Trumponomics in Post-Industrial America: Understanding the Causes of Deindustrialization and its Role in the Emergence of Right-Wing Populist Economics

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By

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Abstract

Since 2001, the American economy has swiftly shed over six million manufacturing jobs. To this day, large swaths of the American rural working class are left struggling to compete with domestic and external forces that are driving American labor away from the production process altogether. Much of the political rhetoric surrounding this economic phenomenon is dominated by politicians pointing fingers across the Pacific towards China and their ‘unfair’ trade practices. This technique of political and economic scapegoating was heralded by Donald J. Trump who emerged onto the American political stage with the immediate incrimination of China in the economic woes of the American working class. Although the American trade deficit with China is an often cited cause of American deindustrialization, are there other factors at play? To what extent can the increasingly widespread variables of automation and service growth explain the “hollowing out” of the American manufacturing sector? Additionally, to what degree is Donald Trump’s anti-globalist and economic nationalist rhetoric responsible for his shocking electoral win in 2016? I explore these topics together and illustrate the troubling recent shifts in the American labor force as well as the American electorate.

Keywords: economics, deindustrialization, manufacturing, employment, China, Donald Trump, automation, services sector, post-industrialism, right-wing populism
Introduction

The development of the American manufacturing sector over the last half century has been defined by a previously unseen dichotomy. While the real output of the US manufacturing sector has maintained its share of the economy constant in price-adjusted terms since 1960, the total manufacturing employment in the United States has more than halved in the same time frame (Baily and Bosworth, 2014). This divergent trend, highlighted in Figure 1, has undermined the United States’ position as a global economic hegemon and placed into question the sustainability of the American external deficit, which has grown exponentially for decades. The shrinking prosperity of the industry has resulted in the tandem decline of the manufacturing industry’s share of national employment as well as the absolute level of manufacturing employment (shown in Figure 2), which has displaced tens of millions of workers, sending enormous ripples through the American economy. The great vanishing act of manufacturing employment has been exacerbated since the recession of 2001, after which the economy shed over 5 million manufacturing jobs, many of which are destined to never return (Figure 1) (Nager, 2017; Houseman, 2018; Scott, 2015).

The deindustrialization of the US economy has been largely politicized for the last several Election cycles, leading many pundits and politicians to point fingers at external conditions such as our unbalanced trade with China and what are considered the unforeseen consequences of globalization (Sweeney, 2018; Scott, 2017; Rodrik, 2018; McKinnon, 2013). Notably, the steady decline of manufacturing employment became a highlight of discussion in the 2016 Presidential Election, leading many to question the success of free trade policies and the US role in the global economy. These views were heralded by Donald J. Trump, whose
trademark campaign promises included the implementation of protectionist policies in order to spur domestic manufacturing output and employment. While countless studies have highlighted the role of the United States’ imbalanced trade relationship with China in American deindustrialization, is it the only factor at play?

Figure 1. Divergence of Real Output and Manufacturing Share of Employment, 1987-2012

![Graph showing divergence of real output and manufacturing share of employment from 1987 to 2012.

Source: Federal Reserve Bank of St. Louis]

The preponderance of the discussion of Chinese import competition in understanding American deindustrialization ignores the other components that lend to the shrinking manufacturing sector. Although Chinese import competition of the last two decades has been shown to dampen the competitiveness of American exports (Baily and Lawrence, 2004; McKinnon, 2013; Autor et al, 2015), specific research identifies two notable factors aside from Chinese trade that contribute to deindustrialization: (1) the role of industrial labor productivity and increase of automation on the decreased labor share of manufacturing output (Tregenna, 2011; Acemoglu et al., 2014) and (2) the effects of increased incomes on relative demands for
manufactured goods and services (Kollmeyer, 2009; Brady and Denniston, 2006). Despite the political scrutiny and scapegoating of the economic linkages with American trading partners such as China in the decline of American manufacturing, how much credence can we give this explanation? Do imbalanced productivity and income effects provide enough significance to explain the decline of American manufacturing employment? If so, can these factors explain the changes in employment levels in American manufacturing better than increased trade with China?

Figure 2. Decline in Absolute Levels of Manufacturing Employment, 1960-2018

In this study, I revisit this often politicized issue, questioning the relationship between globalization and technological advancement on the decline in the manufacturing share of American employment. I deliver my findings on these topics on two parts. The first part discusses the factors that have led the American economy on a path of deindustrialization and their relative shares of importance in accounting for manufacturing job loss. The second part discusses the political rhetoric surrounding this era of manufacturing decline and the resulting
rise of right-wing economic populism, which as a result led us to the Presidency of Donald J.
Trump. This part will discuss Trump’s rhetoric around economics and trade, and the degree to
which his campaign policies led to his electoral win in November 2016.

While the trade and technology shocks to the American manufacturing sector are well
established, the degree and magnitude to which they respectively account for deindustrialization
is topic for much debate in the field (Tregenna, 2011; Sterniczky, 2017; Scott, 2017; Rose, 2018;
Pierce and Schott; 2012). I hope to disaggregate the deindustrializing effects of Chinese trade
and rates of capitalization and automation in American manufacturing to dissect each factor’s
relative share of the sector’s employment decline. Ultimately, I aim to prove that although often
ignored in the canon of the discussion on manufacturing employment, imbalanced intersectoral
productivity growth and the income-effect induced demand for services have aided the evolution
of the American economy from an industrialized manufacturing hub to a post-industrial service
economy. Following this discussion of contemporaneous shocks to the American economy, I
touch on the harrowing implications of the continued “hollowing out” (Levinson, 2013) of the
manufacturing sector as well as policy recommendations which aim to equalize the imbalanced
environment in which this phenomenon was allowed to occur.

In order to prove my hypothesis and evaluate the relative significance of the several
aforementioned variables that affect deindustrialization, I employ the Ordinary Least Squares
(OLS) Regression approach. This allows me to quantify the relative coefficients of variance that
lead to the diminishment of the relative manufacturing employment of the American economy,
measured in total persons employed in the manufacturing sector. I disaggregate the factors that
influence this dependent variable by identifying proxy variables that stand in for my explanatory
variables. Following my discussion of recent trends and implication of American
deindustrialization, I appraise the variables of the US trade deficit with China (TRDCHN), levels
of labor productivity in the manufacturing sector (MANPROD), and the consumer price index of
services (SERVX) in order to quantify the decline in the manufacturing share of employment
(MANEMP). Ultimately, the regression that I will use to further my findings on manufacturing
loss takes the form of:

\[ MANEMP = b_0 + b_1 MANPROD + b_2 TRDCHN + b_3 SERVX + e_0 \]

Despite the argued significance of productivity and service sector effects on the
manufacturing sector, many pundits from both sides of the aisle continuously highlight the
negative effects of globalization and what they see as imbalanced trade relationships with the
United States’ trading partners. The 2016 Presidential Election served as a broadcast for these
views, during which candidates such as Donald J. Trump cited trade deals such as the North
American Free Trade Agreement (NAFTA) and the Trans Pacific Partnership (TPP) as catalysts
of American deindustrialization (Stiglitz, 2018). These largely controversial trade deals have
been used in political discussion as proxies for the view of globalization as a net negative for the
US economy (Monnat and Brown, 2017). The campaign of Donald J. Trump notably
championed stances of anti-globalization and economic nationalism as a reaction to what it
described as an undermining of American economic interests by foreign powers, placing specific
emphasis on Mexico and China (Stiglitz, 2018; Noland et al, 2016). This economic outlook was
coupled with Trump’s social and political policies which included staunch stances on
immigration and establishment politics (Morgan and Lee, 2018). This reactionary stance was
seen as an appeal to the struggling American working class, large swathes of which still struggled to reenter the labor force after decades of job loss (BLS, 2017).

However, Donald Trump failed to mention other factors that led to manufacturing employment decline and based his economic stances on pointing fingers externally in order to bolster his other nationalistic policies that attempted to incriminate foreign powers like China and Mexico. Trump tried to appeal to blue collar workers by labelling China a currency manipulator and blaming them for the rusting out of much of American industry (Stiglitz, 2018). Donald Trump’s eventual electoral victory on November 8th, 2016, which came as a surprise to much of the media and political establishment, was credited by many to the economic anxieties of working America and the increasingly negative view of globalization which Trump himself had accented during his campaign (Roth, 2017). Moreover, his victory was credited to the successful appeal to rural America which is argued to have been ignored by establishment politicians and policy makers over the course of several decades (Monnat and Brown, 2017). While the leading cause of Trump’s victory has been a subject of much contention, I aim to prove the argument that his electoral win was based on his policies regarding American manufacturing and industrial competitiveness. More specifically, I analyze the relationship between manufacturing employment decline on a county level to the result of the 2016 Presidential Election. Ultimately, I pose the following question: Does a county’s decline in manufacturing employment affect how its citizens voted in the 2016 Election? Were Donald Trump’s manufacturing policies statistically significant in his electoral victory?

In attempt to prove this hypothesis, I apply multiple Ordinary Least Squares (OLS) Regressions in order to quantify the relationship between an American county’s decline in
absolute manufacturing employment and that county’s results in the 2016 Presidential Election. I intend to prove a direct relationship between a county’s decline in manufacturing employment and the percentage of that county’s citizens that voted for Donald J. Trump. I use this estimate as a proxy of the effectiveness and appeal of Trump’s manufacturing and industrial policies that were presented during his campaign. Following my discussion of the rhetoric of the 2016 Election and its economic and social implications, I quantify the effect of the county level manufacturing employment change between the years 2001-2016 (MANEMP) on Trump’s county level margin of electoral success (TRUMPVOTE). The regression therefore to illustrate this relationship takes the form of:

\[ TRUMPVOTE = b_0 + b_1 \Delta MANEMP + e_0 \]

**Literature Review**

For decades, many economists have implicated globalization in the declining share of manufacturing in the Gross Domestic Product (GDP) of the United States as well as other industrialized developed nations (Brady and Denniston, 2006; Wood, 2004). In a preliminary analysis of this relationship, Frobels, Heinrichs, and Kreye (1980) suggest a process of fractionalization of global labor known as the “classic international division of labor”. This study suggests that developing nations specialize in producing primary goods such as raw goods and agriculture, while developed and industrialized nations specialize in using those agricultural and raw goods as inputs for the manufacture of finished goods. This naturally spurred industrialization and an increase in manufacturing share of GDP in developed countries (Frobels, et al., 1980).
However, the international division of labor soon restructures once multinational firms headquartered in industrialized countries begin to offshore production in order to save production costs and make use of lower cost labor in developing countries. This process begins to accelerate in the late 20th century, when development in technology allows for the reduction of transportation and telecommunication costs (Kollmeyer, 2009). Multinational firms began to make use of these developments in order to disaggregate their production processes, offshoring the low-skilled labor required for production to developing countries. This created a new duality wherein the now industrializing developing countries specialized in low-skilled labor and developed nations now specialized in high-skilled labor associated with the non-manufacturing aspect of industry, including supply chain management, finance, and marketing (Kollmeyer, 2009; Brady and Denniston, 2006).

