results to identify efficiency improvement efforts that will make the biggest impact on industry per dollar of expenditure.

## **Conclusion**

The results of this analysis show that costs for assembly-centric manufacturing are disproportionately distributed, suggesting that reductions in resource consumption in some cost areas can disproportionately reduce total resource consumption. Efforts to develop and disseminate innovative solutions can, therefore, be targeted to these areas, resulting in larger efficiency improvements than might otherwise be achieved. A number of supply chain cost areas were identified, including *wholesale trade*, *energy*, *truck transportation*, and the *management of companies and enterprises*. Additionally, *team assemblers*, *general operations managers*, and *sales representatives (wholesale and manufacturing, except technical and scientific products)* were identified as top labor costs. A sensitivity analysis varying the top 30 industry costs confirms that the rankings of the supply chain categories and labor costs is fairly robust. Future research might investigate the consumption of non-monetary resources such as environmental impacts and natural resources.

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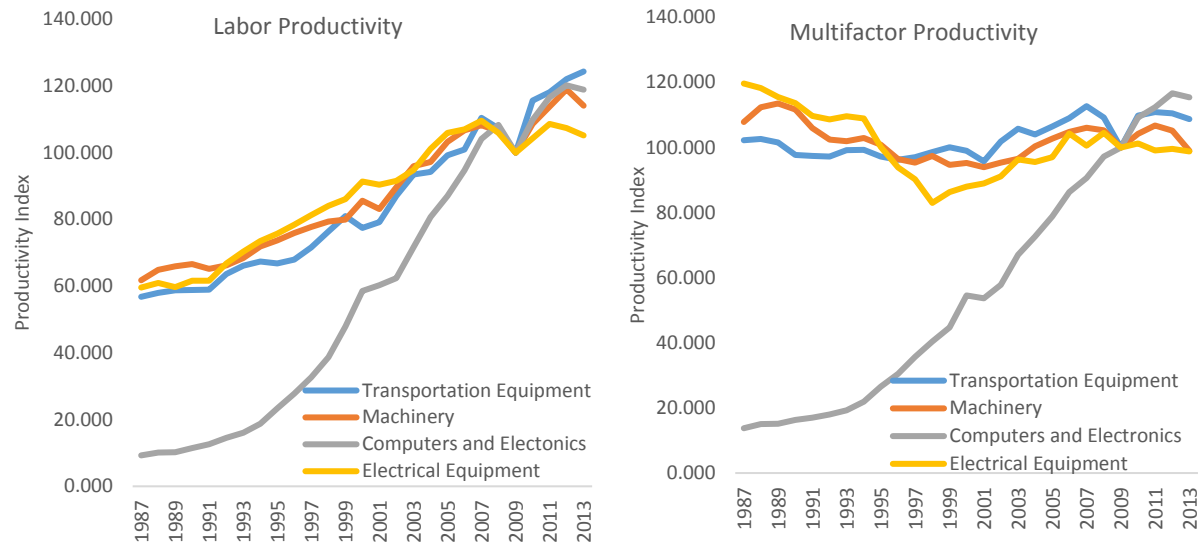
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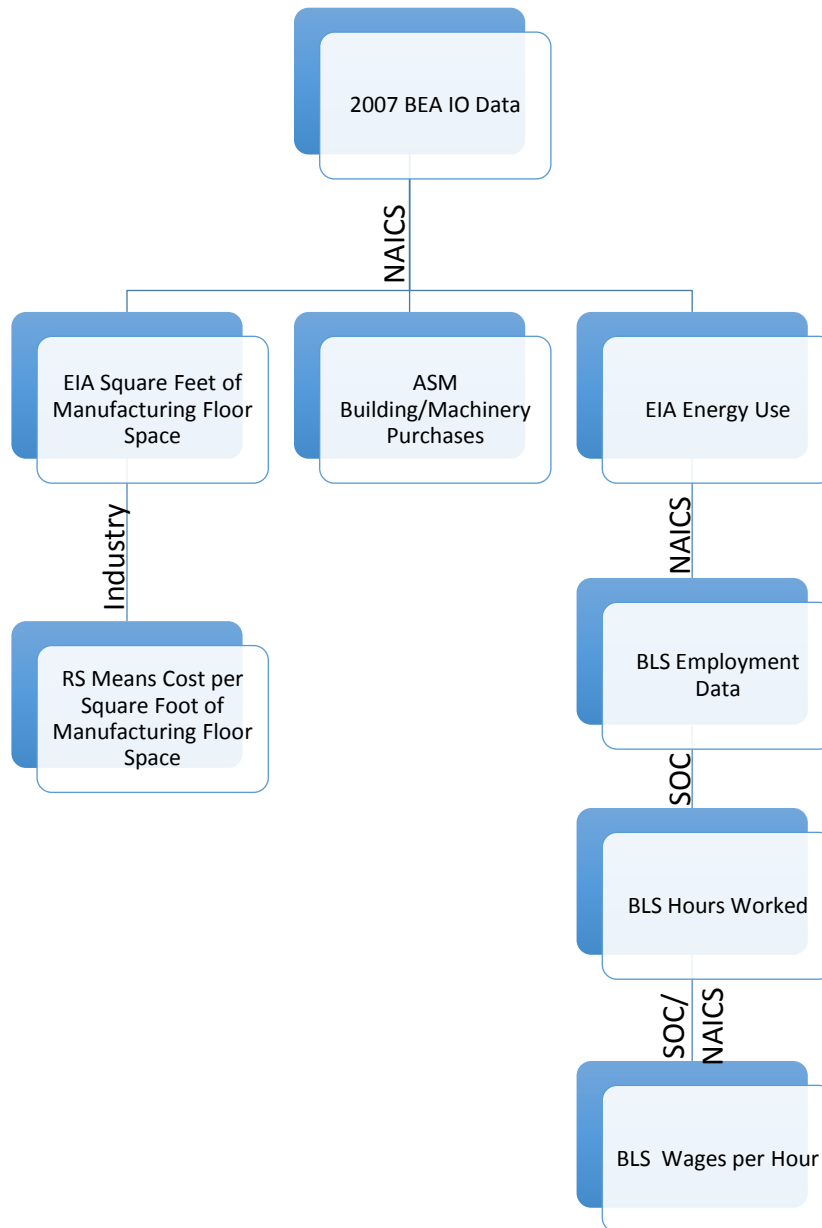
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Figure 1: Productivity in Assembly-Centric Manufacturing



Source: Bureau of Labor Statistics. BLS Productivity Statistics. <https://www.bls.gov/bls/productivity.htm>

Figure 2A: Map of Data Connections



Note: NAICS and SOC are used in the figure to indicate the classification system to link data sets. NAICS is the North American Industry Classification System and SOC is the Standard Occupation Classification system.



