Predicting Future Transformations and Labor Market Changes in the U.S. Manufacturing Sector Due to Industry Use of Automation and Robotics.

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

Beginning in the Industrial Revolution in the early 19th century, the primary goal of technology was to increase the productivity of individual workers by allowing them to generate more output compared to their previous methods in a given amount of time. This is evident from the relationship between the growth of the world population and production over time, where in the rate of production accelerated dramatically starting in the year 1800 compared to its stagnant and nearly constant rate up to that point (Lucas, 2004, p.4). This pattern can be seen following the development of the spinning jenny, power loom, cotton gin, and similar technological advancements in the mid to late 1700s. From 1790 to 1810, American cotton production increased from 1.5 million pounds to 85 million (Mohajan, 2019, p.8) and the production of textiles increased by 862 percent from 1770 to 1831 (Jackson, 1992, p.12). Rather than continuing the same processes and using the same tools as in earlier times, researchers including Lucas and Mohajan endorse the claim that technological advancements allowed human workers to become more productive in their given fields during this period.

Within the past 50 years, the use of robotics and the quest for automation has quickly accelerated. In 1993, the global stock of robots was roughly around 500,000 units, compared to 2019, where the global stock has increased to more than 2.5 million (Jurkat et al., 2022, p.673). At the same time, total factor productivity (TFP) from 1970 to 2007 has been continuing to grow by an average annual rate of one log point per year (Autor & Salomons, 2018, p.44). *Forbes* endorsed this trend as well, predicting that automation within manufacturing would "Dominate the Business 2022 Agenda" (Foster, 2022). While these trends indicate increased usage of robots, several scholars (Garcia et al.; Autor & Salomons; Baily & Bosworth) have researched the impact that this technology poses to the existing manufacturing labor force. Their analyses measure the degree to which these technologies are labor-displacing in the long term to workers in the manufacturing industry (displacement effect) as well as their impact on the changing labor demands for this industry that result in the growth and formation of new jobs (compensation effect). For the existing 15 million workers in manufacturing and laborers in similar industries such as construction, this issue is particularly pressing due to the uncertain future of their jobs and their ability to qualify for new roles within this industry. If automated robots later prove to be dominantly labor-displacing, millions of Americans in this industry will be vulnerable to losing their middle-class socioeconomic status and may have to settle for lower-paid positions based on their existing skills and education level.

Through this research, there is strong evidence to conclude that the use of automated robots in manufacturing will continue to displace blue-collar manufacturing workers into the future. However, I argue that this population's socioeconomic security is not under any significant threat due to the growth and expansion of employment in adjacent industries that provide similar incomes to their existing jobs. Therefore, this paper will advocate for the increased adoption of automated robots in the manufacturing sector by incentivizing U.S. businesses to implement this technology through the use of government subsidies.

In this paper, I will use labor market segmentation theory (Reich et al., 1973) and structural change theory (Agbenyo, 2020; Rodrik, 2013) to analyze how to use of automation has led to the decline of traditional jobs in manufacturing in favor for highly-skilled and highly-compensated roles. Additionally, I will investigate trends in the labor market to predict the industries and jobs where this demographic will be reallocated given their existing skillset and education level. Through a consequentialist examination, I will assess the overall impact of the use of automated robots on this demographic of workers in the U.S. using a utilitarian and social welfare framework to evaluate the best course of action to take regarding the use of this technology within this industry.

Literature Review and Background Information

The use of technology has a profound impact on the role of human workers in industry as well as the demands for the subsequent labor market. A 2006 paper published through MPRA states that as innovations and tools enter the labor market, productivity and the type of work performed by humans naturally change (Garcia et al., 2006, pp. 3-4). The displacement effect and compensation effect describe how technology structurally transforms the economy and labor market. While several scholars (Garcia et al.; Autor & Salomons; Baily & Bosworth) have described this relationship, most generally agree that although both effects naturally offset each other to a certain degree, the compensation effect ultimately dominates, predicting a net-positive effect for the labor market by growing its opportunities for employment in the long-term despite shifting labor market demands (Garcia et al., 2006, p.4).