Wood (1994) also contends the argument of new division of labor and spatial structuring of global supply chains. He argues that increased trade and commercial openness contributes to the reduction of demand for low-skilled labor in developed countries. This process of the outsourcing of low-skilled labor allows for developing countries to attain the comparative advantage in labor intensive industries. This trend is also elaborated on by Alderson (1999), who concludes that “Globalization [manufactured exports +, outward foreign direct investment -, and manufacturing imports from developing countries -]” has accounted for the deindustrialization of developed countries. Although the findings of Wood and Alderson accurately identify trends in labor division, their work has been critiqued for the overemphasis of the effect of “North-South” trade on deindustrialization of developed countries (Krugman, 1996; Bairoch, 1996).

Disaggregated data on international trade and commerce shows that the majority of international
economic activity of the United States in the late 20th century was with other developed regions such as the European Union and North America (Bureau of Economic Analysis). Therefore, trade relations with developing countries would not have an immediate significant effect on the industry structure of the United States.

**Crouching Tiger, Hidden Tariff: The Role of Chinese Trade**

The discussion of “North-South” trade in discussing American trade with the developing world has been recently replaced with rhetoric of American trade with China. In many respects, China is central in discussing the modern consequences of globalization and increased trade. In 2015, China overtook Canada as the United States’ largest trade partner in terms of total trade volume, and in 2017 was the source of nearly 20% of America’s yearly imports (Census Bureau, 2018). While China is the third largest importer of American goods, it is the world’s largest exporter and is the beneficiary of the United States’ largest trade deficit, which reached $318 billion in 2017, as shown in Figure 3 (Census Bureau, 2018). With the largest population of low-skilled workers in the world, China has been able to reach explosive growth levels since its initial economic reforms of 1978 under Deng Xiaoping and overtook the United States as the largest economy by GDP (PPP) in 2016 (Nergis, 2016; World Bank, 2017).

Many economists attribute the tandem growth of Chinese global market share and the heavy import competition of American manufactured goods on what is often considered unfair trade practices used by the Chinese (Thorbecke, 2014; Pierce and Schott, 2012). This critique of Chinese trade policies is coupled with respective critique of what is considered a lack of American response (Pierce and Schott, 2012; Lin and Wang, 2018; Kang et al, 2018). The
argument of these economists are rooted in the assertion that the Chinese government, contrary to its statements and perceived ambitions for development, undermines its trading partners, and in effect the global economic order, in order to achieve a leg up on global market share of import demand. This is also part in parcel of the rhetoric of many populist pundits on both sides of the political spectrum in the United States, who allege that the shrinking of the American middle class is in part caused by unfair trade deals and the overwhelming adverse effects of globalization as a whole (Rodrik, 2017; Berlet and Lyons, 2000).

Figure 3. US Trade Deficit with China, Billions of USD, 1987-2017

An often criticized part of China’s trade policies is the perceived currency manipulation employed by Chinese authorities (Bown and McCulloch, 2009; Ramirez, 2013; Moghaddam and Duan, 2017; Cwik, 2011). According to this allegation, China intentionally hordes international monetary reserves and inspires a “savings glut” (McKinnon, 2013) among Chinese firms and individuals to artificially appreciate the value of the dollar, thus decreasing the competitiveness
of American manufacturing. This tactic, along with what is considered an artificially inflated Chinese current account (Seghezza et al, 2017), is used to undermine American economic interests and is said to be an important factor in the ballooning American trade deficit with China which peaked at $761 billion USD in 2006 (Lin and Wang, 2018). This accusation, the credibility of which is often questioned (Moghaddam and Duan, 2017; Nolt, 2016), has pressured many in the American political system to label China a “currency manipulator” (Ramirez, 2013) and essentially blame China for the domestic economic woes. While trade with China has been shown to have a substantial effect on American manufacturing competitiveness (Imbruno, 2016; Lin and Wang, 2018; Thorbecke, 2015), the undervaluation of the Chinese Renminbi (RMB) has had marginal effect on this phenomenon (Imbruno, 2016). Furthermore, studies have shown that realignment of the RMB-USD exchange rate to market dictated levels would not lead to considerable changes in the American trade deficit with China (Groenewold and He, 2007).

Although currency manipulation does not seem to be the cause of trade imbalances between the United States and China, the trade imbalance exists regardless. This imbalance has unimpededly increased over the last several decades, even surpassing expected levels of trade models. According to Thorbecke (2015), real Chinese exports to the United States have surpassed gravity model expectations by $100 billion every year since 2005. Furthermore, Thorbecke labels the American situation with China as an economic outlier contrary to the models and expectations of many economic models. Notably, while the US’ trade deficit with the Rest of the World decreased by 45% between 2006 and 2014, the US deficit with China actually increased by 40% during that same time (Thorbecke, 2015). Much of this is credited to Chinese government policies to support Chinese export-oriented development through limited
privatization, value-added manufacturing subsidies, and preferential treatment of Chinese firms in international trade arbitration (Lester, 2018; Lin and Wang, 2018; Bown and McCulloch, 2009).

Pierce and Schott (2012) attribute the large drop in the manufacturing share of the US economy in the decade between 2001 and 2007 to the grant by the United States to China of Permanent Normal Trade Relations (PNTR). The authors contend that thanks to the PNTR designation, Chinese imports were able to penetrate US markets with no annual change in import tariff and allowed for Chinese import competition to continue largely unimpeded for almost a decade. During this same time period, US manufacturing employment share of the total workforce fell from 13.5% to 11.2%, a change in total manufacturing employment of -17.3% (Federal Reserve Bank of St. Louis). According to this study, the continued duty free trade with the labor intensive goods from China directly put downward pressure on American manufacturing employment. Furthermore, in addition to preferential tariff treatment by the United States, China has retained many tariff levels despite its commitment to rid itself of tariffs as a condition of its ascension into the World Trade Organization in 2001 (Imbruno, 2016). Although Chinese average import tariffs decreased dramatically following The Deng Xiaoping era of economic reforms from 43% in 1985 to 15% 2001, average import tariff levels remain mostly unchanged since then, despite WTO membership requirements (Imbruno, 2016). Imbruno (2016) goes on to assert that average tariff levels fell to 9.7% in 2005.

Additionally, the study of Pierce and Schott (2012) does not consider the type of accounting that goes into calculating imports from China. More specifically, Pierce and Schott do not distinguish between exports of goods produced by Chinese firms and those produced by
the relocated plants of American firms that are otherwise considered re-imported American goods. While this ultimately does disrupt American manufacturing employment due to the relocation of American production, this is often categorized as a change in productivity of American firms (Boehm, Flaaen, Pandalai-Nayar, 2017). In fact, the share of manufacturing unemployment that is borne from the relocation of American multinationals has increased with time. Microdata panel data provided by Boehm, et al. (2017) indicates that over the course of 1993-2011 (timespan during which manufacturing employment share fell 33% (Federal Reserve Bank of St, Louis)), American multinational corporations were accountable for 41% of the decline of manufacturing employment. This disproportionate change in employment stems from the structural change in the global supply chain that has occurred over a similar time frame. From 1993-2011, the percentage of intermediary inputs for further value added manufacturing nearly doubled, and multinational companies accounted for 90% of that difference (Boehm, et al., 2017).

This growth in outsourcing and offshoring of labor intensive jobs widens Frobels’ concept of the division of labor, as US manufacturing companies separate the labor intensive operations to labor efficient markets while allocating resources for domestic white collar jobs (Frobels, et al., 1980; Kollmeyer, 2009). While offshoring is seen as a result of increased trade openness of developing countries and thus a consequence of globalization, it is in fact a factor change in supply chain productivity, which is shown by many studies to be symptomatic of globalization trade openness (Kollmeyer, 2009; Ottaviano, Peri and Wright, 2013; Dey, Houseman and Polivka, 2006; etc.). The relocation of manufacturing processes through international offshoring in the last several decades has been the focus of much policy debate and
has been emblematic of the American discussion on manufacturing employment. The offshoring of American manufacturing firms and multinationals is the focal point of much of populist trade rhetoric and is seen by many as a symptom of the unfair global economic order in which the United States operates in. The offshoring of US jobs is shown in Figure 4.

**Figure 4. The Offshoring of Domestic Jobs Abroad**

The undoubtedly imbalanced growth in trade with China and the continued offshoring of manufacturing jobs has spurred protectionist sentiments among many in the developed world (Rodrik, 2017). The unforeseen consequences of trade with the China’s emerging economic powerhouse have been perceived by those harboring economic populist sentiments as an inevitable and structural part of globalization (Sweeney, 2017). A rising tide of anti-globalism has taken the form in the form of economic nationalism in developed Western countries, aimed at closing national borders and raising import barriers to protect domestic industry (Owen and Johnston, 2017). Anti-globalist rhetoric have manifested in criticism of China as a trading
partner and a malicious player in the global economic arena. One newly minted political figure famously ran for the Presidency of the United States in 2016 on a platform aimed at vilifying China for what he considered egregious trading tactics and the employment of an all-out campaign to undermine the integrity of the United States economy. The rising culture of China-bashing and the scapegoating of trading partners for America’s economic woes were heralded by Donald J. Trump leading up to the 2016 Presidential Election, during which he infamously asserted that even “The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive” (@DonaldJTrump, 2012). The anger expressed in response to the rising deficit and general imbalanced relationship with China by pundits such as Trump is a symptom of the nationalist sentiments that rise as a result of the adverse shocks of globalization.