### Figure 2B: Illustration of Data Categorization

Value Added								
Compensation				Taxes*	Gross Operating Surplus			
SOC Code	SOC Code	SOC Code	...		Net Operating Surplus	Depreciation		
						Machinery	Buildings	Inventory
NAICS Code								
NAICS Code								
NAICS Code								
NAICS Code								
:								

\* Taxes on production

Table 1: Assumptions for Monte Carlo Analysis

NAICS	Description	Distribution	
420000	Wholesale trade	+/- 25 %	Triangular Distribution
336411	Aircraft manufacturing	+/- 25 %	Triangular Distribution
550000	Management of companies and enterprises	+/- 25 %	Triangular Distribution
336112	Light truck and utility vehicle manufacturing	+/- 25 %	Triangular Distribution
336111	Automobile manufacturing	+/- 25 %	Triangular Distribution
334413	Semiconductor and related device manufacturing	+/- 25 %	Triangular Distribution
211000	Oil and gas extraction	+/- 25 %	Triangular Distribution
334511	Search, detection, and navigation instruments manufacturing	+/- 25 %	Triangular Distribution
336412	Aircraft engine and engine parts manufacturing	+/- 25 %	Triangular Distribution
334510	Electromedical and electrotherapeutic apparatus manufacturing	+/- 25 %	Triangular Distribution
336413	Other aircraft parts and auxiliary equipment manufacturing	+/- 25 %	Triangular Distribution
331110	Iron and steel mills and ferroalloy manufacturing	+/- 25 %	Triangular Distribution
336370	Motor vehicle metal stamping	+/- 25 %	Triangular Distribution
333111	Farm machinery and equipment manufacturing	+/- 25 %	Triangular Distribution
334220	Broadcast and wireless communications equipment	+/- 25 %	Triangular Distribution
336611	Ship building and repairing	+/- 25 %	Triangular Distribution
333130	Mining and oil and gas field machinery manufacturing	+/- 25 %	Triangular Distribution
333120	Construction machinery manufacturing	+/- 25 %	Triangular Distribution
336390	Other motor vehicle parts manufacturing	+/- 25 %	Triangular Distribution
484000	Truck transportation	+/- 25 %	Triangular Distribution
541100	Legal services	+/- 25 %	Triangular Distribution
52A000	Monetary authorities and depository credit intermediation	+/- 25 %	Triangular Distribution
333920	Material handling equipment manufacturing	+/- 25 %	Triangular Distribution
336350	Motor vehicle transmission and power train parts manufacturing	+/- 25 %	Triangular Distribution
561300	Employment services	+/- 25 %	Triangular Distribution
33391A	Pump and pumping equipment manufacturing	+/- 25 %	Triangular Distribution
33399A	Other general purpose machinery manufacturing	+/- 25 %	Triangular Distribution
533000	Lessors of nonfinancial intangible assets	+/- 25 %	Triangular Distribution
531ORE	Other real estate	+/- 25 %	Triangular Distribution
332720	Turned product and screw, nut, and bolt manufacturing	+/- 25 %	Triangular Distribution
	All other industries	+/- 10 %*	Triangular Distribution

\* Calculated as a multiplier for all industries

Figure 3: Dollar Flow for Selected Commodities (private sector)

