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Is Automation Replacing Routine Jobs

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I. **Introduction**

The purpose of this paper is to examine the ways in which technology may be affecting employment in the manufacturing industry and specifically within three manufacturing sectors.

The structural unemployment that follows a period of technological improvement is not necessarily a new phenomenon. For example, the invention of the car put many farriers out of work. Whether to employ machines or retain human laborers for means of the production of a good or service is a question that has been grappled with before. The difference nearly a century-and-a-half later is that the rise in technology over the previous few decades has surpassed the precedent that has been previously set by prior ages of technological advancement.

Previous research has examined the sophistication of newfound technology for the sake of gaining a better understanding of how new technology works. Furthermore, research has also focused on which sectors of employment are most likely to be affected by more sophisticated technology. Specifically, the sectors that have been identified as being most prone to rises in technology are those sectors that include repetitive, simple tasks that do not include a sense of necessary critical thinking.

However, research has lacked in identifying the extent by which employment is affected by technology in sectors identified as being vulnerable to automaton. While it is important to gain a deep understanding for newfound technology, it is equally as important to discern the extent by which such technology may be affecting employment, if at all.

This paper will address this identified gap in current research by specifically looking into how technology affects employment outcomes in the manufacturing industry, overall. In essence, I am examining whether there is a discernable substitution of technology and labor demand. Furthermore, this paper will identify how technology is affecting employment level in three specific sectors in the manufacturing industry. These sectors are as follows: Motor Vehicle Production, Fabricated Metal Production, and Food Manufacturing Production. While these three sectors are a few of the vast number of sectors within the manufacturing industry, I think they provide a sound sample for the following reasons.

First, these specific sectors are comprised of work that is capable of being done without exponentially sophisticated technology. Thinking back to the turn of the century confirms this idea when evaluating the technology that was used in the production of older cars and metal products. Moreover, the process of food manufacturing, namely the process of turning raw agriculture into a finished food product, may be completed in the span of a few hours as opposed to a few days. Thus, as these sectors are comprised of work that is capable of being performed without extremely sophisticated technology, albeit slower, they are ideal in terms of identifying how more sophisticated technology may affect levels in employment.

Second, these industries are comprised of repetitive work. Observing industries that are comprised of repetitive work is ideal because such sectors are the most vulnerable to be affected by more sophisticated technology. If these sectors included tasks that involved a deep capacity for critical thinking, it would be difficult to assess how technology is affecting employment because the technology in question is more apt to perform repetitive, somewhat rudimentary tasks.

Nevertheless, the limitations of this study are as follows. First, only identifying three specific sectors within the manufacturing industry may not provide a sound, holistic view of the ways in which an increased usage of technology may be affecting sectors within the manufacturing industry. The reason being that there are hundreds. Thus, there is need for further research in this area.

Second, it would be noteworthy to identify the ways in which technology may be affecting employment in traditionally white-collar industries such as medicine or business. Discerning the affect that technology poses to employment in these industries would provide further insight in to how technology may affect employment levels among multiple sectors across the United States economy.

The rest of this paper is organized as follows. First, I will provide a synthesis of prior research on the effects of sophisticated technology on employment. Second, I will describe the data used. Third, I will explain the methodology used to pinpoint my results. Fourth, I will describe my results in detail and offer concluding remarks, as well as identify opportunities for further research in the field.

II. Literature Review

A growing body of literature has tried to answer the question of how, and the extent to which, rising automation and artificial intelligence may be displacing workers. Technology is a tool whose primary goal is to improve worker efficiency. However, data is showing that technology may be completing work more efficiently than workers. Overall, the studies that have been done over the past 20 years focus on explaining the extent by which automation is capable of displacing workers by analyzing data on employment levels, labor demand, and the changes in the levels of output of various goods and services. The following literature serves as examples of the work researchers have done to answer questions surrounding the displacement effect.

In *Artificial Intelligence, Automation and Work*, Acemoglu and Restrepo (2018) summarize a framework to discern the implications that rising automation poses for the demand on employment. The authors are practical in their analysis and dispel prevailing, extreme dialogue regarding the end of human employment. The authors' question at hand focuses on trying to measure the extent by which displacement is a product of automation. This paper effectively addresses the extent of the displacement effect by explaining other deriving questions that result from the displacement effect such as how the economy may adjust to rapid changes in employment and how workers with varying skill levels may fare in a rapidly changing labor market.

In his paper *Are Robots Replacing Routine Jobs,* Chen (2018) uses an empirical model to explore the impacts of the use of robotics in the labor market by constructing industry-level robot intensities to measure the effects on employment by industry. There is a growing amount of attention being paid to the use of robotics in the day-to-day operations of firms, but the view is not entirely new. Chen concludes that the increased use of robotics results in a decrease in wages but not a significant decrease in levels of employment. Dixon, Wong, and Hu's work confirm this trend.

