Major Themes in Economics

Volume 20 Article 6

Spring 2018

Technological Unemployment in the United States: A State-Level Analysis

Courtney Krousie
University of Northern Iowa, krousiec@uni.edu

Recommended Citation

Krousie, Courtney (2018) "Technological Unemployment in the United States: A State-Level Analysis," *Major Themes in Economics, 20,* 87-101.
Available at: https://scholarworks.uni.edu/mtie/vol20/iss1/6

Technological Unemployment in the United States: A State-Level Analysis

Courtney Krousie*

ABSTRACT. This paper aims to analyze the relationship between technological change and unemployment across the United States. Building on previous research, I run a two-stage least- squares regression that links technological change to unemployment. Technological change is proxied with commercially-supplied research and development expenditures. I acquire data from the Bureau of Labor Statistics on unemployment rates and data from the National Science Foundation on research and development expenditures from 2002-2013 for each state. Control variables include GDP, the minimum wage, education expenditures, violent crime and property crime rates, union coverage, unemployment benefits, and poverty rates. I find evidence that technological change displaces labor in the United States, but the magnitude of the effect is small.

I. Introduction

> "The development of full artificial intelligence could spell the end of the human race."
>
> \- Stephen Hawking

For centuries people have been worried about being replaced by machines and left without work. These fears began during the Industrial Revolution among textile workers and have continued today among all occupations. This is an especially important concern because work is the main source of income for the majority of people in the United States. If we are not fully prepared for what may come, we may be left behind as we watch robots take our jobs. At the moment this is all hypothetical. If we look to the past we see that employment has continued to grow alongside technological innovations, so why are some experts afraid that our jobs will be replaced by robots? The recent exponential growth of technology is the main reason. To see if this technological outburst is the beginning

*I would like to extend a sincere thank you to Dr. Bryce Kanago for his help with this study. All remaining errors are my responsibility.

of robots permanently taking our jobs, I will analyze the present relationship between technological change and unemployment. After running the regression, I found that technological change is displacing jobs in the United States, though at present the effect is small.

II. Historical Background

The discussion of how technology affects unemployment dates back centuries to the Industrial Revolution. During the period 1811-1816, there was a group of English textile workers concerned about losing their jobs to machines. Known as the Luddites, they protested by destroying weaving machinery that would potentially replace their labor. Sharing their view was Thomas Mortimer, an economic writer who opposed these machines because they would "exclude the labour of thousands of useful workmen" (Mortimer 1772, 72). Mortimer's idea that machines would directly replace workers is known as the displacement effect.

Not everyone shared this entirely negative view of machines. Economist Sir James Steuart recognized that machines could cause a man to become idle temporarily, but the advantages of higher productivity would be permanent (Steuart 1767, 122). Steuart addresses the displacement effect, but also realizes that automation could actually produce positive productivity growth, known as the productivity effect. The Industrial Revolution showed that both of these effects existed. A study by *The Economist* reported that during the 19th century, the amount of cloth a single weaver could produce in an hour increased by a factor of 50 while the amount of labour required per yard fell by 98% (The Economist 2016, 7). Cloth eventually became cheaper so the quantity demanded of it increased, creating four times more jobs in the long run. This case suggests that during the Industrial Revolution the displacement effect was prominent in the short run, while the productivity effect took over in the long run. Unlike the negative views of economists like Mortimer, employment increased once workers were able to adjust to the shock of the machines.

For some time after the Industrial Revolution, negative views toward machines were rare. It was not until unemployment rates skyrocketed during the Great Depression that machines again became the favored scapegoat. Like during the Industrial Revolution, there was some disagreement about the extent to which machines were affecting unemployment rates. On the negative side of this debate was eventual commissioner of the U.S. Bureau of Labor Statistics, Ewan Clague. He stated the displacement effect would exceed the productivity effect so that unemployment caused by machines would be large (Clague 1935, 210). Clague thought the advantages of machines would be temporary while the unemployment would be permanent. Other economists rejected the idea that machines had an effect on unemployment. Edna Lonigan recognized the displacement and productivity effects of machines, but said that machines during the Great Depression had little if anything to do with unemployment (Lonigan 1939, 255). It is important to realize that technological change is a simple explanation for higher unemployment rates, but this does not necessarily mean that machines are to blame.