In a perfect market, the use of new technologies initially results in a short-term period of reduced labor demand (Autor & Salomons, 2018, p.1). At this stage, companies optimize processes and increase productivity, allowing them to do more work with fewer resources, thus creating a competitive advantage by operating at lower costs to generate more profit (Autor & Salomons, 2018, p.7). As a result, increased efficiency allows companies to take advantage of economies of scale by increasing employment which is described by the compensation effect (Garcia et al., 2006, p.2). To demonstrate this effect Garcia's paper compares the performance of several Spanish manufacturing firms during the 1990s through a curated mathematical and economic model that predicts how these two principles affected the long-term labor market.

Their result was net-positive, noting that “Innovation displaces labour but also creates the firm level conditions to over-compensate this displacement” (Garcia et al., 2006, p.28). Given that these analyses were conducted in perfect market conditions, many factors such as government intervention and the availability of a qualified labor market can skew the impact of the compensation effect. However, given that these analyses were done considering perfect market conditions, it is not conclusive to suggest solutions based off of models alone. Verification using data and market trends is required to validate the phenomena described in this previous research. In the context of this problem frame, these papers suggest that many traditional manufacturing jobs would become obsolete from the use of automated robots in favor of higher-skilled and technical roles. Here, market research will be used to verify and test these claims.

At the industry level, the displacement effect has made headlines and been noted in numerous studies and data sets. From 1990 to 2007, it was estimated that automation had replaced over 400,000 jobs (Semuels, 2020, p.2). A McKinsey report concluded similar findings: from 1980 to 1995, large sector employment in manufacturing dropped 38 percent, and predicted that future employment in this industry would drop by an additional 32 percent from 2016 to 2030 (Manyika et al., 2017, p.36). While the future of traditional jobs in manufacturing appears to be limited, this report indicated that the nature of work and labor required in this industry would shift towards skilled, technology-dominated positions including software development, computer science, and management, resulting in a net positive number of jobs being created within manufacturing as a whole (pp.14, 17). However, these future positions require different skill sets than what is provided by existing production line manufacturing workers, leading many to believe that this demographic will likely not qualify for many of these future jobs in manufacturing (Gumbel, 2018). To illustrate this gap, in 2016, Georgetown University and

JPMorgan Chase & Co. released a report that found that only 9% of production workers in manufacturing held a bachelor's degree (Carnevale et al., 2019, p.21). This report also noted that in 35 states, jobs in this industry for individuals without bachelor's degrees "earned more, on average, than workers in other blue-collar and skilled-services industries" (p.31). Since the majority of current manufacturing workers do not have strong educational backgrounds, as many as 15 million Americans would be in jeopardy of losing their jobs due to the impact of autonomous robotics and would be unqualified to fill the new positions being created (Burke, 2019; Weaver & Osterman, 2017).

While Garcia acknowledges that displacement is a direct side effect of technology's influence on the labor market, he claims that the compensation effect should counteract this phenomenon through the expansion of the market, driven by increased demand due to lower-priced goods (Garcia et al., 2004, p.2). However, the increased rate of demand for manufacturing has not been consistent with the displacement effect and the reduction of jobs within this industry, resulting in a net-negative trend for the American manufacturing labor market. As the manufacturing employment share has decreased linearly from 1960 to 2010, the manufacturing share of real GDP over the same period has stayed constant at about 12 percent of the overall U.S. economy (Baily & Bosworth, 2014, p.4). Recent trends in growth have indicated a similar pattern. According to the same journal report, from 2000 to 2010, the annual rate of growth in value added to the U.S. manufacturing sector was a mere 1.6% (p.6) while the aggregate stock of robots being developed has increased significantly (Jurkat et al., 2022, p.673). Similarly, the growth and demand for manufacturing can be determined from the relationship between total factor productivity (TFP) and rates of industry-level employment. Traditionally, these two factors have had an inverse relationship, meaning that as the number of workers decreases within an industry, the productivity of individual workers consequentially increases (Autor & Solomons, 2018, p.43). This same study from Autor and Solomons about automation as an employment-augmenting and labor-share displacing force found that the majority of manufacturing sectors have decreased their aggregate labor share from 1970-2007 while the number of workers shifting between industries was nearly negligible (Autor & Solomons, 2018, p.60).