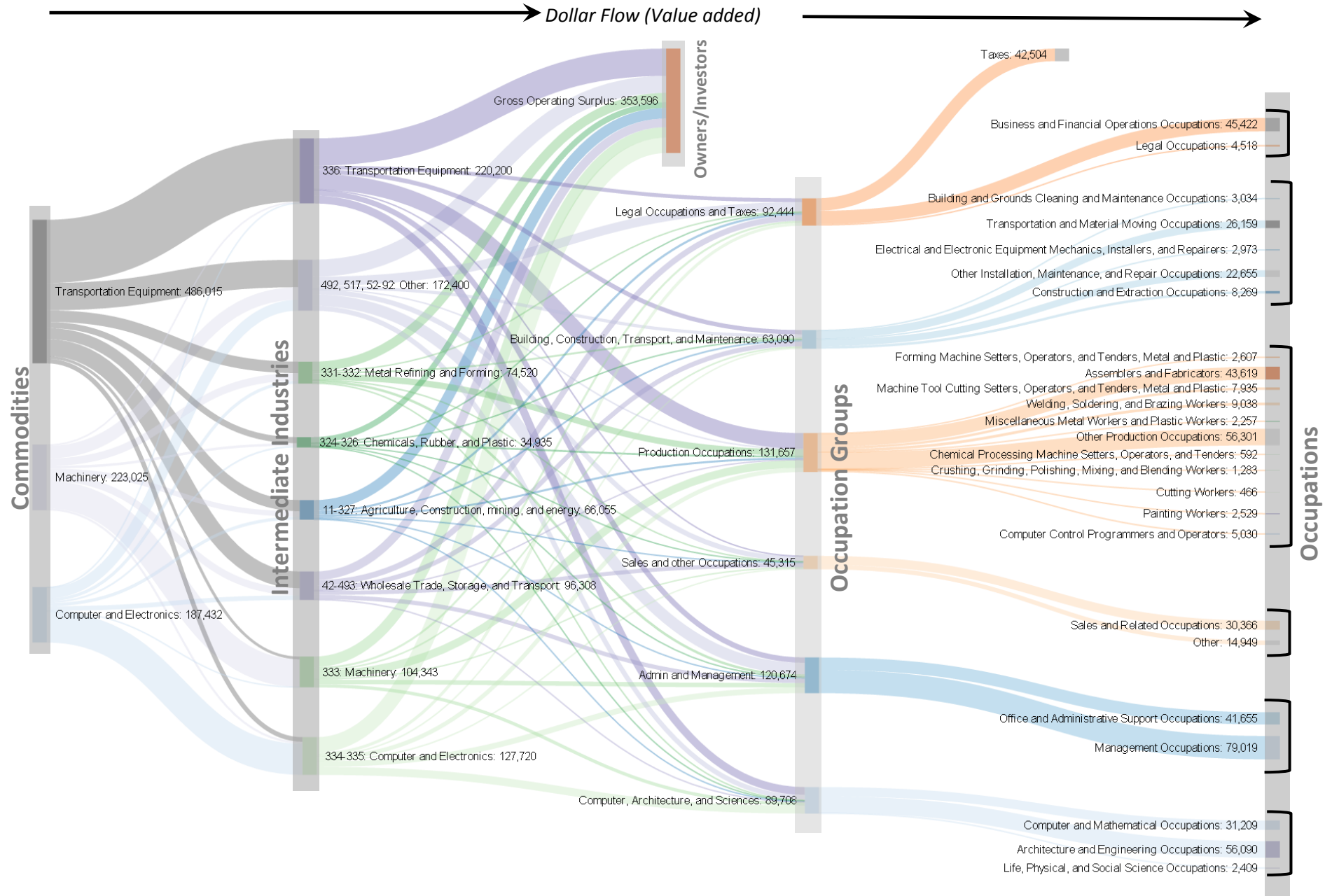


Table 2: Percent of Monte Carlo Iterations by Industry by Rank, Top 20 Value Added Components of Assembly-Centric manufacturing (ordered by base case rank)

NAICS	Description	Rank - Top 20																				Baseline (\$Billion)
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
420000	Wholesale trade	99.9	0.2																			73.45
336411	Aircraft manufacturing	0.2	88.3	11.5	0.1																	49.24
550000	Management of companies and enterprises		11.5	80.9	7.6																	41.24
336112	Light truck and utility vehicle manufacturing		0.0	7.7	90.9	1.4																33.44
336111	Automobile manufacturing				1.4	77.2	15.4	4.9	1.1	0.0	0.0											24.35
334413	Semiconductor and related device manufacturing					15.2	46.6	23.1	11.3	3.2	0.5	0.0										21.16
211000	Oil and gas extraction					4.5	24.4	35.4	23.7	8.8	2.6	0.6	0.0									19.71
334511	Search, detection, and navigation instruments manufacturing					1.7	12.5	28.1	34.1	14.4	7.1	1.9	0.2	0.0								18.80
336412	Aircraft engine and engine parts manufacturing					0.0	0.7	4.7	14.9	31.8	27.8	14.1	5.8	0.2								16.32
334510	Electromedical and electrotherapeutic apparatus manufacturing						0.4	3.7	13.3	30.5	29.2	15.5	7.1	0.3								16.13
336413	Other aircraft parts and auxiliary equipment manufacturing							0.1	1.3	7.3	19.1	34.6	34.0	3.4	0.1							14.28
331110	Iron and steel mills and ferroalloy manufacturing							0.0	0.4	3.9	13.1	30.9	45.6	5.6	0.5	0.1						13.79
336370	Motor vehicle metal stamping											0.1	0.8	22.7	21.1	15.7	11.9	8.7	6.6	5.3	3.3	9.83
333111	Farm machinery and equipment manufacturing											0.0	0.4	17.4	19.3	15.6	13.4	10.7	7.6	5.5	4.3	9.63
334220	Broadcast and wireless communications equipment											0.0	0.4	15.7	18.6	16.5	13.0	10.1	8.1	6.6	4.5	9.59
336611	Ship building and repairing												0.1	7.7	13.0	14.0	13.4	13.1	10.9	8.2	6.6	9.19
333130	Mining and oil and gas field machinery manufacturing									0.1	0.5	2.3	5.6	19.3	7.2	6.1	5.1	4.5	4.2	4.0	3.8	8.95
333120	Construction machinery manufacturing													3.1	7.2	9.9	12.0	12.6	12.1	11.2	9.7	8.76
336390	Other motor vehicle parts manufacturing													2.2	5.4	8.7	10.5	12.5	13.2	11.9	9.5	8.67
484000	Truck transportation													1.6	4.3	6.9	9.5	11.7	12.3	12.1	11.3	8.54
541100	Legal services													0.7	3.3	5.9	8.4	10.0	11.7	12.6	11.3	8.39
52A000	Monetary authorities and depository credit intermediation													0.0	0.1	0.3	1.1	2.2	4.4	6.5	8.7	7.51
333920	Material handling equipment manufacturing													0.0	0.1	0.3	1.2	2.1	4.2	6.3	8.6	7.50
336350	Motor vehicle transmission and power train parts manufacturing														0.0	0.1	0.4	1.2	2.9	4.3	6.9	7.33
561300	Employment services															0.0	0.1	0.4	1.1	2.4	4.2	7.06
33391A	Pump and pumping equipment manufacturing																0.0	0.0	0.3	0.9	2.0	6.80
33399A	Other general purpose machinery manufacturing																	0.1	0.2	0.8	1.8	6.77
533000	Lessors of nonfinancial intangible assets																	0.0	0.1	0.8	1.8	6.76
5310RE	Other real estate																	0.0	0.1	0.4	1.1	6.62
332720	Turned product and screw, nut, and bolt manufacturing																	0.0	0.0	0.2	0.6	6.51

Table 3: Percent of Monte Carlo Iterations by Industry by Rank, Top 20 Value Added (with Imports) Components for Assembly-Centric manufacturing (ordered by base case rank)