It is no surprise that the debate over the extent to which technology affects unemployment has continued well into the 21st century. The current growth rate of technology is high and there is still unemployment, so connecting the two is not a far reach. For example, since the introduction of manual computing, which involved using machines such as the abacus to do manual computations, computer performance has improved by a factor of at least 1.7 trillion (Nordhaus 2007, 128). This creates a strong incentive for businesses to substitute machines for workers as machines are relatively more powerful, more reliable, and sometimes less expensive than human labor.

As the power of machines increased, the number of tasks they could perform without human interaction increased as well. As opposed to weaving machinery that needed humans to operate, we now have self-driving cars that can operate themselves. I will refer to these autonomous machines as robots. These robots are the beginning of the new threat for technology on unemployment: artificial intelligence. Artificial intelligence involves giving machines the ability to imitate intelligent human behavior. This involves tasks such as visual perception, speech recognition, and decision-making. As soon as technology can do everything that humans can do, especially without the flaw of human error, there is no need for our labor. We have not reached this point yet, but we should be prepared for what could happen once we do.

Looking back at the Industrial Revolution, one would think the labor force has nothing to worry about. The overall effects of weaving machines were positive as they created four times as many jobs as they destroyed. The McKinsey Global Institute warns that this time it's different. Compared to the Industrial Revolution, technological change is currently happening at roughly 3,000 times the pace (Dobbs, Manyika, and Woetzel 2015). Most of what we know from the past will not prepare us for what could possibly happen to the unemployment rate in the near future. Empirical studies that offer some insight on the relationship between robots and unemployment are therefore of great value.

III. Literature Review

There are many studies that look at the relationship between artificial intelligence, or robots, and unemployment. In a survey done by Aaron Smith and Janna Anderson of 1,896 experts, 48% believe that robots will displace more jobs than they create by 2025 (Pew Research Center 2014, 2). The other 52% expect the displacement effect to happen, but as in the Industrial Revolution, these experts believe the productivity effect will be larger in the long run. One of the most well-known economists who has a positive outlook on robots is Deirdre McCloskey. She states that if technological unemployment were going to happen, it would have already happened (McCloskey 2017). Further, she states that automation is good and actually increases the quality of work. Others have also focused on the quality side of robots replacing human labor, but of course no one can seem to agree. Some economists recognize that not everyone will be better off, although it is easy to assume that most people will be. Michele Loi calls it the humanistic fallacy, which is the tendency to assume the displacement of labor by robots will lead to most humans having better jobs, but this is not always the case (Loi 2015, 202). Although this paper will focus on how robots affect the quantity of work, it is important to understand that this is not the whole issue.

Over the past five years, many empirical studies have been done to quantitatively address how robots are affecting unemployment. Frey and Osborne did a study that looked at how susceptible certain occupations are to computerisation, and found that 47% are in the high risk category (Frey and Osborne 2013, 38). The results of their study may seem scary, but it is important to note they only looked at entire occupations. The focus on occupations is too broad, as each occupation contains tasks with different risks of automation. Economists for the McKinsey Institute then completed a study looking just at tasks, and found that up to 45% of tasks can be automated by adapting currently demonstrated technologies (Chui, Manyika, and Miremadi 2015). Their study found a large displacement effect, but similar studies done later found a much smaller one. Following the task-based approach, a study done by another group of economists found that on average across 21 countries, 9% of jobs are automatable (Arntz, Gregory, Zierahn 2016, 4). The large range of results found from these studies shows how unsure we are about the strength of the displacement effect. Regardless of the strength, the studies do show us something important: the displacement effect does exist and some skills are more vulnerable than others.

Some economists think the only way to survive in the labor force is to focus on the skills in which humans have a comparative advantage over robots. As Erik Brynjolfsson and Andrew McAfee discuss in their book *The Second Machine Age*, "there's never been a better time to be a worker with special skills or the right education, because these people can use technology to create and capture value" (Brynjolfsson and McAfee 2014, 11). These economists recognize that at present, the kind of tasks that robots can do is limited. Even if robots substitute for human labor in certain tasks, the remaining tasks completed by humans will be complemented, according to David Autor. As an economic expert in this area, he argues that inputs from both robots and humans play essential roles, so improvement in tasks done by robots will almost certainly increase the economic value of the human tasks (Autor 2015, 6). This observation is basic economic theory, as giving workers more or better capital increases labor's productivity. Focusing on specific tasks allows us to look at ways in which, besides the productivity effect, humans can directly benefit from robots. Now the question arises, are these benefits enough to offset the displacement effect? I will address this relationship with my model.