**Moving Toward Automation: The Role of Imbalanced Productivity Growth**

Many economists have underlined the role of industrial productivity in the reduction in the labor share of manufacturing output (Tregenna, 2011; Acemoglu et al., 2014). As labor productivity increases, as it has over the last half century, marginal additions to stocks of labor become redundant and increased output can be replicated with a smaller labor share (Tregenna, 2011; Kollmeyer, 2009). In the case of global manufacturing value added chains, productivity increases can also take the form of production outsourcing (Kollmeyer, 2009). This is due to the distinction between the labor productivity of a manufacturing firm and the productivity of the specific unit of labor employed by the firm. In other words, as a manufacturing firm outsources its operations to say China, its own manufacturing becomes more productive due to the lower
labor costs that it incurs. All the while, the lower manufacturing employment that it leaves behind domestically as it ships its operations abroad clearly get less productive as the workforce being laid off is now left producing nothing (Tregenna, 2011). Productivity increases can also take the form of a changing combination of production inputs. Should a manufacturing firm not offshore its production, it also has the option of supplying more capital to higher-tech industrial production, in order to employ less labor (Kollmeyer, 2009). This process is also known as automation, and it has had a large disruptive effect on the American manufacturing labor market (shown in Figure 5). Additionally, as firms automate much of their industrial production, this increases their capital to labor ratio, otherwise known as the capital intensity of their production. A larger capital to labor ratio implies a lower absolute level of employment due to the substitutionary effect of capital, primarily in high tech industry (Tregenna, 2011). The trend of increasing capital intensity and its effect on manufacturing employment is shown in Figure 6.

**Figure 5. Increases in Productivity and its Effect on Manufacturing Employment**

![Graph showing increases in productivity and employment](image)

Source: Data obtained from Federal Reserve Bank of St. Louis
To further expand on the relationship between trade openness and productivity opportunities, Pierce and Schott (2012) contend that the Permanent Normal Trade Relations designation of China by the United States may have incentivized US manufacturers to increase the capital intensity of their operations. This implies that the capital to labor ratio increased for American operations and therefore less labor had to be employed in order to maintain levels of output (Pierce and Schott, 2012). In addition to this, Kollmeyer (2009) finds of a non-linear direct relationship between what he calls unbalanced productivity growth and deindustrialization. In this finding, Kollmeyer describes the effect of an economy in which the productivity growth rates for its manufacturing industry are larger than the productivity growth rates for the rest of its economy. Following the logic of the inverse relationship between productivity growth and relative employment share (Gordon, 1995), as the manufacturing productivity exceeds the productivity of its non-manufacturing industries (finance, services, non-farm business, etc), an
economy should be experiencing deindustrialization. More specifically, it should be experiencing a downturn in the employment share of a manufacturing industry relative to the total workforce of the economy as the manufacturing sector experience redundant labor employment. Kollmeyer continues to explain that although high manufacturing productivity rates (rates of capital intensity, rates of offshoring, investment in IT capital, etc.) will deindustrialize the manufacturing sector, it will also do so at increasingly smaller rates (Kollmeyer, 2009; Houseman, 2018).

In some respects, trade openness and productivity gains may be interrelated (Nager, 2017; Autor, Dorn, and Hanson, 2015). As globalized linkages increase and an economy performs more trade, domestic firms are more free and likely to outsource labor internationally. This would reflect as a decrease in the domestic trade balance as well as a productivity gain. This is because as firms outsource low-skilled positions to developing markets, the production processes that are left in the domestic market become more specialized and therefore more productive (Autor, Dorn, and Hanson, 2015). For this reason, accounting for disaggregated employment effects may be difficult as some changes in industrial structure could be indirectly the effect of both trade and productivity.

Data obtained for both quarterly and annual productivity growth rates of the manufacturing and the nonfarm business sectors tell two contradictory stories (Bureau of Labor Statistics). In accordance to the theories of both Kollmeyer (2009) and Gordon (1995), annual productivity growth rates for the manufacturing sector exceeded productivity rates for the non-manufacturing sector for most annual recordings between the years 1988 and 2012 (Figure 7). However, this graph reveals something interesting about the supposed theories of Kollmeyer
and Gordon, among others (Acemoglu, et al, 2014). While it is true that manufacturing productivity exceeded the non-manufacturing sector in most cases, this productivity overperformance does not show an obvious effect on the total manufacturing employment. The relationship between imbalanced manufacturing productivity growth and diminished manufacturing employment is only implied in certain time frames (notably in quarters of 2001 and 2009, times of recession). Moreover, this productivity-employment relationship does not seem to have an effect anytime prior to 2000, at which time productivity and employment actually grew parallel to each other. Clearly, there must be another factor that spurred the accelerated deindustrialization of the 21st century.

**Figure 7. Productivity Growth Rates of Manufacturing and Non-Manufacturing Sectors**

![Productivity Growth Rates](image)

Source: Data obtained from the Federal Reserve Bank of St. Louis and the Bureau for Labor Statistics

Additionally, adopting the model used by Houseman, Kurz, Lengermann, and Mandel (2011), we can illustrate possible inconsistencies in the argument that productivity is the main
contributor to American deindustrialization of the 21st century (Depicted in Figure 8). In this model, total manufacturing employment in the American economy is graphed against what is called a labor productivity index. This index is essentially the ratio of manufacturing labor productivity to nonfarm business manufacturing labor productivity (Both datasets of productivity indexed as 2009 = 100). Following the theories of Kollmeyer and Gordon, periods wherein the ratio of manufacturing to non-manufacturing productivity exceeds 1.00 should experience a decline in manufacturing employment. However, according to Figure 8 which depicts this model, this ratio only exceeded 1.00 starting in January of 2005, after which the productivity index remained above parity for most quarters until 2017. The dashed black line indicates the parity line which marks the points at which manufacturing productivity exceeds nonfarm business productivity. Most remarkable about this approach is that this parity shows that imbalanced productivity growth does not account for any manufacturing decline prior to 2005. While the precipitous decline in manufacturing employment began in 2000 with the Dot Com recession, Houseman et al. shows that productivity imbalances were not reflected until half a decade after. However, the theory of imbalanced productivity growth seems to reflect the changes in the structure of the labor force following the Great Recession. At this time, manufacturing employment saw slow upticks coupled with very slow or even negative productivity growth rates, concurrent with the models of Kollmeyer and Gordon. It follows that when labor productivity rates are low, manufacturing firms are inclined to hire more workers to compensate for the marginal productivity of each worker (Gordon, 1995).

Data and research on the effect of productivity growth rates on the rate of change on manufacturing employment varies across studies and time frames (Nager, 2017; Houseman, et al,
2011; Rose, 2018; Hicks and Devaraj, 2017). Although this variance in data exists, it does not disqualify productivity as a contributor to deindustrialization. This is due to the fact that many other inputs and factors can influence productivity and as a result influence manufacturing employment. In terms of its influence on structural aspects of economic metrics, productivity is a relatively nebulous concept that is easily influenced by many other factors and can often be correlated to other factors through a feedback loop that feeds off of itself (Syverson, 2016; Mallick and Sousa, 2017; Acemoglu, et al, 2014).

Figure 8. Imbalanced Cross-Sector Productivity Growth and its Effect on Employment

Yet something that still remains striking is the period before the 2001 recession, when productivity rates in the manufacturing sector did not reflect the reality of employment well. In a reasoning against the role of productivity in the shrinking of manufacturing employment, Nager (2017) argues that the relative productivity growth in manufacturing was not enough to explain the large decrease in manufacturing jobs during that time. Nager uses the model of Kollmeyer
and Gordon to show that manufacturing employment can and will decrease only in situations in which the productivity growth rate manufacturing exceeds that of the nonfarm business sector. Nager reminds the reader that the reason manufacturing employment is supposed to decline is not because of productivity, but relative productivity growth. Following this logic, Nager attempts to contend that the data do not support the idea of relative productivity inspired job loss. From 1990-2000, manufacturing productivity was 25.8% higher than that of the entire American economy. For the years 2000-2012, this number was only 22.7. Yet despite this slowdown of productivity, the decade of 2000-2012 experienced manufacturing job losses ten times higher than than of the decade prior (Nager, 2017). While this analysis does not take into account important factors happening during this time such as the enormous credit crunch of 2000-2002 and 2007-2009, Nager still makes the point that clearly relative productivity imbalances alone cannot explain the rapid deindustrialization of the United States (Nager, 2017; Tregenna, 2011).

**Achieving Post-Industrialism: The Role of the Services Sector**

Another significant yet historically overlooked component that affects the competitiveness of American manufacturing and therefore the manufacturing share of employment is the steadily rising income or GDP/cap of Americans (Kollmeyer, 2009; Alderson, 1999; McKinnon, 2004; McKinnon, 2013). Notable work in this field has researched the relationship between changes in income and changes in net exports (Chinn, 2005). Chinn elaborates on the original Houthakker-Magee Effect which dictates that the income elasticity for imports tends to be near double the income elasticity for exports in the United States (Chinn, 2005; DeCanio, 2016). Following this logic, Chinn explains that as the United States developed
economically over the 20th century and continues to do so, it naturally created the conditions for its steadily growing trade deficit (Relationship depicted in Figure 9) (Chinn, 2005; Alderson, 1999).

**Figure 9. National Income Led Decreases in External Surplus**

![Graph showing economic data over time](image)

*Note: Data obtained from Federal Reserve Bank of St. Louis*

The discussion of the effect of income on industry also talks about what is considered the natural course of economic development (Alderson, 1999). It is widely accepted that as an economy develops into its industrial stage, demand for agricultural goods relative to that of manufactured goods falls (Alderson, 1999; Kollmeyer, 2009). This is due to the higher demand for manufactured goods due to the changing structure of industry during industrialization. This leads to increased prices of manufactured goods and a declining terms of trade for agrarian economies. Because most developing countries which depend on export orientation specialize in agrarian production in the beginning stages of development, this leads to an increase of inequality between nations (Perry, 1967). This theory of natural structural change in industry
lends itself to explaining a phenomenon that has been occurring in the past several decades. Once an economy surpasses a certain level of national income, the relative demand of manufacturing actually decreases relative to that of services (Kollmeyer, 2009; Perry, 1967). This creates a rising relative price of services and a lower domestic demand for manufacturing. The higher aggregate demand for services will have an effect on the employment share of services in the United States, especially when accounting for the Houthakker-Magee model of manufacturing imports. These two theories combined explain that due to the unbalanced increase in the trade deficit with increasing income, the income and manufacturing share of manufacturing as an industry will decrease with time (Perry, 1967; Alderson, 1999; Thirlwall, 1980). This tandem decline in manufacturing employment and value added share along with the increase in services employment and value added share in the US economy is illustrated by Figure 10.