		Rank - Top 20																				Baseline (\$Billion)	
NAICS	Description	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20		
420000	Wholesale trade	99.9	0.2																			73.45	
336411	Aircraft manufacturing	0.2	87.1	11.1	1.6	0.1																49.24	
550000	Management of companies and enterprises		11.1	60.7	21.3	5.6	1.1	0.2	0.0													41.24	
211000	Oil and gas extraction		1.7	23.5	47.8	17.3	6.8	2.4	0.5	0.1												37.25	
336112	Light truck and utility vehicle manufacturing		0.0	3.7	19.1	38.3	21.2	10.6	5.1	1.7	0.2											33.44	
331110	Iron and steel mills and ferroalloy manufacturing			0.9	7.9	23.3	31.3	19.3	11.1	4.9	1.3	0.0										31.33	
334413	Semiconductor and related device manufacturing			0.1	1.8	10.4	21.9	28.4	19.8	12.3	4.7	0.6	0.0									29.25	
336412	Aircraft engine and engine parts manufacturing				0.5	4.2	12.0	22.4	28.3	19.8	10.6	2.1	0.2									27.78	
336390	Other motor vehicle parts manufacturing				0.0	0.8	4.6	12.0	22.6	31.4	21.0	6.3	1.2	0.1	0.0							26.07	
336111	Automobile manufacturing					0.0	1.1	4.6	11.9	24.7	38.8	13.7	4.2	0.9	0.1							24.35	
336413	Other aircraft parts and auxiliary equipment manufacturing							0.1	0.7	4.4	17.4	42.7	19.8	8.6	3.7	1.7	0.6	0.2	0.1			21.29	
334511	Search, detection, and navigation instruments manufacturing								0.0	0.7	4.5	20.8	32.6	17.8	9.5	5.4	4.2	2.7	1.5	0.4	0.0	19.47	
334220	Broadcast and wireless communications equipment									0.1	1.4	8.8	21.0	24.4	15.3	9.1	7.3	5.9	4.7	1.8	0.2	18.31	
336350	Motor vehicle transmission and power train parts manufacturing										0.2	3.8	13.1	19.1	18.0	13.2	10.4	9.0	8.0	4.4	0.7	17.50	
336310	Motor vehicle gasoline engine and engine parts manufacturing											0.3	4.2	18.6	33.4	31.5	11.2	0.7	0.0			17.38	
331419	Primary smelting and refining of nonferrous metal (except copper and aluminum)												0.0	0.6	5.7	21.8	39.0	28.3	4.4	0.2		16.39	
334510	Electromedical and electrotherapeutic apparatus manufacturing											0.9	3.8	9.4	12.7	13.4	13.2	14.0	16.4	12.1	3.7	16.27	
333618	Other engine equipment manufacturing														0.1	0.9	7.6	28.7	44.8	16.2	1.7	15.45	
333120	Construction machinery manufacturing													0.3	1.0	2.5	5.2	8.2	14.4	39.6	21.9	14.16	
333111	Farm machinery and equipment manufacturing															0.0	0.2	0.7	3.1	17.7	48.4	12.66	
336370	Motor vehicle metal stamping																			0.6	5.6	10.45	
336360	Motor vehicle seating and interior trim manufacturing																				1.0	10.38	
333130	Mining and oil and gas field machinery manufacturing													0.0	0.0	0.3	0.6	1.1	1.7	2.6	6.8	11.7	10.30
333920	Material handling equipment manufacturing																			0.0	0.3	3.7	10.22
33399A	Other general purpose machinery manufacturing																			0.0	1.2		9.67
336611	Ship building and repairing																				0.2		9.20
484000	Truck transportation																				0.0		8.73
332720	Turned product and screw, nut, and bolt manufacturing																				0.0		8.64

Table 4: Value Added Statistics from Monte Carlo Analysis on US Assembly Centric Manufacturing (\$millions 2014)

NAICS Codes and Description	Value Added					Value Added + Imports				
	Base Case	Base Case %	Median	Minimum	Maximum	Base Case	Base Case %	Median	Minimum	Maximum
11: Agriculture	2 546	0.3%	2 546	2 292	2 795	3 289	0.3%	3 289	2 961	3 610
21A: Energy - Processes	4 848	0.5%	4 847	4 364	5 321	4 898	0.4%	4 897	4 409	5 376
21B: Energy - Facilities	1 038	0.1%	1 038	935	1 140	1 044	0.1%	1 044	939	1 146
21C: Energy - Other/Undesignated Onsite	2 990	0.3%	2 990	2 692	3 282	3 013	0.3%	3 012	2 712	3 307
21D: Oil and Gas Extraction	19 709	2.2%	19 768	14 903	24 570	37 246	3.1%	37 357	28 164	46 432
21E: Mining	10 721	1.2%	10 719	9 650	11 768	11 794	1.0%	11 792	10 616	12 945
2213: Other Utilities	166	0.0%	166	149	182	166	0.0%	166	149	182
331-332: Metal Refining and Forming	74 520	8.3%	74 545	66 218	83 277	137 940	11.7%	138 008	121 949	154 902
333: Machinery	104 339	11.6%	104 314	90 533	118 621	147 794	12.5%	147 821	129 484	167 025
334: Computer and Electronics	108 809	12.1%	108 846	95 878	121 731	144 045	12.2%	144 081	127 306	161 167
335: Electrical Equipment	18 910	2.1%	18 907	17 022	20 757	30 024	2.5%	30 019	27 026	32 955
336: Transportation Equipment	220 198	24.4%	220 098	195 819	246 705	293 418	24.8%	293 274	263 174	325 720
324-326: Chemicals, Rubber, and Plastic	34 935	3.9%	34 929	31 446	38 345	53 930	4.6%	53 921	48 544	59 195
23-327: Construction and Other Materials	24 035	2.7%	24 031	21 635	26 381	35 612	3.0%	35 607	32 056	39 089
42: Wholesale Trade	73 448	8.1%	73 245	55 268	91 694	73 448	6.2%	73 245	55 268	91 694
44-45: Retail Trade	4 033	0.4%	4 033	3 631	4 427	4 033	0.3%	4 033	3 631	4 427
48-49: Transportation	16 290	1.8%	16 302	13 590	18 972	16 800	1.4%	16 813	14 027	19 554
493: Warehousing and Storage	2 537	0.3%	2 537	2 284	2 785	2 537	0.2%	2 537	2 284	2 785
492, 517: Communications	10 627	1.2%	10 626	9 566	11 665	10 643	0.9%	10 641	9 580	11 682
52: Finance, Insurance, and Real estate	27 370	3.0%	27 407	23 730	31 560	28 013	2.4%	28 049	24 318	32 252
53: Equipment Rental	10 063	1.1%	10 072	8 219	11 885	10 063	0.9%	10 072	8 219	11 885
54: Legal and Professional Services	27 384	3.0%	27 390	23 883	30 869	28 237	2.4%	28 247	24 654	31 802
541: Engineering, Consulting, and Research	13 801	1.5%	13 799	12 423	15 148	15 484	1.3%	15 481	13 938	16 996
55: Management of Companies	41 242	4.6%	41 208	31 042	51 354	41 242	3.5%	41 208	31 042	51 354
56: Admin and Support	21 855	2.4%	21 856	19 001	24 901	21 928	1.9%	21 930	19 061	24 988
485, 511-515, 61-92: Other	25 681	2.8%	25 677	23 116	28 188	25 786	2.2%	25 782	23 211	28 303
All Industries	902 098	100.0%	902 005	839 451	973 031	1 182 427	100.0%	1 182 431	1 103 662	1 269 776