Methods

To ethically evaluate the use of robotics and automation in the U.S. manufacturing industry, this paper will use utilitarianism as a moral framework to justify the increased adoption or opposition of this technology. It will be used to weigh this technology's impact on existing manufacturing workers relative to the growth of the United States as a whole. This research will also investigate two economic theories, labor market segmentation theory, and structural change theory, to illustrate how the use of automation drives the displacement and compensation effects as outlined earlier. While structural change theory and labor market segmentation theory are not inherently ethical frameworks, they can provide a basis for ethical considerations in government policy when applied through a moral lens such as utilitarianism. These effects will be later described and monetarily quantified for their impact on this demographic of existing manufacturing workers as well as on the United States economy as a whole through measures like GDP. Propositions for future efforts will be justified according to utilitarian reasoning by determining the difference in relative monetary value for these two groups.

Modern labor market segmentation theory states that individuals are stratified into different categories within the labor market based on several factors including education, skill set, and geography, thereby categorizing their career opportunities into different segments depending on these factors (Reich et al., 1973). This theory classifies individuals into two sectors, primary and secondary, that generalize the overall labor market. The primary sector includes stable, high-paying, and skilled professions for both white and blue-collar professionals, while the secondary sector describes low-skilled jobs that generally require little training, often experience high turnover, and inconsistent demand (Reich, et al., 1973, pp. 359-60). Historically, many jobs within manufacturing have been categorized under the primary sector due to their consistent demand and relatively high-paying nature for their given skill set. While a majority of these workers do not hold bachelor's degrees, manufacturing serves as a high-paying career path for people with basic skills, allowing them to earn more on average than working in similarly-skilled service industries (Carnevale et al. 2019, p.5). This economic theory will be used to predict the future sectors or industries that this demographic will transfer to, given their generalized skillsets and education levels. These various career paths will be normalized according to the expected labor demands in these adjacent industries and will be used to calculate an approximate expected income after relocation. For the utilitarian analysis, this difference in income will be measured against the current median income for these blue-collar jobs in manufacturing.

Structural change theory describes how changes in technology and other factors can lead to fundamental shifts in the economy (Rodrik, 2013, p.5-7). This theory is used to describe how certain catalysts, such as the use of automation and robotics within manufacturing, have resulted in economic growth and transformed economies on a macroeconomic scale. It has typically been used to describe how the economies of developing countries have transformed from agricultural-based to industrial-based markets (Agbenyo, 2020). Beneath this theory are two models to identify how economies change due to the use of technologies, specifically, ‘structural transformation’ and ‘fundamentals’ (Rodrik, 2013, p.2). Structural transformation considers how factors impact the overall economy such as a technology’s impact on raising or lowering GDP for a particular industry. Fundamentals, on the other hand, analyze how individuals are impacted within the general economy such as their income and socioeconomic status, including the jobs available to them in the market. For this analysis, structural change theory will be used to predict the large-scale financial impacts of automation on the manufacturing industry. Through scholarly research and market data, this theory will be used to forecast the change in expected GDP from this industry and its consequent impact on the citizens of the United States as a whole.

Together, these theories will be used to predict the ways in which autonomous robots are transforming the manufacturing industry in the U.S. and its impact on individuals currently working in this field. While modern labor market segmentation theory will consider the small-scale economic impacts on this current demographic of manufacturing workers, structural change theory will be used to consider the large-scale economic impacts of this technology on the overall economy. Given that two theories have a mutual influence on each other, they will both be used to gauge the impact of the restructuring of the economy, as well as its effect on the distribution of wealth in the U.S. Many scholars (Keister & Moller, 2000; Berg & Ostry, 2011) have noted a trend of an increasingly skewed distribution of wealth in the U.S., where the population of middle-class earners has been decreasing while the ownership of wealth in the top percentile of earners has been increasing. This continuing rise in income inequality has been shown to erode social cohesion, lead to political polarization, and ultimately lower economic growth (Berg & Ostry, 2011; Rodrick, 1999).

Using utilitarianism as a moral framework, the absolute and relative economic impacts of the use of automated robots will be determined. Recommendations for future actions will consider the quantity and magnitude of economic impact that this technology poses to this demographic and the general economy including citizens not directly affected by manufacturing. Utilitarianism was appropriately chosen due to its versatility in being able to compare economic outcomes on both a large and small scale. Analyzing this issue from a utilitarian standpoint ensures that the greatest number of people benefit while minimizing social costs (Secchi, 2007, pp. 351-353), meaning that the decision to promote or oppose the use of automation and robotics in the U.S. manufacturing industry will be determined with the intention to improve the largest number of people's lives and to the greatest degree.