In *Will Robotization Really Cause Technological Unemployment,* Brian Sorells (2018) discusses the ways in which technology has become omnipresent in the everyday lives of many, and thus it is hard to dispute that rising automation and sophisticated technology are affecting the nature of work in some respect. Specifically, Sorells discuses that this fact is especially true when considering the sophistication of the technology being used. This literature also uses their model to think of job projections in the future, and the sectors that may be accelerating or decelerating, respectively.

In *New Perspectives on the Decline of US Manufacturing Employment,* Fort et al. (2018) use an empirical approach to prove how output per person has increase exponentially over the past decade. The authors attribute this trend to the use of technology in the production process.

The authors also discuss that firms integrate technology into the production process as a means to stay competitive with each other.

Dr. Shahrukh Rafi Khan (2018) discusses in his paper, *Reinventing Capitalism to Address Automation,* focusses on the wave of automation-induced unemployment that seems to specifically affect blue collar workers. He concludes that the nature of work is changing and cites further research should be done to further identify the ways in which society could best cope with large job losses among vulnerable workers.

III. Data

The data used may be found at the Federal Reserve Economic Data via the Federal Reserve Bank of St. Louis. The data is annual national data collected on January first of every year beginning in 1987 and ending in 2016.

The data itself is broken down into separate sections, and those sections are as follows: Employment, Output, Motor Vehicles Output, Food Manufacturing Output, and Fabricated Metals Output. Employment measures the number of employees recorded as working in the manufacturing sector in a specific year. Furthermore, the employment data is seasonally adjusted. The employment data is also sourced from the Bureau of Labor Statistics.

Output measures Real Output for the manufacturing sector in a specific year. Output data is also seasonally adjusted, and real output is adjusted for inflation. Moreover, real output is aggregate across all registered sectors of manufacturing. Next, I will describe three specific manufacturing sectors that I used to discern effects on employment on a more specific level.

Motor Vehicles Output measures the Industrial Production of Durable Manufacturing of Motor Vehicles and Parts. I included motor vehicle parts in addition to motor vehicles because I did not want to exclude the production of parts that go into the construction of the final motor vehicle.

Fabricated Metal Output measures the Industrial Production of Durable Manufacturing of Fabricated Metal Products. Specifically, fabricated metal are metal products that have been transformed from a rudimentary state into that of a finished product. The necessary production process includes forging, stamping, bending, forming, and machining, used to shape individual pieces of metal.

Food Manufacturing Output refers to the Industrial Production of the nondurable manufacturing of food, beverage, and tobacco products. Nondurable goods are those goods that are not expected to be used for long periods of time or consumable goods. The process of food, beverage, and tobacco manufacturing is the process of taking raw, edible materials and transforming them into products that may be consumed or ingested.

Moreover, Motor Vehicles Output, Fabricated Metal Output, and Food Manufacturing Output all measure industrial production. Industrial production measures the real output of all relevant establishments located in the United States, regardless of their ownership, but not those located in U.S. territories. Note that the specific, sectoral output for the above mentioned sectoral is also adjusted for inflation to ensure that the data is in keeping with the measure of aggregate output. Last, the above-mentioned sectors are also seasonally adjusted.

Capital Intensity measures the ratio of capital services to hours worked in the production process. The higher the capital to hours ratio, the more capital intensive the production process is (FRED). Capital intensity specifically measures the capital and purchased services used in the production process and includes capital such as technology and other efficiency improving products. I included this variable to specifically measure the extent to which technology is being used in the production of manufacturing goods. Without a measure of capital intensity, it would be difficult to attribute the divergence in employment and output to a specific cause. Therefore, measuring the amount of output produced against the amount of inputs used to produce the goods is a very important variable in terms of determining whether technology may be affecting employment.

The noted caveat to the capital intensity data is that it is not seasonally adjusted as the other variables. As the predictable seasonal patterns were not statistically accounted for in this variable, it may not be as precise a measurement as compared to the other before mentioned variables. Nevertheless, I think any statistical anomaly may be relatively insignificant as the three specific sectors often house production indoor, and thus changes in seasonal patterns may not be as significant as if I were measuring output in a farming sector, for example.

IV. Methodology

I used a variable regression approach to predict the outcome on employment based on a selected set of variables. The dependent variable of employment is based on the interaction of the independent variables of Output, Motor Vehicle Output, Fabricated Metal Output, Food Manufacturing Output, and Capital Intensity. All of these variables are continuous variables.

$$\text{Employment} = \beta o + \beta 1\text{Output} + \beta 2\text{MotorVehicleOutput} + \beta 3\text{FabriatedMetalOutput} + \beta 4\text{FoodManufacturingOutput} + \beta 5\text{CapitalIntensity} + \varepsilon$$

I used this model to quantitatively evaluate the relationship between employment and the use of technology in the production process. In order to test this, I used data on employment, output, and capital intensity. As described before, capital intensity is a ratio of the level of technology used in the production process. To measure production, I include output at the industry and sectoral level as output is the finished good(s) of the production process. Regressing employment output, at the industry and sectoral level, and capital intensity provides a precise estimation by which the extent employment is affected by the use of technology in the production process.