Figure 4: Line Graph of the Cumulative Percent of cost by Percentile of Industry/Occupation Cost (Assembly-Centric Products)

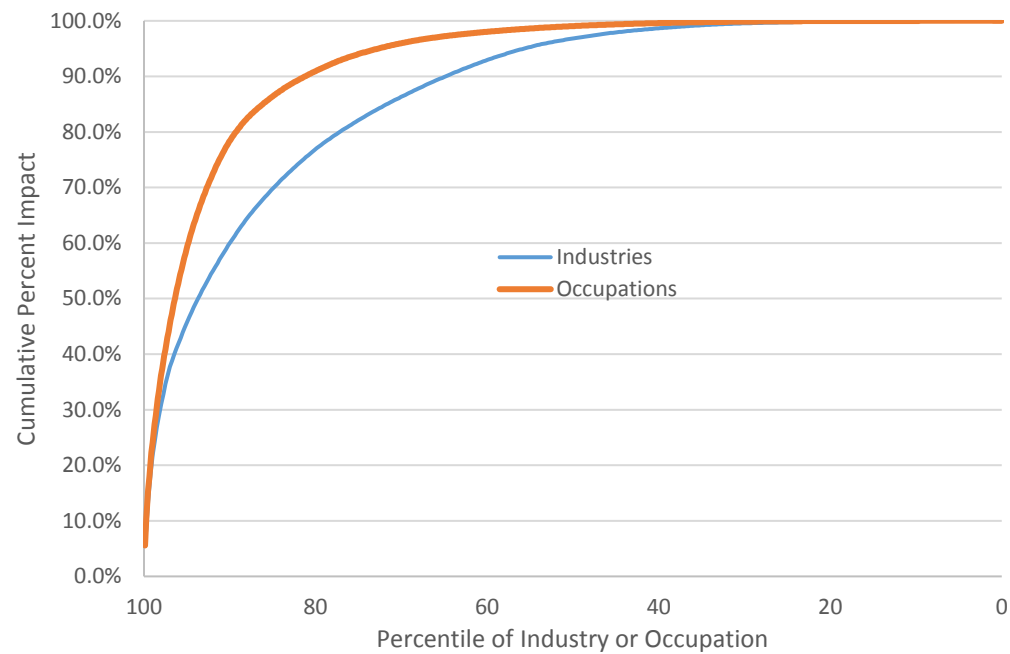


Figure 5: Cumulative Probability for Value Added from Monte Carlo Analysis

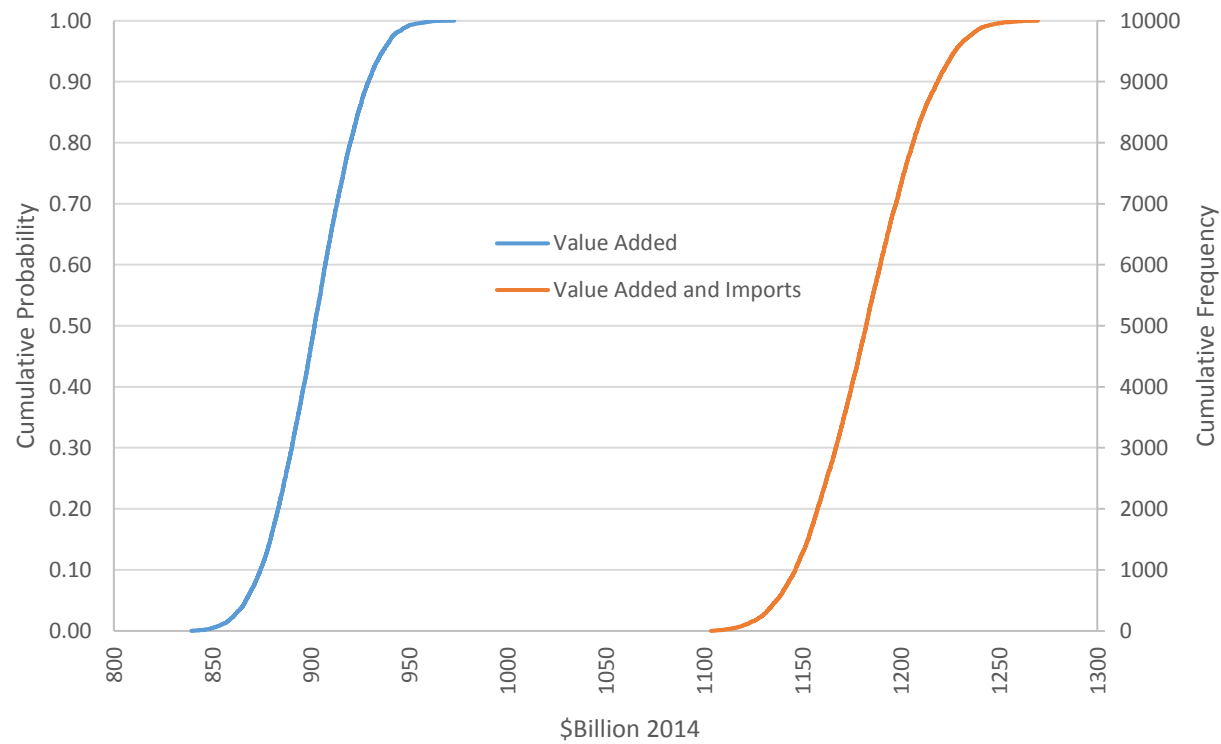


Table 5: Percent of Monte Carlo Iterations by Occupation by Rank, Top 20 Occupation Components for Assembly-Centric manufacturing (ordered by base case rank)

[illegible]



Table 6A: Total Compensation by Occupation for Assembly-Centric Products – Base Case