**Figure 10. Services Overtakes Manufacturing as a Source of American Employment**

![Graph showing the domination of services over manufacturing employment](image)

*Note: Data obtained from the Federal Reserve Bank of St. Louis*
American Deindustrialization and the Rise of Right-Wing Populism

While the employment decline in the manufacturing sector has been a hot topic in political debates over the last several decades, the discussions therein are dominated by the incrimination of imbalanced trade with China (Sweeney, 2018; Scott, 2017; Rodrik, 2018; McKinnon, 2013). The other factors at play such as capital intensity and demand for services are often underplayed and even omitted (Levine, 2018; Spivack, 2018; Dyer, 2016). The appropriation of deindustrialization and the plight of blue collar workers into political agendas is common among populist candidates for public office, most of whom espouse views of economic nationalism and isolation in light of the negative effects of globalization (Berlet and Lyons, 2000; Stiglitz, 2018). Populist pundits often recommend trade policies such as tariffs, import quotas, and abandonment of trade agreements in order to restore a country’s industrial capacity (Stiglitz, 2018). This approach to economic policy was found throughout the 2016 Presidential campaign of Donald J. Trump, who often scapegoated foreign powers and immigrants in the economic plight of the American workforce.

Donald Trump’s campaign is said to have pandered to economic fears of disaffected workers who felt increasingly powerless over their own economic fate (Casselman, 2017). Trump promised to restabilize the American manufacturing sector and “drain the swamp” of establishment politicians who he argued allowed the economy to deindustrialize (Stiglitz, 2018). These assertions are based on platforms of right-wing populism, a rising school of conservative economics that highlights divisions between social and economic groups in an attempt to describe the negative effects of globalization (Otsch et al, 2018). This resurgence of economic
thought has been on the rise among developed nations in North America and Europe facing deindustrialization, with an increasing share of pundits adopting right-wing populist views of trade and immigration. While the 2016 Presidential saw the emergence of both left and right wings of populist thought which are seen as reactionary forces against the unforeseen shocks of globalization, the latter highlighted ethnic and nationalist differences and their role in the changing dynamics of American industry (Rodrik, 2018). The views of Donald Trump and his campaign were examples of this as they described globalization and the increasing interconnectedness of the American economy as undermining and even malicious forces countering American economic interests. While these assertions were dismissed by the political establishment in Washington, they quickly took root among large sections of the American electorate.

With trade and industry central to the hot button issues of the Election, the Trump campaign proposed major shifts to establishment policies that marked a critical departure from traditional conservative policies of the GOP. A party once known as champions of free trade and market oriented policy was now backing the campaign of a businessman who proposed economic protectionism and nationalism. Notably, Trump was set on hardlining China on trade and convincing the Chinese Communist Party to work on shrinking the American trade deficit. Moreover, China faced the brunt of Trump’s economic dissatisfaction and was scapegoated for most of America’s economic struggles. China was cited as the major source of deindustrialization occurring in the Rust Belt states from Wisconsin to Mississippi (Levine, 2018). The scapegoating of China by the Trump campaign manifested itself in staunch protectionist policies, including but not limited to large tariffs on Chinese goods, designation of
China as a currency manipulator, and the general departure of the United States from the forefront of the global economy (Noland and Hufbauer, 2016). Trump captured this anti-globalist sentiment among displaced laborers by separating himself from the trade policies of his predecessors whom he credited with the rusting out of American Industry using his often used medium of Twitter. “From Bush 1 to present, our Country has lost more than 55,000 factories, 6,000,000 manufacturing jobs and accumulated Trade Deficits of more than 12 Trillion Dollars. Last year we had a Trade Deficit of almost 800 Billion Dollars. Bad Policies & Leadership. Must WIN again! #MAGA” (@DonaldJTrump, 2018).

Additionally, Trump capitalized on this divorce of consensus between establishment politicians and many of their constituents, playing on the view of elected officials as “out of touch” and removed from the interests of the everyday American (Camosy, 2016). He used this continuous rebuke of Washington politics to debunk what he saw as a myth of economic recovery under President Barack Obama, whom Trump very often criticized. This ‘myth’ was mirrored by the supposed reality that Trump highlighted throughout his campaign, a reality that Trump himself described during his inauguration speech as an economy of “rusted-out factories scattered like tombstones across the landscape of our nation” (Trump, 2017). This highlight of communities largely disaffected by the post-financial crisis economic recovery under President Obama won Trump favor in more rural and isolated areas of the United States (Balz, 2017).

Moreover, Trump’s rhetoric on the campaign trail was said to have established him a champion of the working class and of the manufacturing sector. As Trump alleged himself, “I will be the greatest jobs President that God ever created” (Trump, 2015). While this declaration was one of many self-aggrandizing claims made by Trump during the campaign, it also served as a
 thinly-veiled scolding of the Obama Administration’s success in economic recovery. This marriage of populist economic policy coupled with admonition of President Obama played very well among the industrial base of the American electorate, adding critical momentum to the Trump campaign (Monnat and Brown, 2017).

As an extension of his rebuke of Obama’s economic legacy, Donald Trump went on to criticize his opponent for the Presidency Hillary Clinton, often referring to her as a status quo candidate who would be a simple continuation of Obama era policies. Along with the other slanderous terms used by Trump and his campaign to refer to Clinton, this categorization of Clinton as an extension of Obama’s Presidency helped stir support for Trump from a working class electorate who desperately craved economic change (Bittman, 2016). In many ways, the 2016 Presidential Election was seen as a referendum on the approval of the status quo and of the success of Obama’s economic recovery. Although it is true that the Obama Administration saw the creation of over 11 million jobs over the course of 75 consecutive months of job growth, entire sections of the United States saw little to no change of their economic well being (Bureau of Labor Statistics, 2018). More specifically, over the course of its lowest and highest levels of the Obama era (March 2010 - November 2016), manufacturing only gained 900,000 jobs of the 11 million total jobs created under Barack Obama (BLS, 2018). While the job creation under Obama undoubtedly was significant and made major gained since the implosion of the economy in 2008, the American economy silently underwent a major shift in industrial structure. As Obama was praised for the success of his economic policies, much of the manufacturing labor force still had trouble being reabsorbed into the labor force. This led to the emergence of a new
“silent majority” that demanded change as most of the country was experiencing economic gains (Inglehart and Norris, 2016).

The capturing of the economic anxieties of this silent majority carried Donald J. Trump past the 270 electoral vote threshold and into victory on November 8th, 2016, an event that stunned the establishment in Washington as well as in the media. In a departure from traditional voting patterns, Trump successfully ‘flipped’ several key states which voted for Barack Obama in the 2012 Election. This success was widely credited to the political realignment of the industrial Midwestern states away from establishment Democratic support and toward support of the newly branded GOP under Donald Trump (Balz, 2017). This realignment (depicted in Figure 11), allowed Trump to carry the states of Pennsylvania, Michigan, Wisconsin, Iowa, Ohio, and Florida, all of which voted for Barack Obama in 2012 (Politico, 2017). States which were mostly projected to vote for Hillary Clinton spoke out against the status quo and put their trust into a man who promised to bring their jobs back from abroad.

Figure 11. State Level and County Level Results of the 2016 Presidential Election

Note: Both State and County level maps taken from New York Times. Areas in red indicate states/counties won by Donald J. Trump. Areas in blue indicate states/counties won by Hillary Clinton. States marked dark red indicate states won by Barack Obama in 2012 and ‘flipped’ by Donald J. Trump in 2016.
On a county level, it has been shown that the widespread abandonment of Democratic support among the electorate is rooted in the changing voting patterns of rural voters. While voters in urban and suburban areas of the United States actually saw stagnation in their support for Democratic Presidential candidates between 2008-2016, rural support for Republican candidates on average increased from 53% to 62% in the same time period (Kurtzleben, 2016). While most industrial activity in manufacturing output is concentrated in urban areas, the relationship between the spatial distribution of industry and voting patterns in the 2016 Election is unclear (US Department of Agriculture, 2017; Helper et al, 2012). Furthermore, it has been shown that metropolitan counties lost manufacturing jobs at a rate faster than nonmetropolitan counties (Helper et al, 2012). When the relationship between manufacturing capacity per county and its voting results in the 2016 Election are disaggregated by rate of deindustrialization (that is, rate of decline of employment share of manufacturing), the literature exposes an interesting dichotomy.

**Looking Deeper: A County Level Analysis of Deindustrialization and Voting Patterns**

The majority of American counties have experienced deindustrialization between 2001 and 2016 (BLS, 2017). Even when accounting for the economic recovery after the financial crisis, the counties in which manufacturing employment increased is extremely spatially concentrated (Figure 12). This figure interestingly shows a lack of counties with manufacturing employment growth in states such as Pennsylvania, Michigan, Wisconsin, and North Carolina, all of which were critical to Donald Trump’s electoral victory. This trend is congruent to the argument presented by the ‘silent majority’, which contends that the economic recovery under
Barack Obama is overvalued and the realities of many Americans remains stagnant, and in some cases, even worse. On the aggregate, the total manufacturing employment in the United States barely edged over 2009 levels, but many counties still face record low absolute levels of manufacturing employment (BLS, 2017; Politifact, 2018).

While most of American counties have experienced net losses in manufacturing employment, many have successfully reabsorbed the displaced labor into other sectors, primarily services (BLS, 2017). The services sector represents industries such as retail, food service, healthcare, finance, etc. On the other hand, counties that have seen less success in allocated the excess labor have seen a populace more economically disenfranchised and politically polarized. In depicting the effect of the aforementioned deindustrializing factors that I studied, several authors find correlation between rising trends of these variables and county level support for Donald Trump (Autor et al, 2016; Frey et al, 2017).