Looking generally at how unemployment is affected by robots, several empirical studies have either shown no relationship or a small one between robots and unemployment. A recent study by economists Daron Acemoglu and Pascual Restrepo found that the displacement effect, which tends to cause a decline in the share of labor in national income, is counteracted by the productivity effect, capital accumulation, improvements of existing machinery, and the creation of new tasks in which labor has a comparative advantage (Acemoglu and Restrepo 2018, 32). The growth of robots, in this instance, had no large overall effect on the rate of unemployment. A year earlier, however, the same two economists did a study with a different model and got different results. Using panel data between 1990 and 2007 in the US, they found that one additional robot per thousand workers reduces the employment to population ratio by at least 0.18 percentage points (Acemoglu and Restrepo 2017, 35). This older study points to the displacement effect being larger than the combination of the productivity effect and any other benefits.

More common are studies that result in insignificant relationships between robots and unemployment. In one study, three economists ran a two-step generalized method of moments by using panel data from 25 European countries during 2000-2012 and found no significant relationship between technological innovations and unemployment (Matuzeviciute, Butkus, and Karaliute 2017, 7-10). A second study with insignificant results was completed using panel data from seven Latin American countries from 1996-2011 (Aguilera, Gabriela, and Barrera 2016, 63). The education expenditures variable used in their study will be used for this paper and will be discussed later in greater detail. A third study with insignificant results was completed by Yuqing Cang, who ran a two-stage least squares regression using state-level data (Cang 2017, 12). She used company-supplied research and development expenditures as a proxy for technological innovation, which is what I will use in this paper. I will also be following the regression model that she used in her study. Out of all the studies I researched, I believe this model to be the best to use because it is based on a study by Feldmann (2013). Feldmann ran a regression on 21 industrial countries using panel data from 1985-2009, and found patents, his technology variable, to have a significant positive effect on unemployment in the short run, but found no long-term effect (Feldmann 2013, 1120). This model is discussed next.

IV. Model

The model used for this paper will follow the two-stage least squares regression used by Feldmann (2013) and again by Cang (2017) in the following form:
Second stage:

$$UNEMP_{i,t} = \beta_1 (\hat{RD})_{i,t} + \beta_2 X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}$$

First stage:

$$(\hat{RD})_{i,t} = \sum_{s=1}^{4} \beta_3 RD_{i,t-s} + \beta_4 X_{i,t} + \gamma_i + \kappa_t + \eta_{i,t}$$

$UNEMP_{i,t}$ is the unemployment rate of state *i* at year *t*, RD is the research and development variable, and X is a vector of the independent control variables. State fixed effects in the second-stage and first-stage regressions are α_i and γ_i , respectively. Year fixed effects are λ_t and κ_t while the error terms are $\varepsilon_{i,t}$ and $\eta_{i,t}$. In the first-stage regression, the research and development variable, RD, is instrumented to extract its exogenous component. The instruments are the research and development variable lagged over the previous four years. The research and development expenditures of the previous four years are likely to have a direct effect on the level of research and development in the current year, and are also likely to affect the unemployment rate in the current year (Feldmann 2013, 1116).

The independent variable RD is defined as domestic research and development paid for by companies in the country and performed by the companies. Also known as commercially-supplied research and development, this variable will be in millions of dollars. I chose this as my main independent variable of interest after reading studies like Cang's. She found that commercially-supplied research and development is the best proxy at present for technological innovation (Cang 2017, 12). As discussed earlier, the relationship between robots and unemployment can either be positive, negative, or zero depending on the strength of the displacement and productivity effects.

The first independent control variable, GDP, is defined as per capita real GDP by state, chained to 2009 dollars. I chose this variable because it proved to be statistically significant in the Latin America case (Aguilera, Gabriela, Barrera 2016, 69). I predict the sign of this variable to be negative, because as GDP increases the unemployment rate should decrease.