SOC	Description	\$millions	Percent of Labor	Percent of Value Added w/Imports
510000	Production Occupations	131 655.8	26.4%	11.1%
110000	Management Occupations	79 018.7	15.9%	6.7%
170000	Architecture and Engineering Occupations	56 090.0	11.3%	4.7%
130000	Business and Financial Operations Occupations	45 421.8	9.1%	3.8%
430000	Office and Administrative Support Occupations	41 655.0	8.4%	3.5%
150000	Computer and Mathematical Occupations	31 208.5	6.3%	2.6%
410000	Sales and Related Occupations	30 365.9	6.1%	2.6%
530000	Transportation and Material Moving Occupations	26 159.2	5.3%	2.2%
490000	Installation, Maintenance, and Repair Occupations	25 627.9	5.1%	2.2%
470000	Construction and Extraction Occupations	8 268.8	1.7%	0.7%
230000	Legal Occupations	4 518.0	0.9%	0.4%
270000	Arts, Design, Entertainment, Sports, and Media Occupations	4 489.5	0.9%	0.4%
370000	Building and Grounds Cleaning and Maintenance Occupations	3 034.0	0.6%	0.3%
190000	Life, Physical, and Social Science Occupations	2 409.4	0.5%	0.2%
290000	Healthcare Practitioners and Technical Occupations	2 137.7	0.4%	0.2%
350000	Food Preparation and Serving Related Occupations	2 062.5	0.4%	0.2%
330000	Protective Service Occupations	1 840.0	0.4%	0.2%
450000	Farming, Fishing, and Forestry Occupations	701.6	0.1%	0.1%
390000	Personal Care and Service Occupations	500.1	0.1%	0.0%
310000	Healthcare Support Occupations	248.0	0.0%	0.0%
250000	Education, Training, and Library Occupations	236.0	0.0%	0.0%
210000	Community and Social Service Occupations	212.5	0.0%	0.0%
		497 860.8	100.0%	42.1%

Table 6B: Top 25 Occupations within Production Occupations from Table 6A, by Contribution to Value Added (\$billions) – Base Case

SOC	Description	Compensation \$billions
512092	Team Assemblers	27.24
511011	First-Line Supervisors of Production and Operating Workers	13.01
514041	Machinists	10.87
519061	Inspectors, Testers, Sorters, Samplers, and Weighers	8.02
514121	Welders, Cutters, Solderers, and Brazers	7.53
512022	Electrical and Electronic Equipment Assemblers	4.50
514011	Computer-Controlled Machine Tool Operators, Metal and Plastic	4.16
514111	Tool and Die Makers	3.71
514031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	3.36
512099	Assemblers and Fabricators, All Other	3.30
512011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	2.74
519198	Helpers--Production Workers	2.68
514081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	2.52
519199	Production Workers, All Other	2.18
514072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	1.95
512031	Engine and Other Machine Assemblers	1.75
514033	Grinding/Lapping/Polishing/Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	1.74
514122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	1.61
512041	Structural Metal Fabricators and Fitters	1.56
512023	Electromechanical Equipment Assemblers	1.37
519121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	1.34
514034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	1.21
514021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	1.20
519122	Painters, Transportation Equipment	1.02
519111	Packaging and Filling Machine Operators and Tenders	0.89

Table 6C: Top 25 Occupations for Assembly-Centric Products when Including Associated Taxes and Gross Operating Surplus, by Contribution to Value Added (\$billions) – Base Case

NAICS	Description	Baseline (\$Billion)
512092	Team Assemblers	52.96
111021	General and Operations Managers	40.97
414012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	24.53
511011	First-Line Supervisors of Production and Operating Workers	23.38
172112	Industrial Engineers	20.02
172141	Mechanical Engineers	17.82
514041	Machinists	17.51
119041	Architectural and Engineering Managers	15.08
132011	Accountants and Auditors	14.40
519061	Inspectors, Testers, Sorters, Samplers, and Weighers	13.98
113051	Industrial Production Managers	13.53
151133	Software Developers, Systems Software	12.77
514121	Welders, Cutters, Solderers, and Brazers	11.95
113031	Financial Managers	11.67
537062	Laborers and Freight, Stock, and Material Movers, Hand	11.29
151132	Software Developers, Applications	11.22
499041	Industrial Machinery Mechanics	10.52
112022	Sales Managers	10.45
533032	Heavy and Tractor-Trailer Truck Drivers	10.25
499071	Maintenance and Repair Workers, General	10.07
434051	Customer Service Representatives	9.90
172071	Electrical Engineers	9.68
131199	Business Operations Specialists, All Other	9.50
131023	Purchasing Agents, Except Wholesale, Retail, and Farm Products	9.23
414011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	8.80

Table 7: Percent of Monte Carlo Iterations by Industry/Occupation Combination and by Rank, Top 20 Industry/Occupation Combinations for Assembly-Centric Manufacturing (ordered by base case rank)

[illegible]