**Figure 12. County Level Manufacturing Employment Growth**

Note: Data taken from Bureau of Labor Statistics, Areas in green represent counties which have experienced increases in absolute levels of manufacturing employment.
Autor et al (2016) found that counties with higher job losses as a result of import competition saw larger rates of political polarization. Additionally, congressional districts with higher import competition have seen decreased support for moderate candidates for local representatives and higher support for candidates considered on the fringe of the political spectrum. Most of this polarization has been manifested in the increased support for right-wing populism, with a larger array of candidates nationwide adopting the economic and social platforms of Donald J. Trump. This is also seen as a reaction to the increased economic dissatisfaction of the working class and the inability of some workers to reenter the labor force through other sectors outside of manufacturing. (Autor et al, 2016). While this relationship between import competition and support for Donald Trump can be seen as structural, it can also be cited as the success of Trump’s rhetoric in stirring ant-globalist and anti-China resentment throughout the electorate. This strategy of scapegoating China for economic problems has trickled down into local Elections as well, which have seen an increase in the frequency of candidates citing China as a source of American economic woes (Ramirez, 2012). This rhetoric often uses the argument of alleged Chinese currency manipulation and industrial dumping to explain the imbalanced trade deficit with China and its effect on American manufacturing employment (Ramirez, 2012).

Frey et al (2017) use a similar approach in understanding the shifts in industrial composition and their political outcomes by examining changes in county level voting records based in rates of capital intensity of manufacturing and automation. The authors find a positive correlation in American counties between rates of capitalization and the increase in capital intensity of manufacturing processes, and the support for Donald Trump in the 2016 Election.
This is congruent to my argument and shows that the shift toward mechanization of manufacturing displaces labor, much of which becomes politically polarized and is more prone to vote against the interests of establishment politicians (Frey et al, 2017). Moreover, the authors find higher rates of support for Trump in counties which are more dominated by low-educated workers in routine jobs. Workers displaced by the “Computer Revolution” demand structural change in establishment economic policy (Sterniczky, 2017). This increase in luditic sentiments bring into question the future of labor relations and the gentle balancing act of human involvement in industry and the inevitable technological progress in industry and society.

Although economic output and productivity depends on capitalization and automation in order to meet the demands of the global economy, the increasing rate of labor displacement is beginning to call a new era in welfare economics, as larger proportions of the labor force demand social programs to alleviate the shock of displacement (Bonvillian, 2017).

Although there is established relationships between the factors that affect deindustrialization and the voting patterns of the resulting displaced labor, there is no clear evidence that deindustrialization in general is statistically significant in predicting electoral support for Donald Trump in the 2016 Election (Freund and Sidhu, 2017). While controlling for standard voting determinants such as party affiliation and regional economic structure, Freund and Sidhu examine the changes in Republican shares of Election results between 2012 and 2016 among American counties experiencing a decline in manufacturing employment. Although deindustrialization was a hot issue in the 2016 Presidential Election, Freund and Sidhu find that changes in manufacturing employment on a county level are not statistically significant in determining Republican shares of Election results.
Although this finding provides critical insight into the role of manufacturing in the 2016 Election that is contrary to my hypothesis, it also provides perspective on the issue that can help explain the social and economic factors that led to Trump’s victory. Freund and Sidhu explain that the changes to the manufacturing sector might be intersectional. That is, there may be a correlation between the types of workers being displaced and how they voted in the Election. When disaggregating the displaced workers by factors such as ethnicity and education, the regression results offer interesting results. This study finds that while change in manufacturing employment did not account for changes in Election results, it did yield results between predominantly white and non-white manufacturing counties. The change in Republican vote share in the 2016 Election is positively correlated to manufacturing decline in white counties and negatively correlated to manufacturing decline in non-white dominated counties. While the decline in manufacturing employment may have had an effect on the voting patterns of white manufacturing workers, this was offset by the negative relationship in non-white dominated counties and therefore did not yield any aggregate results across American counties (Freund and Sidhu, 2017).

The extent to which manufacturing employment played a part in determining voting results was manifested through race. While Donald Trump’s other social and political policies that polarized much of the electorate were not deal-breakers for white majority counties, they were more than enough to sway non-white majority manufacturing counties away from voting for him. The authors go on to explain that the political outcomes of Trump’s manufacturing policies were not exclusive of his other stances. Freund and Sidhu’s work indicates that Trump supporters did not have an affinity for any one single issue in particular, but rather voted at the
intersection of his social and economic policies. That is to say that his economic policies of anti-globalization and trade openness attracted the same people who had an affinity for his social policies of anti-immigration. In essence, many Trump voters wanted to ‘Build The Wall’ against immigrants as well as foreign imports. As a result, Trump’s victory served as a loud rebuke of decades of neoliberal policies that were seen as a great siphoning of wealth and social status away from the white American majority.

The findings of Freund and Sidhu are congruent to the mainstream consensus in the post-Election literature (Monnat and Brown, 2017; Tyson and Maniam, 2016; Lopez, 2017). The overwhelming overperformance of white support for Donald Trump propelled him over the 270 electoral vote threshold into victory in what has been described as a “whitelash” (Ryan, 2016). Morgan and Lee (2018) show that Trump’s victory was based on his appeal toward anxious white blue-collar workers. However, this anxiety was not based in economic performance as I hypothesized, but instead was an anxiety of losing social status. White Trump supporters were more likely to fear losing majority status and sociopolitical power rather than fear economic underperformance (Morgan and Lee, 2018; Pettigrew, 2017; Mutz, 2018; Chokshi, 2018).

However, this does not necessarily discount the role of Trump’s manufacturing policies on the outcome of the Election. This is because white voters did not see his industrial policy as mutually exclusive of his other economic and social policies. Voters who supported Trump’s policies more likely than not supported them in tandem rather than in isolation of each other. That is to say, people who supported tariffs against China were also likely to also support building a southern border with Mexico and placing a moratorium on Muslim immigration (Morgan and Lee, 2018). This marriage of economic and social right-wing populism allowed for
Trump to capture the anxious sentiments of many white rural voters. Therefore and thus, the literature on this subject cannot clearly conclude that manufacturing decline in isolation had any significance in affecting the way citizens voted in the 2016 Election. However, in the same vein, it cannot conclude that manufacturing decline did not have an effect on the way citizens voted in tandem with Trump’s other policies. While manufacturing employment decline is traditionally viewed as an issue divorced from ethnicity and race relations, it has become politicized into an issue of social control by right-wing populist candidates like Donald J. Trump through tactics of political manipulation and playing to the fears of the white majority.

**Methodology for Part One**

The first part of this research project aims to provide comparative data on relative shares of variance in manufacturing employment based on volume of trade with China, relative productivity growth rates, and domestic demand for services. Ultimately, I aim to prove that trade with China is not the sole reason for the deindustrialization of the United States, and that the other two variables at play play a much larger role in the decline in American manufacturing than thought in the mainstream literature. In order to do this, I have compiled aggregate data on all variables and running an Ordinary Least Squares Regression. This way, I will be able to disaggregate the regression data in order to see how much variance in manufacturing employment each variable accounts for individually. As a result, I hope to prove that the $R^2$ statistic for Productivity and Service is close to if not exceeding the same statistic for Chinese Trade.
Therefore, I will be using three independent variables, each one representing the US volume of trade with China (TRDCHN), growth rates of productivity in the US manufacturing sector (MANPROD), and consumer price indexes for services (SERVX), respectively. I will be using these variables to find the variance in my dependent variable, which is the manufacturing employment share of the US economy (MANEMP). Ultimately, I am aiming to prove that these three aforementioned variables are statistically significant in measuring the levels of deindustrialization which faced the United States for several decades.

In compiling data, I will be using the Federal Reserve Bank of St. Louis database (FRED) to research information on my proxy variables. For Chinese trade volume, I have compiled quarterly and yearly levels of American exports to China, Chinese exports to the United States, and the United States’ trade balance with China. These figures are obtained using both FRED and the United States Census Bureau database (Census.gov). For productivity growth, I have compiled data from FRED on the monthly and yearly percent changes in productivity growth rates in the manufacturing and non-manufacturing sectors from quarter/year one year ago as well as manufacturing productivity indexes for base year 2009=100. For service demand, I have compiled data from FRED, the Bureau of Economic Activity (BEA), and the Bureau of Labor Statistics (BLS) on quarterly and yearly Consumer Price Indexes for services for base year 1983=100 in the United States. I will be regressing all three of these datasets against data on the absolute level of manufacturing employment in the US economy measures in thousands of persons.

In measuring the success of my hypothesis, I will be seeing (1) whether all three independent variables are statistically significant (whether they have a p-value of less than 0.05,
the value threshold necessary for rejecting $H_o$ at a 95% confidence interval) and (2) whether the $R^2$ and Coefficients of MANPROD and SERVX are equal to or larger than that of TRDCHN. The latter metric will allow me to understand the relative shares of variance that each variable accounts for. Should my hypothesis be proven correct, this will further my stance on the issue and allow me to talk on the hyperbolized effect of Chinese import competition and the politicization of Chinese trade in attempt to justify protectionist policies against China.