Initial regression for Output, MotorVehicleOutput, and FabricatedMetalOutput initially resulted in statistically insignificant results, but statistically significant results when regressed separately. Therefore, I employed a joint significance test in order to determine whether results were truly insignificant or significant.

V. Results

This section describes my main results. Table 1 shows the results for effect of capital intensity on employment in the production process. Upon inspection, capital intensity in the production process has a clear, negative effect on employment. In other words, a one unit increase of capital intensity results in a loss of employment of one worker. The negative effect is statistically significant for all four specifications in Table 1. Data describes an expected trend in which employment increases with output but decreases when technology is introduced in the production process. This line of thinking makes sense when one evaluates that additional workers are needed to produce marginal output, but that workers may be negatively affected when technology is introduced that may perform some of the tasks that they were once employed to do. Interestingly, the statistical significance varies among the sectors of output. Output and employment show a positive, statistically significant relationship in each specification, except for specification number four. Moreover, the statistical significance of among the various estimations between employment and motor vehicle output and food manufacturing output vary as well. I employed a test of joint significance on the coefficients that later indicates a positive relationship between employment and sectoral output.

The first test of joint significance between Output and MotorVehicleOutput indicated that MotorVehicleOutput is significant as Prob > F = .0030, which is less than the standard value of .01. The second test of joint significance between MotorVehicleOutput and FabricatedManufacturingOutput indicated that MotorVehicleOutput is statistically significant as Prob > F = .0367, which is less than the standard value of .05. The third test of joint significance was among Output, MotorVehicleOutput, and FabricatedMetalOutput. For these variables, Prob > F = .0015, which is less than the standard value of .05.

The overarching result is that capital intensity, or the use of technology in the production process, indicates a negative effect on employment. Last, my favored specification is specification four. While the relationship between employment and various measures of sectoral output were not initially statistically significant, the relationship described between employment and capital intensity is specifically significant. Furthermore, I believe the additional variables in specification four add merit to the conclusion that capital intensity negatively affects employment because the estimation is evaluated among many sectors.

I will evaluate the robustness of my results by investigating whether the results may be subject to any omitted variable bias. Due to the small sample size used in my analysis, my empirical model consists of only five variables. Therefore, additional variables, e.g. adding additional manufacturing sectors, to my empirical model may affect the statistical significance of the relationship between employment and capital intensity. Also, I did not measure the educational attainment of the workers studied. Omitting the levels of education among the workers evaluated may cause the estimation of the effect of technology used in the manufacturing production process to be over-estimated among all workers.

Furthermore, it is difficult to assess whether some mutual trend may be driving the strong, statistically positive relationship between employment and capital intensity. Having a better understanding of some of the underlying characteristics within the data itself could potentially shed light on whether the relationship between employment and capital intensity is indeed intrinsically significant as opposed to a mere coincidence due to mutual trends.

VI. Conclusion

In this paper I tried to estimate a possible relationship between employment and technology used in the production process. My findings showed that technology used in the production process does affect employment levels in the manufacturing industry. Further research would benefit from observing the effects that technology may have on other manufacturing sectors, as well as other industries encompassing work in White-collar industries, in order to gather a holistic understanding for the ways that technology may be affecting employment. As this study accounted for so few sectors within the manufacturing industry, further research could specifically estimate the relationship between employment and technology in other manufacturing sectors. Nevertheless, broader implications of these findings should focus specifically on resolving the structural unemployment that may result in a digital age. Such efforts used to address structural unemployment may include retraining programs and social programs such as universal basic income.

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Tables

Table 1. *Capital Intensity Impact on Employment in Production Processes*

	(1)	(2)	(3)	(4)
Output	0.306^{***}	0.300^{**}	0.820^{***}	0.509
	(0.0783)	(0.0985)	(0.208)	(0.258)
Capital Intensity	-0.927^{***}	-0.927^{***}	-1.102^{***}	-1.109^{***}
	(0.0456)	(0.0465)	(0.0760)	(0.0725)
Motor Vehicle Output		0.00449	0.0578	0.0780
		(0.0458)	(0.0453)	(0.0445)
Fabricated Metal Output			-0.527^{*}	-0.479^{*}
			(0.192)	(0.184)
Food Manufacturing Output				0.601
				(0.320)
Constant	163.7^{***}	163.8^{***}	175.2^{***}	139.7^{***}
	(4.931)	(5.119)	(6.182)	(19.79)
Observations	30	30	30	30
R^2	0.969	0.969	0.976	0.979

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Capital Intensity measures the ratio of capital services to hours worked in the production process. The higher the capital to hours ratio, the more capital intensive the production process is