Industry NAICS	Description	Occupation SOC	Description	11	12	13	14	15	16	17	18	19	20	Baseline (\$billion)
420000	Wholesale trade	414012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products											7.25
336111	Automobile manufacturing	512092	Team Assemblers											6.34
484000	Truck transportation	533032	Heavy and Tractor-Trailer Truck Drivers											3.15
336112	Light truck and utility vehicle manufacturing	512092	Team Assemblers	0.1										2.94
420000	Wholesale trade	111021	General and Operations Managers	0.0										2.91
550000	Management of companies and enterprises	111021	General and Operations Managers	0.1	0.0									2.71
541100	Legal services	231011	Lawyers	1.2	0.4	0.1	0.0	0.0						2.46
336411	Aircraft manufacturing	172011	Aerospace Engineers	3.2	1.3	0.6	0.3	0.1	0.0					2.26
420000	Wholesale trade	414011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	7.4	3.6	2.2	1.1	0.6	0.3	0.0	0.0			2.08
550000	Management of companies and enterprises	113031	Financial Managers	13.6	8.4	5.7	3.5	2.1	1.1	0.5	0.3	0.1	0.0	1.88
541200	Accounting, tax preparation, bookkeeping, and payroll services	132011	Accountants and Auditors	22.3	18.8	12.9	8.5	5.9	3.4	1.6	0.6	0.2	0.1	1.67
336120	Heavy duty truck manufacturing	512092	Team Assemblers	17.8	19.4	16.6	12.0	8.8	5.9	3.4	1.6	0.6	0.1	1.60
336411	Aircraft manufacturing	512011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	13.0	13.6	13.3	12.2	10.8	10.3	7.0	4.4	1.9	1.0	1.53
550000	Management of companies and enterprises	132011	Accountants and Auditors	9.7	11.4	12.2	13.1	12.6	11.3	9.7	7.7	4.2	1.9	1.47
332710	Machine shops	514041	Machinists	4.6	8.1	12.2	15.3	16.7	15.0	11.6	7.5	3.7	1.8	1.43
523A00	Securities and commodity contracts intermediation and brokerage	413031	Securities, Commodities, and Financial Services Sales Agents	3.0	6.9	11.3	14.9	16.1	15.5	12.9	8.7	4.8	2.1	1.41
420000	Wholesale trade	537062	Laborers and Freight, Stock, and Material Movers, Hand	2.7	4.8	6.9	8.9	10.8	13.1	14.4	13.2	7.9	4.2	1.33
336411	Aircraft manufacturing	172112	Industrial Engineers	1.1	2.4	4.1	6.0	8.9	11.4	14.9	14.2	11.2	7.1	1.27
420000	Wholesale trade	112022	Sales Managers	0.4	0.8	1.6	3.2	4.1	7.6	11.7	14.2	14.3	9.2	1.20
550000	Management of companies and enterprises	131199	Business Operations Specialists, All Other	0.0	0.1	0.3	1.0	2.2	4.1	6.9	10.5	11.6	11.0	1.11
550000	Management of companies and enterprises	119199	Managers, All Other					0.1	0.3	1.7	4.3	9.1	12.1	1.05
336411	Aircraft manufacturing	172141	Mechanical Engineers					0.0	0.2	1.1	4.4	9.3	11.7	1.04
550000	Management of companies and enterprises	111011	Chief Executives						0.0	0.1	0.9	3.2	7.2	1.03
336390	Other motor vehicle parts manufacturing	512092	Team Assemblers				0.0	0.1	0.5	1.9	4.5	7.3	9.3	1.03
420000	Wholesale trade	533032	Heavy and Tractor-Trailer Truck Drivers						0.0	0.5	1.8	6.4	11.4	1.03
336411	Aircraft manufacturing	151133	Software Developers, Systems Software							0.1	0.5	2.2	5.9	1.01
550000	Management of companies and enterprises	113021	Computer and Information Systems Managers									0.1	0.7	0.97
336370	Motor vehicle metal stamping	512092	Team Assemblers						0.0	0.1	0.9	1.9	3.3	0.95
550000	Management of companies and enterprises	112021	Marketing Managers										0.0	0.92
561600	Investigation and security services	339032	Security Guards										0.0	0.87
420000	Wholesale trade	411012	First-Line Supervisors of Non-Retail Sales Wo										0.0	0.85
336411	Aircraft manufacturing	119041	Architectural and Engineering Managers										0.0	0.84
336350	Motor vehicle transmission and power train parts manufacturing	512092	Team Assemblers									0.0	0.1	0.79

Table 8: Percent of Monte Carlo Iterations by Industry by Rank, Depreciable Building Assets for Assembly-Centric Products, Top 20 Industries

NAICS	Description	Rank - Top 20																				Baseline (\$Billions)
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
336411	Aircraft manufacturing	54.4	45.6																			11.68
336112	Light truck and utility vehicle manufacturing	45.6	54.4																			11.48
336111	Automobile manufacturing			77.6	15.0	5.5	1.5	0.3	0.0	0.0												4.82
336413	Other aircraft parts and auxiliary equipment manufacturing			10.4	35.4	26.9	14.5	7.3	3.4	1.4	0.6	0.2	0.0									4.10
336412	Aircraft engine and engine parts manufacturing			10.0	32.8	27.7	15.5	7.9	3.5	1.7	0.7	0.3	0.0									4.07
333120	Construction machinery manufacturing		1.4	11.4	21.1	26.2	16.2	9.6	5.8	4.0	2.6	1.2	0.4	0.1								3.71
331110	Iron and steel mills and ferroalloy manufacturing		0.3	3.8	11.3	20.0	22.2	14.5	10.0	7.0	5.1	3.2	2.0	0.7	0.1	0.0						3.50
332720	Turned product and screw, nut, and bolt manufacturing		0.0	0.4	3.2	8.0	14.8	16.4	14.5	12.7	10.3	8.6	6.2	3.5	1.1	0.3	0.1	0.0				3.24
332710	Machine shops				0.1	1.3	7.1	19.5	27.9	25.5	13.9	4.4	0.5									3.20
333920	Material handling equipment manufacturing		0.3	1.5	6.1	11.9	14.6	14.6	13.8	12.9	9.6	8.1	4.3	1.6	0.5	0.2	0.1	0.0				3.18
336370	Motor vehicle metal stamping		0.0	0.5	2.6	6.4	10.4	12.4	13.7	15.5	13.5	11.5	7.5	3.4	1.4	0.7	0.5	0.2	0.0			3.04
326190	Other plastics product manufacturing							0.2	1.4	8.0	20.2	31.9	26.4	10.6	1.3	0.1						2.88
333111	Farm machinery and equipment manufacturing					0.3	1.5	3.5	6.4	9.1	12.5	16.1	19.0	13.6	6.9	3.6	2.9	2.5	1.6	0.4		2.83
333130	Mining and oil and gas field machinery manufacturing		0.1	1.0	2.4	4.0	4.7	4.7	3.9	4.4	4.5	5.1	6.2	8.3	4.9	3.0	3.0	3.9	5.5	4.0		2.54
33291A	Valve and fittings other than plumbing										0.0	0.5	5.0	21.1	35.0	27.7	9.6	1.1	0.1			2.48
336350	Motor vehicle transmission and power train parts manufacturing								0.1	0.5	1.8	4.2	9.4	16.1	16.2	10.2	8.4	10.3	11.7	6.7		2.46
33329A	Other industrial machinery manufacturing												0.1	1.6	11.7	29.3	34.0	19.2	3.9	0.3		2.38
336390	Other motor vehicle parts manufacturing								0.0	0.1	0.3	1.6	5.1	11.2	13.6	10.4	9.6	12.6	15.6	10.4		2.36
331510	Ferrous metal foundries													0.1	0.8	8.0	24.5	35.7	23.7	6.4		2.34
33399A	Other general purpose machinery manufacturing											0.0	0.2	1.5	3.0	4.7	5.4	9.0	17.1	22.4		2.11
333618	Other engine equipment manufacturing																0.0	0.8	7.0	23.7		2.00
336611	Ship building and repairing												0.0	0.0	0.3	0.7	1.5	3.1	8.8	15.5		1.95
33391A	Pump and pumping equipment manufacturing														0.0	0.1	0.3	1.3	4.9	10.0		1.86
333295	Semiconductor machinery manufacturing																			0.2		1.77