After identifying my dependent variable, independent variables, and applicable proxy data, I have concluded that the applicable regression equation reads as follows:

$$MANEMP = b_0 + b_1P\text{RODMAN} + b_2CHNTRD + b_3SERVX + e_0$$

Whereas:

- $b_0 =$ Intercept
- $b_1 =$ Coefficient for MANPROD
- $b_2 =$ Coefficient for CHNTRD
- $b_3 =$ Coefficient for SERVX
- $e_0 =$ Error Terms

**OLS Assumptions and Results**

The statistical process I have chosen yielded many surprising revelations. First, regarding the results of my regression:

| Table 1. ANOVA Results for Relative Significance of Factors in Manufacturing Decline |
|----------------------------------------|---------------------------------|
| **Regression Statistics**              |                                 |
| **Multiple R**                         | 0.958998                        |
With a regression significance F statistic of 1.65E-65, I can confidently say that the regression is statistically significant and that my independent variables all account for at least some of the variance in my dependent variable. The question remains to what degree each explanatory variable accounts for the variance in MANEMP. To my surprise, the combined effects of all three independent variables account for more variance in my dependent variable than I thought. With an adjusted R Square statistic of 0.917, I can confidently say that these variables play a very important role in considering the causes of relative manufacturing
employment and the trend of deindustrialization. Specifically, these three dependent variables combined account for precisely 91.77% of the variance in the downward trend of manufacturing employment since 1987. With individual p-values well below 0.05, the regression analysis also shows that each variable is independently statistically significant and accounts for the decline of the share of manufacturing. With these results, I have conducted a regression that reads as follows:

\[ RME = 21.067 - 0.094\text{MANPROD} + 0.0000313\text{TRDCHN} + 0.0151\text{SERVX} + e_o \]

The assumptions of my Ordinary Least Squares Regression must also be cleared for my regression to remain credible. The following seven OLS assumptions ensure that the data I have gathered and derived are normally distributed, are not autocorrelated, and produce residuals that are not correlated to the explanatory variables or the predicted regression values. First and foremost, it is important to weed out any data points that are considered outliers. This is defined as any point in the data that is at least three standard deviations away from the mean of the residuals. With a residual mean of near zero (0.000000185), my data clears the first assumption of a residual zero mean. Additionally, the residuals of my regression are mostly independent of each other, as represented in Assumption Figure 1.

**Assumption Figure 1. Residual Independence**
Furthermore, Assumption Figure 2 and Assumption Figure 3 show the normal distribution of the residuals as well as the predicted regression values. Although the representation of the value distribution visually seems sporadic and random, these values are still within three standard deviations of the mean and are distributed normally around the mean, albeit with a relatively small sample size which stunts its distribution.

**Assumption Figure 2 and 3. Normal Distribution of Residuals and Predicted Values**

The regression results go on to pass the Variance and Homoscedasticity assumption tests, which show that the residuals have a mostly similar variance around its mean 0 when plotted against the predicted values of the regression (Assumption Figure 4).
Assumption Figure 4. Constant Variance and Homoscedasticity

The autocorrelation assumption is expanded on in Assumption Figure 5, which shows the computation of the Durbin Watson Statistic. This shows the degree to which the residuals are autocorrelated and how much they depend on each other for their values.

Assumption Figure 5. Autocorrelation and the Durbin Watson Statistic

<table>
<thead>
<tr>
<th>Sum of Squared Residuals</th>
<th>55.499</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of Squared Difference of Residuals</td>
<td>8.512</td>
</tr>
<tr>
<td>Durbin Watson Statistic</td>
<td>0.15337</td>
</tr>
</tbody>
</table>

The Durbin Watson Statistic is a metric between 0 and 4 that measures autocorrelation. Readings near 0 depict higher rates of autocorrelation. The Statistic of my regression is approaching 0 implying some autocorrelation, but this is expected as the regression is depicting the trend in manufacturing employment which has steadily exclusively trended downward with similar rates of change for most of the timeline in focus.

Assumption Figure 6 shows the correlation assumption test which tests the degree to which the residuals are correlated to the values of the dependent variables. Although the variables are highly correlated, this is to be expected from variables which are highly correlated.
in nature and have been used to measure employment for centuries. As mentioned in the literature review, trade and productivity are indicators of the status of the manufacturing labor market through the Houthakker-Magee model and the Average Product of Labor. However, the residuals are highly uncorrelated to the dependent variables. Seeing as though my error terms follow normal distribution, this allows us to consider my regression results as credible.

### Assumption Figure 6. Collinearity

<table>
<thead>
<tr>
<th></th>
<th>Manufacturing Productivity, 2009=100</th>
<th>Trade Balance with China</th>
<th>Consumer Price Index: Services</th>
<th>Manufacturing Employment</th>
<th>Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing Productivity</td>
<td>1</td>
<td>-0.95344</td>
<td>-0.95344</td>
<td>-0.95218</td>
<td>0.2834</td>
</tr>
<tr>
<td>Trade Balance with China</td>
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<td>1</td>
<td>-0.96479</td>
<td>0.93757</td>
<td>-0.00000003652</td>
</tr>
<tr>
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<td>-0.96479</td>
<td>1</td>
<td>-0.9353</td>
<td>-0.00000005040</td>
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<tr>
<td>Manufacturing Employment</td>
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<td>1</td>
<td>0.2834</td>
</tr>
<tr>
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<td>-0.00000005040</td>
<td>0.2834</td>
<td>1</td>
</tr>
</tbody>
</table>

### Analysis and Discussion

Based on the relative coefficient values for each of my independent variables, we can see a startling result. Based on these coefficients, we can see that both manufacturing productivity rates as well as demand for services actually account for more variance in manufacturing employment decline than trade with China. While all three of the independent variables are statistically significant with p-values well under the 0.05 threshold, manufacturing productivity actually has the highest share of variance in the dependent variable with a coefficient of -0.09. Although this seems meager, it is relatively much larger than the coefficients of the other two
variables. The share of variance of productivity is nearly nine (9) times more than the next more significant variable which is service demand. While all three are significant in identifying the causes of deindustrialization, it is clear that imbalanced productivity growth is the most prominent and is able to explain more of the decline in manufacturing employment. With all this being said, this regression analysis proves my hypothesis, providing evidence that the factors of productivity and services are indeed undervalued when considering the causes of declining employment shares of manufacturing in the United States.

Although there are many more tests against more complex datasets that can be run to measure the relative weight of each of these variables, it is still remarkable to see that despite the volume of rhetoric that is reserved for the issue of the American deficit with China, Chinese trade actually accounts for less employment decline that productivity and services growth. Due to the frequency at which pundits refer to China as a scapegoated source of the American manufacturing misery, one can expect that this hyperbole would be reflected statistically. However, despite the rhetoric against Chinese and American trade practices, the numbers seem to reflect a larger importance of capital substitution, income elasticity of services demand, and an increasing volume of productive offshoring. Contrary to the popular argument, my regression analysis shows that we can not conclude that trade volume with China has more significance in determining manufacturing employment levels in the United States.

**Policy Recommendations: What Can Be Done?**

Despite this revelation, it is still important to acknowledge that although Chinese trade does not seem to be the main component in American deindustrialization, it is still the largest
component by far in the American external deficit. Although I offer no definite evidence that Chinese trade is the main contributor to the decline of American manufacturing, the trade deficit with China, which hit a record 375 billion USD in 2017, is putting a strain on the American economy and is no longer sustainable in the long run (Census.gov; McKinnon, 2004). The determinants of the imbalanced trade with China is a topic of contentious debate among intellectuals, but it is ultimately an issue that puts the United States between a rock and a financial hard place.

But what can be done about this glaring disparity in American external economic posture? While some experts seem to give up on the idea that outbound jobs are never coming back (Casselman, 2016), others stay optimistic and expect the return of offshored jobs in a process dubbed “reshoring” (Buchanan, 2017). Although this was once thought impossible, many find hope in the campaign promises and the administrative stature of the Trump administration (Bloomberg, 2017; New York Times, 2017). Trump’s campaign sought early on to establish itself as the savior of American manufacturing with promises of protectionism, preferential tax treatment, and the restructuring of America’s trade deals (United States Trade Representative, 2017). Although Trump promised to bring jobs back by being hard on China and renegotiating NAFTA, his intentions may be misplaced (Altamirano-Jimenez, 2017). After all, the American economy historically has been one of the biggest proponents and beneficiaries of free trade (Federal Reserve Bank of St. Louis). Despite concerns of economic protectionists like Trump, the American economy actually gained 22 million jobs in the seven years following the ratification of the North American Free Trade Agreement (NAFTA) (Rose, 2018). Contrary to the perceived net losses of globalization and increased trade, the majority of economists still
agree that free trade create net positives for everyone (Rose, 2018; Hicks and Devaraj, 2018; Nager, 2017; Autor et al, 2017).

Additionally, the recent initiatives undertaken by the Trump administration in placing duties on Chinese imports may exacerbate the deindustrialization issue (Harwood, 2018). As the two countries retreat into economic isolation from each other, the benefits of free trade that American consumers have been enjoying over the past several decades may fade away (Yglesias, 2018). Ultimately, the trade wars that the Trump administration is oddly enthusiastic about (Yglesias, 2018) will not reap positives for anyone. Increased tariffs and quotas will not only raise prices for global consumers, but could potentially create a massive credit crunch on a global scale (Domm, 2018). As the old saying goes, no one wins in a trade war.

Alternatively, the United States should try to alleviate its trade-induced woes by further encouraging free trade. Although this may sound counterintuitive, promoting free trade includes promotion on both sides of the trading aisle. This means the negotiation of trade deals that are bilateral and fair, as opposed to negotiations and trade talks that leave too much room for remaining trade barriers. Examples of this would be the direct negotiation with China in order to convince the nation to continue lowering its tariffs as per WTO guidelines and reduce government subsidy that restrict import competition. China has been an outlier in imbalanced trade volume due in part to these trade policies and it would behoove all parties involved should China decide to let go of its stronghold of its industry (Thorbecke, 2015).

In regards of the concerns of the continuing vulnerability of the American manufacturing sector due to free trade, the United States should accept the natural restructuring of its economy and move toward the encouragement of industries in which it can obtain a comparative
advantage. Due to the overabundance of cheap low-skilled labor in China and other parts of East Asia, it is highly unlikely that low-skilled divisions of industrial production processes will return to the United States (Casselman, 2016). Alternatively, the United States should refocus on promoting industries in which it already had global advantage. This includes sectors such as high-tech industry (industrial machinery, semiconductors, computer equipment, etc.), information technology (software, programming, etc.), and financial and logistical services (Wolf and Terrell, 2016).

The only issue in this is that these industries of high value added growth are geographically concentrated in high-tech cities and innovation hubs (Wolf and Terrell, 2016). Outside of these isolated bubbles of growth, employment in manufacturing has recovered at a sluggish pace following the financial crisis and Great Recession (The Century Foundation, 2016). Due to limited opportunities for re-employment in manufacturing and rigid labor markets in higher tech industry, many workers who have been displaced following the massive manufacturing job loss of the early 2000s still find themselves stuck in the cycle of frictional unemployment. Labor force participation is at a 40 year low following the hemorrhage of job loss in the last two decades (Bureau of Labor Statistics). This is due in part to the low rate of human capital and vocational training available to displaced workers.