The second independent control variable WAGE is defined as the minimum wage of non-farm employment under state law measured in US dollars. I chose this as another independent variable because it was another one of the statistically significant variables in the Latin America case (Aguilera, Gabriela, and Barrera 2016, 69). The expected sign of this variable is positive, because as the minimum wage increases the unemployment rate should also increase (Cang 2017, 21).

The third independent control variable EDUCATION is defined as expenditures for public elementary and secondary education by state, measured in thousands of US dollars. I chose this independent variable because it was used in the Latin America study, and because some of the literature says that education expenditures affect unemployment. The expected sign of EDUCATION is negative, because as more money is spent on education, the skills of the workforce should improve, leading to lower rates of unemployment.

The fourth independent control variable VIOCRI is defined as offenses of murder, forcible rape, robbery, and aggravated assault. The fifth independent control variable PROPCRI is defined as offenses of burglary, larceny-theft, and motor vehicle theft. Both of these variables are measured in the rate per 100,000 inhabitants of the state. I chose violent crime as an independent variable because it was found to be significant in Cang's study (2017, 43). Although property crime wasn't found to be significant in her study, I still included it to see if it is significant now. The expected sign of both of these crime variables is positive because as there is more crime, there is likely more unemployment.

The sixth independent control variable UNIONCOV is defined as the percent of employed workers who are covered by a collective bargaining agreement. This variable was found to be significant in Cang's study

(2017, 43). The expected sign of union coverage is unknown, because it was found to be positive in a study by Montgomery (1989) but negative in Cang's study (2017).

The seventh independent control variable UNEMPBEN is unemployment benefits, which are the benefit checks issued during the calendar year, adjusted for voided checks and is measured in thousands of dollars. This variable was found to be significant in Cang's study (2017, 43). The expected sign of the unemployment benefits variable is positive, because as more benefits are paid, one would expect more people to be or stay unemployed to receive these payments.

The eighth independent control variable is POVERTY which is the percentage of people in poverty by state. This variable wasn't used in the studies I looked at, but I included it because in theory the unemployment rate should increase as there are more people in poverty. I expect the sign of this variable to be positive.

V. Data

The data I collected is state-level data spanning the years 2002-2013. I gathered monthly data on the unemployment rate from the Bureau of Labor Statistics then used the data to calculate an average for each year by state. Data on the independent variable RD was gathered from the National Science Foundation. This study focuses on how robots are affecting the unemployment rate, but there are no exact data on the introduction of robots into a company. I chose domestic research and development paid for and performed by companies as a proxy for technological innovation. This is a better proxy variable than government funded research and development because privately-funded research and development was the only statistically significant variable in a study by Terleckyj (Terleckyj 1980, 376). It was also used in the Cang study.

The Bureau of Economic Analysis provided data on the independent variable per capita real GDP by state. No alterations were needed for this data. Information on the minimum wage independent variable was gathered from the United States Department of Labor. A limitation of this data is that some states had different minimum wages per year because there was a lower rate set for companies with a small amount of sales. In these instances I used the average of the highest and lowest values. When a state did not have any minimum wage data, I used the federal minimum wage for that year. I then deflated the minimum wage by the consumer price index for that year. Data on the independent variable public education expenditures was gathered from the National Center for Education Statistics. One limitation is that data on education expenditures is calculated for a school year, not a calendar year like the other variables. To make the data comparable, I assumed that expenditures during the school year took place during the year that school began. For example, education expenditures for 2002-2003 were used for 2002 and expenditures for 2003-2004 were used for 2003.

Data on violent crime and property crime rates was gathered from the Federal Bureau of Investigation. Data on union coverage was collected from the Union Membership and Coverage Database created by Hirsch and Macpherson, which is compiled from the monthly household Current Population Survey. Information on the unemployment benefits was collected from the Department of Labor, specifically the Employment and Training Administration. Finally, data on poverty rates was collected from the United States Census Bureau. Table 1 shows the summary statistics information for all of the variables.