Table 9: Percent of Monte Carlo Iterations by Industry by Rank, Depreciable Machinery/Equipment Assets for Assembly-Centric Products, Top 20 Industries

NAICS	Description	Rank - Top 20																				Baseline (\$Billions)
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
334413	Semiconductor and related device manufacturing	96.0	4.1																			47.69
336111	Automobile manufacturing	4.1	87.4	8.6	0.0																	37.05
331110	Iron and steel mills and ferroalloy manufacturing		8.6	85.1	6.3																	30.31
336112	Light truck and utility vehicle manufacturing		0.0	6.4	93.2	0.5																24.29
336370	Motor vehicle metal stamping				0.4	70.7	23.8	3.9	1.0	0.1												16.83
336350	Motor vehicle transmission and power train parts manufacturing				0.0	27.4	53.0	12.3	5.5	1.6	0.2	0.0										15.46
336310	Motor vehicle gasoline engine and engine parts manufacturing					1.0	16.9	60.7	18.2	2.9	0.2											13.82
334510	Electromedical and electrotherapeutic apparatus manufacturing					0.3	3.9	12.8	31.2	25.2	13.5	8.0	5.0	0.2								12.35
334511	Search, detection, and navigation instruments manufacturing					0.1	2.2	8.3	26.4	28.4	16.2	10.2	7.7	0.5	0.0							12.05
336411	Aircraft manufacturing					0.0	0.2	1.8	12.2	21.8	24.8	18.7	16.9	3.1	0.6	0.0						11.26
325190	Other basic organic chemical manufacturing								0.9	7.0	24.7	41.0	26.2	0.2								10.72
336390	Other motor vehicle parts manufacturing						0.0	0.2	4.7	13.0	20.3	21.3	31.0	7.2	2.3	0.2						10.66
325211	Plastics material and resin manufacturing										0.0	0.3	8.4	67.7	23.4	0.2						8.98
336412	Aircraft engine and engine parts manufacturing									0.0	0.0	0.6	4.8	20.6	36.7	23.2	7.9	2.6	1.2	0.9	0.7	8.32
333618	Other engine equipment manufacturing													0.2	33.3	58.9	6.9	0.6	0.1			7.98
33329A	Other industrial machinery manufacturing															2.3	27.6	35.3	23.2	9.1	2.2	6.84
336611	Ship building and repairing														1.0	5.0	19.1	12.9	8.0	5.6	6.8	6.59
324110	Petroleum refineries																0.7	15.5	30.0	29.5	17.5	6.59
336360	Motor vehicle seating and interior trim manufacturing																	0.7	15.1	29.7	29.6	6.58
336413	Other aircraft parts and auxiliary equipment manufacturing														0.5	3.8	16.4	12.7	7.9	5.6	6.6	6.51
331200	Steel product manufacturing from purchased steel																		0.2	7.8	21.5	6.38
332720	Turned product and screw, nut, and bolt manufacturing														0.1	2.2	12.0	11.5	7.0	5.5	6.2	6.35
333611	Turbine and turbine generator set units manufacturing																			0.0	1.5	6.03
333120	Construction machinery manufacturing															0.2	1.7	3.4	3.7	3.5	3.9	5.81
334220	Broadcast and wireless communications equipment																0.2	0.6	1.1	1.3	1.8	5.50
333130	Mining and oil and gas field machinery manufacturing													0.4	2.2	4.1	7.4	4.4	2.6	1.7	1.7	5.30

Table 10: Percent of Monte Carlo Iterations by Industry by Rank, Purchased Building Capital for Assembly-Centric Products, Top 20 Industries

[illegible]



Table 11: Percent of Monte Carlo Iterations by Industry by Rank, Purchased Machinery Capital for Assembly-Centric Products, Top 20 Industries

[illegible]

Table 12: Depreciable Assets and the Rate of Change, 2012 (\$million 2012)

	Buildings	Machinery and Equipment	Total
Gross value of depreciable assets (acquisition costs), end of year	545 316	2 290 718	2 836 034
Retirements	9 224	39 466	48 690
Capital Expenditures	30 859	132 031	162 890
Capital Expenditures less Retirements	21 635	92 565	114 200
Percent of Depreciable Assets that are Replaced	1.69%	1.72%	1.72%
Percent of Depreciable Assets that are New	3.97%	4.04%	4.03%
Percent of Depreciable Assets that are New or Replaced	5.66%	5.76%	5.74%

Table 13: Electricity and Natural Gas Use (Including Industries that Contribute to Electricity and Natural Gas) for Assembly-Centric Production, Value Added and Imports (\$million)

NAICS and Description	Value Added	Contributing Industry Value Added	Associated Imports	Total
<b>Electric power generation, transmission, and distribution</b>	<b>5 923</b>	<b>7 488</b>	<b>2 294</b>	<b>15 704</b>
221100 Undesignated and non-manufacturing	2 172	2 746	841	5 760
221100-A Indirect Uses-Boiler Fuel	254	321	98	674
221100-B Process Heating	573	725	222	1 521
221100-C Process Cooling and Refrigeration	171	217	66	455
221100-D Machine Drive	1 238	1 565	479	3 282
221100-E Electro-Chemical Processes	292	369	113	774
221100-F Other Process Use	97	122	37	257
221100-G Facility HVAC	373	471	144	988
221100-H Facility Lighting	248	314	96	658
221100-I Other Facility Support	78	98	30	206
221100-J Onsite Transportation	110	139	43	291
221100-K Other Nonprocess Use	26	32	10	68
221100-L End Use Not Reported	291	368	113	771
<b>Natural gas distribution</b>	<b>2 439</b>	<b>6 426</b>	<b>3 260</b>	<b>12 125</b>
221200 Undesignated and non-manufacturing	344	905	459	1 708
221200-A Indirect Uses-Boiler Fuel	622	1 639	831	3 092
221200-B Process Heating	1 057	2 785	1 413	5 254
221200-C Process Cooling and Refrigeration	11	28	14	54
221200-D Machine Drive	32	85	43	160
221200-F Other Process Use	30	78	40	147
221200-G Facility HVAC	332	874	443	1 649
221200-I Other Facility Support	8	20	10	39
221200-K Conventional Electricity Generation	2	5	2	9
221200-L Other Nonprocess Use	3	7	3	13
<b>TOTAL</b>	<b>8 361</b>	<b>13 914</b>	<b>5 554</b>	<b>27 830</b>