For the United States to reinvigorate its labor force in industries which it can excel and be competitive in, workers must be able to feel comfortable and ready when leaving the frictional unemployment trap. This is difficult for many who might have been employed in a manufacturing sector for years or decades, and might have low levels of computer literacy and vocational training. This is why it’s important to reinvest in the American worker and provide
opportunities to those abandoned by offshoring for them to explore the possibilities of American
industry. In order for the United States to achieve prosperity in the post-industrial age as other
nations are currently (Piore, 2011), it’s important to provide citizens with the opportunity to
advance their own human capacity. This can be done through the promotion of trade schools,
encouraging enrollment in secondary and tertiary education, and specialization in vocational
training.

Furthermore, the United States should accept its new identity as a post-industrial service
economy by promoting research and development across sectors and industries through tax
incentives and savings promotion. The United States recorded its lowest personal savings rate on
record in 2017 with 2.7% of total disposable income and corporate savings have taken a
downturn since 2012 (Federal Reserve Bank of St. Louis). The promotion of savings and
industrial investment can spur innovation in high-tech industries and information services, which
is already one of the fastest growing sectors in the American labor force (Wolf and Terrell,
2016).

**Methodology for Part 2**

The second part of this research project aims to examine the relationship between the
county level decline of manufacturing employment and the corresponding county electoral result
in the 2016 Presidential Election. Ultimately, I aim to prove that American counties with larger
decreases in absolute manufacturing employment voted for Donald J. Trump with wider margins.
In order to do this, I have compiled aggregate data on county level manufacturing employment in
January 2001 and November 2016, to represent the structural shift of the American
manufacturing sector in the 21st century that led to political polarization. I have compiled all data available on the subject from the Bureau of Labor Statistics Quarterly Census of Employment and Wages, as several counties have suppressed manufacturing entries as they do not meet the qualitative and quantitative standards of the BLS. I found the rate of change between these two figures to see either a positive, negative, or stagnant change in absolute manufacturing employment per county.

I additionally compiled county level results of the 2016 President Election for 2,978 American counties (all counties for which this data is available) from the Politico 2016 Presidential Election Results Database. I found the Trump vote differential by subtracting Hillary Clinton’s county level electoral results from Donald Trump’s to find the percentage by which Trump either won or lost each county. Ultimately, I ran 48 Ordinary Least Squares Regressions for each state (minus Alaska, Hawaii, and Delaware, states for which manufacturing employment and election result data is heavily redacted) as well as one regression for a national level analysis to find the relationship between the county level rate of change of manufacturing employment (2001-2016) and the Trump Vote Differential for each respective county. This way, I was able to analyze whether or not manufacturing decline was statistically significant in explaining county level voting patterns in the 2016 Elections in each state. In essence, I hope to prove that the p-value for each state is less than 0.05 signifying that this relationship is statistically significant and that county level manufacturing employment decline can explain the restructuring of the political alignment of the American electorate.

Therefore, I will be using one independent variable and one dependent variable. My independent variable is the county level rate of change in manufacturing employment
(2001-2016) (ΔMANEMP). My dependent variable is the percentage by which Trump won or lost each county, measured by the difference between the percentage results of Trump and Clinton (TRUMPVOTE) (Results for Utah and Idaho counties also measure TRUMPVOTE by the difference between results for Trump and Clinton even for counties for which Gary Johnson or Evan McMullin came in second place).

After identifying my dependent variable and independent variable, I have concluded that the applicable regression equation reads as follows:

\[ \text{TRUMPVOTE} = b_0 + b_1 \Delta \text{MANEMP} + e_0 \]

Whereas:

- \( b_0 = \) Intercept
- \( b_1 = \) Coefficient for \( \Delta \text{MANEMP} \)
- \( e_0 = \) Error Terms

**OLS Assumptions and Results**

The 48 OLS Regressions I used for 49 states and the national level yielded very surprising results. The results of the regression are highlighted as follows:

<table>
<thead>
<tr>
<th>State</th>
<th>R Squared</th>
<th>P-Value</th>
<th>State</th>
<th>R Squared</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>0.012</td>
<td>1.29E-08</td>
<td>Montana</td>
<td>0.0236</td>
<td>0.417</td>
</tr>
<tr>
<td>Alabama</td>
<td>0.0007</td>
<td>0.834</td>
<td>Nebraska</td>
<td>0.080</td>
<td>0.025</td>
</tr>
<tr>
<td>Alaska</td>
<td>N/A</td>
<td>N/A</td>
<td>Nevada</td>
<td>0.176</td>
<td>0.259</td>
</tr>
<tr>
<td>Arizona</td>
<td>0.004</td>
<td>0.828</td>
<td>New Hampshire</td>
<td>0.180</td>
<td>0.294</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.023</td>
<td>0.22</td>
<td>New Jersey</td>
<td>0.261</td>
<td>0.0212</td>
</tr>
<tr>
<td>State</td>
<td>Manufacturing Employment Decline</td>
<td>Election Results</td>
<td>State</td>
<td>Manufacturing Employment Decline</td>
<td>Election Results</td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------------------</td>
<td>------------------</td>
<td>---------------</td>
<td>----------------------------------</td>
<td>------------------</td>
</tr>
<tr>
<td>California</td>
<td>0.007</td>
<td>0.545</td>
<td>New Mexico</td>
<td>0.090</td>
<td>0.185</td>
</tr>
<tr>
<td>Colorado</td>
<td>0.008</td>
<td>0.58</td>
<td>New York</td>
<td>0.080</td>
<td>0.0315</td>
</tr>
<tr>
<td>Connecticut</td>
<td>0.015</td>
<td>0.79</td>
<td>North Carolina</td>
<td>0.013</td>
<td>0.26</td>
</tr>
<tr>
<td>Delaware</td>
<td>N/A</td>
<td>N/A</td>
<td>North Dakota</td>
<td>0.040</td>
<td>0.359</td>
</tr>
<tr>
<td>Florida</td>
<td>0.02</td>
<td>0.27</td>
<td>Ohio</td>
<td>0.037</td>
<td>0.079</td>
</tr>
<tr>
<td>Georgia</td>
<td>0.007</td>
<td>0.319</td>
<td>Oklahoma</td>
<td>0.027</td>
<td>0.2246</td>
</tr>
<tr>
<td>Hawaii</td>
<td>N/A</td>
<td>N/A</td>
<td>Oregon</td>
<td>0.003</td>
<td>0.742</td>
</tr>
<tr>
<td>Idaho</td>
<td>0.007</td>
<td>0.614</td>
<td>Pennsylvania</td>
<td>0.003</td>
<td>0.653</td>
</tr>
<tr>
<td>Illinois</td>
<td>0.002</td>
<td>0.705</td>
<td>Rhode Island</td>
<td>0.998</td>
<td>0.02</td>
</tr>
<tr>
<td>Indiana</td>
<td>0.004</td>
<td>0.538</td>
<td>South Carolina</td>
<td>0.002</td>
<td>0.762</td>
</tr>
<tr>
<td>Iowa</td>
<td>0.002</td>
<td>0.667</td>
<td>South Dakota</td>
<td>0.107</td>
<td>0.0622</td>
</tr>
<tr>
<td>Kansas</td>
<td>0.028</td>
<td>0.145</td>
<td>Tennessee</td>
<td>6.51E-05</td>
<td>0.94</td>
</tr>
<tr>
<td>Kentucky</td>
<td>0.057</td>
<td>0.022</td>
<td>Texas</td>
<td>0.0001</td>
<td>0.852</td>
</tr>
<tr>
<td>Louisiana</td>
<td>0.004</td>
<td>0.649</td>
<td>Utah</td>
<td>0.018</td>
<td>0.531</td>
</tr>
<tr>
<td>Maine</td>
<td>0.026</td>
<td>0.58</td>
<td>Vermont</td>
<td>0.026</td>
<td>0.592</td>
</tr>
<tr>
<td>Maryland</td>
<td>0.072</td>
<td>0.225</td>
<td>Virginia</td>
<td>0.023</td>
<td>0.106</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>0.572</td>
<td>0.007</td>
<td>Washington</td>
<td>0.003</td>
<td>0.735</td>
</tr>
<tr>
<td>Michigan</td>
<td>0.0034</td>
<td>0.608</td>
<td>West Virginia</td>
<td>0.06</td>
<td>0.102</td>
</tr>
<tr>
<td>Minnesota</td>
<td>0.005</td>
<td>0.546</td>
<td>Wisconsin</td>
<td>0.024</td>
<td>0.198</td>
</tr>
<tr>
<td>Mississippi</td>
<td>0.0178</td>
<td>0.264</td>
<td>Wyoming</td>
<td>0.100</td>
<td>0.178</td>
</tr>
<tr>
<td>Missouri</td>
<td>0.00447</td>
<td>0.508</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In a surprising turn, I have found that manufacturing employment decline is not statistically significant in determining Election results in most states. It is however statistically significant for the states of Kentucky, Massachusetts, Nebraska, New Jersey, New York, and
Rhode Island. These states have proven its significance by presenting p-values below the confidence interval of 0.05. On an aggregate national scale however, manufacturing employment decline is a statistically significant indicator of Election results. The national aggregate showed the lowest p-value of any regression but still showed a very low R Squared value, similar to the R Squared values across all regressions. With an R Squared of 0.012, this means that the decline in manufacturing employment between 2001 and 2016 accounted for only 1.2% of the variance in the results of the 2016 Presidential Election. Although this slightly contradicts my initial hypothesis that deindustrialization had a significant role in the variance in the Election results, my hypothesis still stands true as my independent variable remains statistically significant despite its low R Squared. The following Table 2 illustrates the complete regression analysis for the national level:

<table>
<thead>
<tr>
<th>Regression Statistics</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.110792</td>
</tr>
<tr>
<td>R Square</td>
<td>0.012275</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.011898</td>
</tr>
<tr>
<td>Observations</td>
<td>2621</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>ANOVA</th>
<th>df</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>Significance F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>73059.32</td>
<td>73059.32</td>
<td>32.54752</td>
<td>1.29E-08</td>
</tr>
<tr>
<td>Residual</td>
<td>2619</td>
<td>5878862</td>
<td>2244.697</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2620</td>
<td>5951922</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard Error</td>
<td>T Stat</td>
<td>P-value</td>
<td>Lower 95%</td>
</tr>
<tr>
<td>---------------------------</td>
<td>-------------</td>
<td>----------------</td>
<td>--------</td>
<td>---------</td>
<td>-----------</td>
</tr>
<tr>
<td>Manufacturing Employment Decline (2001-2016)</td>
<td>0.17868</td>
<td>0.03132</td>
<td>5.705043</td>
<td>1.29E-8</td>
<td>0.117266</td>
</tr>
</tbody>
</table>

With significance F-Statistic and P-value of 1.29E-08, we can conclude that this regression is statistically significant. The R Squared and Coefficient of the variable in play are low but still significant in explaining voting patterns in the 2016 Election. Therefore, the following equation describes the relationship between manufacturing employment decline and the differential by which Donald Trump won or lost each county in the United States:

\[ TRUMP VOTE = -19.4083 + 0.17868ΔMANEMP + e_0 \]

For the statistical analysis of this regression to be credible, we must also check its Ordinary Least Squares assumptions. First, we isolate any outliers that lie outside of three standard deviations of the mean. Once we have done that, we can move onto the remaining OLS assumptions. According to the OLS assumptions, the data that I have gathered is generally normally distributed, is not autocorrelation, and has residuals independent of the independent and dependent variables, as well as independent of themselves. With a residual mean of near zero (0.000000644028), my data clears the first assumption. Additionally, the residuals for the data I gathered is independent of the predicted values for the regression, as depicted in Assumption Figure 7. This figure also depicts the constant variance of the residual, also known as the state of homoscedasticity, which is crucial for regression data to follow.

**Assumption Figure 7. Residual Independence and Constant Variance of the Residual**
Assumption Figure 8 shows the normal distribution of the residuals and the predicted regression values. This figure shows that this data is normally distributed and exists within three standard deviations of the mean, proving that there are no outliers.

**Assumption Figure 8. Normal Distribution of Predicted Regression Values and Residuals**

The regression data goes on to pass the autocorrelation test with a Durbin Watson Statistic of 1.83, implying very low autocorrelation. This is depicted in Assumption Figure 9. Furthermore, the residual data is independent of itself as depicted in Assumption Figure 10, which shows the residual data plotted against observation number. Lastly, the regression data has low coefficients of correlation meaning the residuals are not highly correlated to the explanatory and outcome variables (Assumption Figure 11).
Assumption Figure 9. Durbin Watson Statistic and Autocorrelation

| Sum of Squared Difference of Residuals | 10810988.88 |
| Sum of Squared Residuals               | 5878862.39  |
| Durbin Watson Statistic                | 1.838959336 |

Assumption Figure 10. Residual Independence Against Observation

Assumption Figure 11. Explanatory Variable and Residual Correlation

<table>
<thead>
<tr>
<th></th>
<th>Manufacturing Employment Decline</th>
<th>Trump Vote Differential</th>
<th>Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing Employment Decline</td>
<td>1</td>
<td>0.110792</td>
<td>0.993843592</td>
</tr>
<tr>
<td>Trump Vote Differential</td>
<td>0.110792</td>
<td>1</td>
<td>1.36E-16</td>
</tr>
<tr>
<td>Residuals</td>
<td>0.993843592</td>
<td>1.36E-16</td>
<td></td>
</tr>
</tbody>
</table>

Analysis, Discussion, and Implications

To my own surprise, my regression shows that while the role of manufacturing employment decline was statistically significant in determining voting patterns on a national
level, the degree of this effect was very small, only accounting for 1.2% of the variance of my dependent variable. More surprising is the lack of statistical significance on state levels. Only six of the 47 states I examined showed any statistical significance in the declines of their manufacturing employment. Furthermore, those six states showed relatively small coefficients of variance with the exception of Rhode Island and Massachusetts. While the average R Squared of the remaining four statistically significant states were somewhat expected, the unusually large R Squared of Massachusetts and Rhode Island is cause for intrigue. While I credit Rhode Island’s near perfect R Squared of .998 to a small sample size of only four counties with enough employment data to be considered, the case of Massachusetts in one that is not obviously explainable. While Massachusetts also has a relatively low quantity of data-counties available (12), it’s moderate large R Squared is enough to warrant further investigation.

In fact, upon further investigation of my regression results, I noticed that of the six states which show statistical significance (Kentucky, Massachusetts, Nebraska, New Jersey, New York, and Rhode Island), only one showed a direct relationship between a decline in manufacturing employment and an increase in support for Donald Trump. Kentucky’s Coefficient of Variance of -0.09 shows a very small but considerable correlation that matches my initial hypothesis. The remaining five states show strong correlation in the other direction. Counties which experience deeper declines in manufacturing employment in Massachusetts, Nebraska, New Jersey, New York, and Rhode Island actually had smaller shares of support for Donald Trump.

One possible explanation for this unforeseen phenomenon is that four of these five states lie within the traditionally liberal leaning North Atlantic region known as “The Blue Wall”. This
metaphorical wall describes the areas of most of the American Northeast which has voted overwhelmingly for Democrats for over thirty years (Donovan, 2016). While this argument may have held true in Presidential Election between 1992 and 2012, the 2016 Election tells a different story. Donald Trump famously “broke” the blue wall when he flipped critical electoral states like Pennsylvania, Michigan, and Wisconsin. While Michigan and Wisconsin were periphery blue wall states which were considered toss ups, the Democratic loss of Pennsylvania was considered one of the biggest shocks of the night of November 8th. While the decline in manufacturing employment was not statistically significant in Pennsylvania, it is interesting to note that Pennsylvania was the only state in the county to have seen manufacturing employment growth in only one county (Figure 12). While the factor of manufacturing employment was not significant in determining voting patterns of Pennsylvanians, my regression analysis does not disqualify the possibility that the decline in statewide manufacturing employment regardless of specific county location spurred anti-globalist and economic nationalist sentiments that wanted to see manufacturing jobs return to the Keystone State.

Moreover, this argument is very well applicable to every states that saw declines in manufacturing employment. Although county level analysis does not bear significant results, there is a possibility that voters by state voted with deindustrialization in mind. Because this has becoming a hot national issue over the last few decades, some worried voters could have finally found their candidate in 2016 who would bring manufacturing back to its historic high.

Ultimately, despite the not bearing the results that I had anticipated, my regression results shed light on some of the issues brought up in the mainstream literature. These findings are notably similar to those of Freund and Sidhu (2017), who found that manufacturing employment
decline was not significant but was when disaggregated on ethnicity and education level. Donald Trump’s campaign, much of which was based on economic isolation and ethnic/cultural divisions, deepened an already sensitive fissure in the American electorate. The American voting population became much more polarized among ethnic groups, gender, age, education levels, and many other categories, as opposed to in 2008 and 2012 (Autor et al. 2017). This fractionalization of the electorate has harrowing implications for the future of our labor force as well as the future of our democracy as a whole. While political polarization and rule by fringe politicians does not have direct and obvious impacts on the economy, it changes the way our government is run and our policies are enacted. Binder (2014) and Masket (2017) find that the increased polarization of our elected officials over the last several decades has prolonged political gridlock and reduced the productivity of our legislators. Polarizing issues such as healthcare, defense, and immigration have led to government shutdowns in the last couple of years alone and continue to hinder the ability of lawmakers to solve the problem of the hollowing out of our economy. It seems that the use of right-wing populism as a bandaid to the problem of declining manufacturing competitiveness might come back and bite the same people who helped its rise.

Conclusion

Productivity growth rates being the main determinant in relative manufacturing employment gives insight into the trend that is creating what Ross Perot called the “great sucking sound” of manufacturing jobs fleeing the country (New York Times, 1992). What is occurring to American industry is the continuous outsourcing and offshoring of jobs in an industry that was at one point the height of modern economic development. With manufacturing accounting for less
than 10% of national employment, the United States is currently undergoing a structural change in the labor market which it might not be able to accommodate for unless it undertakes a large scale investment of education and training (FRED). The financial crisis cost the American economy 8.7 million jobs, many of which were in manufacturing (Center on Budget and Policy Priorities). The hemorrhaging of jobs prior to this collapse due to the systemic global division of labor into low-skilled and high-skilled labor set the industry for a final squeeze during the Great Recession (McKinnon, 2004). Although the American economy has since then recovered the jobs lost since ‘08 plus some, the manufacturing industry has been hard hit, and may not be able to survive the injuries.

Since the Great Recession, manufacturing employment growth has stalled relative to other industries. From its lowest point of the financial crisis, manufacturing employment as an Index to 2009 levels has risen only 8.2% (FRED). Services on the other hand, has risen much faster. From its lowest point of the recession, the industry now employs 13% more people (FRED). While some of this growth in services employment is reflected in the redistribution of laid off manufacturing labor, the remaining displaced manufacturing labor force has yet to find its footing a rapidly computerizing and innovation economy (Autor, Dorn, Hanson, 2013). Although the economy as a whole regained pre-crisis employment levels, the size of the displaced population of workers sets up conditions for economic and social unrest in the long run (Bureau of Economic Activity). The inability for entire swaths of the labor force to reenter the economy festers resentment and political polarization which threatens the integrity of our very democracy. This economic abandonment was a major theme during the 2016 Presidential Election, during which candidates had their own reasoning as to why American laborers were
being squeezed for longer hours and lower wages. Notably, Donald Trump famously heralded a campaign based on protectionism and economic isolation. The discontent of the American working class has culminated in the rise of economic populism which has built walls and tariffs around our country to protect us from an issue that is rooted domestically. Unless we address this issue and face modern problems with modern solutions, we will continue to point fingers externally while we regress into our borders and abandon our long held promise to the world.

Furthermore, the surprising result of the 2016 Election should serve as a distressing tale of the consequences of unaddressed economic woes of everyday Americans. As politicians become distant from economic realities, average Americans fall into the hands of hatred and isolationism. Left unaltered, these newly recently surfaced cleavages within our society will do away with the representative democracy which we as Americans have heralded for over two hundred years. While coming together to create bipartisan answers to our biggest threats is hard, it might be the only thing standing between us from a long fall from socioeconomic grace.
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