Application of Methods and Ethical Analysis

As described earlier, the displacement effect in the U.S. manufacturing sector has gained nationwide attention due to the impact of automation and robotics on the changing demands of the labor market. Employment in manufacturing dropped by a third from 2000 to 2011 (Baily & Bosworth, 2014, p.11, 12) and 60 percent of the labor demand has shifted to favor college-educated labor in manufacturing favoring more computation-based and technical positions in fields such as computer science and data science (Carnevale et al., 2019; Manyika et al., 2017; Weaver & Osterman, 2017). In 2012, just less than a third of all manufacturing workers and only 9 percent of production workers held a bachelor's degree (Carnevale et al., 2019, p.19). These trends indicate that a growing number of manufacturing workers are being displaced into other industries while researchers (Manyika et al., Baily & Bosworth, Weaver & Osterman) suggest that these trends will continue for blue-collar workers.

The scope of influence that automated robots have is not limited to the manufacturing industry. Industries including healthcare, business, food service, and several others have experienced labor displacing effects from recent technology (Autor & Salomons, 2018, p.44). While widespread displacement is becoming increasingly common, the U.S. unemployment rate is independent of these trends and has continued to decrease even during periods of economic prosperity (Bureau of Labor Statistics, 2024). As of April 2024, the unemployment rate was 3.9% (Bureau of Labor Statistics, 2024). While this is not entirely indicative that manufacturing workers specifically are successful in finding work elsewhere, it does give validity to the strength of the compensation effect across all industries.

Labor market segmentation theory indicates that these shifting labor demands can find work in similar or adjacent industries, given their existing skills and education levels (Reich, et al., 1973, pp. 359-60). Research has indicated that while the employment share within manufacturing has declined, other industries requiring similar qualifications compared to manufacturing have grown at a proportional rate. For instance, the number of construction-related and skilled-services jobs, including public administration and education services, has grown by a total of 6 million from 1991 to 2016 (Carnevale et al., 2016, p.33). Similarly, other occupations related to construction that do not require a college degree are projected to grow from 2020 to 2030, including wind turbine service technicians, solar installers, floor layers, and tile and stone setters, all of which have comparable median annual wages of over $47,000 (Farrell & Lawhorn, 2022). Listed in Table I are industries with notable growth in employment with data provided by the U.S. Bureau of Labor Statistics. These industries were selected based on the expansion of industries available to manufacturing workers indicated by worker qualification and as described by Manyika.

Industry	Data Range	Total Employment Change	Percent Change	Median Annual Wage (2023)	Normalization Factor
Manufacturing	1979-2019	-6,715	-34.34%	$47,620	0.65
Construction	2012-2022	2,012	37.23%	$55,680	0.17
Skilled Services Industries (All)	2012-2022	15,577.8	13.37%	-	-
Transportation	2012-2022	2,247.3	51.03%	$40,050	0.12
Health Services	2012-2022	3,127	17.94%	$36,140	0.04
Leisure and Hospitality	2012-2022	2,067	15.01%	$43,840	0.02

Data Provided by the U.S. Bureau of Labor Statistics

Table I: Overview and Growth of Industries with Similar Labor Demands to Manufacturing (Employment in thousands of jobs)

To estimate the approximate earnings for existing workers in manufacturing, the value of the median annual wage will be multiplied by the normalization factor for each industry and will be summed across the five industries listed in Table I. This is a rough approximation for the expected salary of existing workers who may be displaced to other industries due to the use of automation and robotics in manufacturing. These normalization factors are estimated and calculated based on the relative employment change and trends in the transfer of employment described by Manyika, Carnevale et al., and Weaver & Osterman. It should be noted that the precision of this method is not particularly high and only aims to be used as a crude approximation for income considering the availability and growth of jobs in adjacent industries that require similar qualifications. To verify these claims, meta-analyses and comprehensive data assessments of the evolving manufacturing labor market will need to be performed. However, according to this method, the estimated annual income of manufacturing workers was calculated to be $47,547; almost identical to the current median salary in manufacturing.

According to many scholars including Zinser and Kutay, automation and the use of robotics are recognized for their strategic benefits in reducing inventory costs, labor costs, and sales enhancements such as reduced lead times, improved quality, and faster responses to market shifts (Kutay, 1989, pp 11-7). Boston Consulting Group noted that the use of robots can decrease labor costs by as much as 16 percent (Zinser et al., 2015).

From a macroeconomic perspective and according to structural change theory, this use of automation and robotics will create fundamental changes within the economy to help bolster or suppress industrial output which affects the economic structure of society (Rodrik, 2013). At this scale, its effect can be measured by a change in GDP on an industry level or for the economy as a whole (Trinh, 2017, p.13-14; Agbenyo, 2020, p.2). For this technology, it has been noted that the rise in the use of industrial robots has been linked with near-record levels of production has caused sales to spike in the 2010s (Perryer, 2019). While automation has allowed this industry to become more efficient and require fewer workers, as shown by the linearly decreasing of manufacturing's share of employment from 1971 to 2015, this industry's share of real GDP has remained constant at around roughly 12% during this same period (Chien & Morris, 2017).

Due to this relatively constant level of real GDP over the past 50 years within this industry and the linear decrease in manufacturing's share of employment, the expected value of the use of automation and robotics can be determined from the rate of change of this employment share relationship. In this case, from 1971 to 2015, the share of employment decreased by 12 percentage points (Chien & Morris, 2017). Assuming employment is held constant, and that the U.S. will continue to implement industrial robots at the same rate, it can be concluded that the real GDP of the manufacturing industry, at least in the short term, will increase by 0.27 percentage points per year. Using this relationship, in 15 years, manufacturing's share of real GDP will be projected to be at its highest at over 15 percent, compared to its recent level of 11.7 percent in 2015 (Chien & Morris, 2017). On a macroeconomic scale, this implies that the total GDP for the U.S. economy will be expected to rise due to the manufacturing sector without requiring additional labor. Once again, it should be reiterated that these are simplified models that demonstrate the value-adding nature of industrial robots. These are approximations based on correlations from general trends in data. Other factors including the use of industrial robots from foreign countries and the future of employment within this industry will drastically impact these results. More research and controlled experimentation will need to be performed to verify these findings.

When applying these outcomes from a utilitarian perspective, it is apparent that the U.S. should continue to utilize automation and robotics within the manufacturing industry. From a monetary perspective, the future implications of the displacement of workers from this industry are expected to be relatively minimal. This is due to the rise of employment in adjacent industries requiring similar skill sets while offering comparable salaries to these workers' existing jobs. From a large-scale perspective, this technology's use is projected to have a tangible impact on increasing the United States' overall GDP. By increasing GDP, the U.S. economy will function more efficiently, where wealth will be distributed throughout the population through a trickle-down effect by individuals buying and selling goods within the market (Trinh, 2017). While its scope of impact will be relatively minimal for the average citizen, the decision to implement these robots will positively benefit the entire population of the U.S. Due to the total number of people positively affected by this growth and considering the minimal expected changes in income of these workers in different industries, I advocate for the continued implementation of robots and automation within manufacturing.

To promote the continued adoption of this technology in this sector, government policy should be implemented that incentivizes firms to make these changes. A study from *The RAND Journal of Economics* found that the use of subsidies was net positive in increasing company investment in a particular policy or technology, meaning that the amount of money spent on the subsidy was less than the amount of wealth generated from the implementation of the project (González et al., 2005). By creating a subsidized program for the adoption of industrial robots in U.S. manufacturing businesses, the GDP of this industry and the country as a whole will increase without impacting the individual workers' long-term social and economic status.

Conclusion

This research investigated the impact of autonomous robots and automation on the projected demand for labor in the U.S. manufacturing industry. It considers the ethical impacts of labor market segmentation theory and structural change theory on the impact on existing manufacturing workers who likely will be displaced into other industries due to the continued adoption of this technology. At the same time, the advantages of utilizing automation and robotics within this industry were studied and estimated using a simple mathematical model based on general market trends. These factors were compared using a utilitarian moral framework to guide the U.S. regarding the use of this technology in manufacturing.

Through an analysis of historical data and existing published research, I conclude that the use of automated robots is not jeopardizing the social and economic futures of existing manufacturing workers due to the growth of adjacent and skilled-services industries. The labor demand for these industries is consistent with these displaced workers' qualifications while offering similar pay rates to their current positions. Additionally, there is ample evidence for the support of automation increasing productivity and GDP on a nationwide scale, benefiting all U.S. citizens through a trickle-down effect of wealth in the economy. Given that all citizens of the U.S. can benefit from the growth of this industry, and that the displacement of manufacturing workers into other industries is not projected to have a significant effect on their future income, the utilitarian solution to this issue is to advocate for embracing the use of robots and automation within this industry.

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