TABLE 1–Summary Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
UNEMP	6.23622	2.087176	2.591667	13.60833
RD	4391.842	8575.412	21	76851
GDP	48548.99	18300.27	29056	170687
WAGE	3.012782	.4696426	1.230841	3.984157
EDUCATION	9536429	1.13e+07	716006.7	6.16e+07
VIOCRI	4-06.0613	215.6506	77.8	1632.9
PROPCRI	3162.598	812.4221	1619.6	6389.4
UNIONCOV	12.52042	5.467891	3.3	27.5
UNEMPBEN	798003.4	1100631	20753	1.06e+07
POVERTY	12.8884	3.360288	5.4	23.1

VI. Results

Table 2 shows the results from the two-stage least squares regression. The main variable of concern, research and development, is statistically significant at the 1% level. There is a positive relationship, indicating that as research and development expenditures increase, so does the unemployment rate. Specifically, a one million dollar increase in research and development will increase the unemployment rate by .0001. Although the coefficient is small, this is evidence that the displacement effect is larger than the productivity effect in the short-run. For the years and states studied, I found that technological change displaced labor.

The control variables for GDP, unemployment benefits, poverty rates, and education expenditures all have their expected signs. The first three are statistically significant at the 1% level, and education expenditures are statistically significant at the 5% level. Most of these variables have small coefficients similar to the RD variable, but poverty has a larger coefficient of .1109. This means that as the poverty rate increases by one percentage point, the unemployment rate will increase by .1109 percentage points.

Another variable that has a large coefficient is the minimum wage. My results show a coefficient of -.2556, which is different from the positive sign that I expected. As the minimum wage increases by one dollar, the unemployment rate falls by .2556 percentage points. This would suggest that the minimum wage was below the market equilibrium wage for the years studied. The violent crime variable also had a sign different from its expected sign. The results show that as the violent crime rate increases by one percentage point, the unemployment rate decreases by -.0021 percentage points. Previous studies had shown mixed results for this variable relative to unemployment, so it was no surprise for me to get these results. The variables for property crime and union coverage were not statistically significant.

TABLE 2–Regression Results

Variables	UNEMP
RD	.0001039*** (.0000382)
GDP	-.000149*** (.0000117)
WAGE	-.2555767** (.1168916)
EDUCATION	-5.31e-08** (2.54e-08)
VIOCRI	-.0021069*** (.0007224)
PROPCRI	-.0000328 (.0001164)
UNIONCOV	-.0202486 (.0253736)
UNEMPBEN	6.34e-07*** (8.44e-08)
POVERTY	.110887*** (.022701)
Constant	11.63618*** (.9439298)
Wald chi-squared R-squared Root MSE Number of Observations	6576.66*** .9150 .60946 608

Robust standard errors are reported in parenthesis.

***Significant at .01 level, **significant at .05 level, and *significant at .10 level.

VII. Limitations

There are limitations to my study that should be addressed. The first is my use of commercially-supplied research and development expenditures as a proxy for technological change. This is not a perfect measure for technological change, but it is one of the closest in terms of data currently available to us. The research and development expenditures are an input variable, meaning that a company may be spending a lot on research and development that doesn't actually produce a product. Thus, spending on research and development does not necessarily mean technological innovation is happening. Better data for technological innovations would improve future studies.

Second, there may be a spillover of research and development across state lines. A company may spend on research and development in one state to create a product in that state, but then the product is also used in different states where the company operates. This could affect unemployment in multiple states due to the spillover. Again, this is not a perfect variable.

Third, my model is focused in the short-run and therefore doesn't offer evidence for long-run results. I wanted to include an education expenditures variable, but the data I could find only went back to 2002 so doing a long-run focus would be difficult. Also, looking back at the results from the Industrial Revolution, we weren't sure of the long-run results until after a century passed. That being said, we may have to wait a century to be able to analyze the long-run results of the technological change that is happening right now.

VIII. Conclusion

Technological change has often made people worry about the future of employment. With the new threat of artificial intelligence, their worries are at an all-time high. Hoping to give people a clearer picture of the issue, this paper analyzed the current relationship between technological change and unemployment in the United States. I gathered data on the two main variables of interest and included numerous control variables. Using a two-stage least squares regression to estimate the results, I found a positive relationship between technological change and unemployment from 2002-2013. This shows the displacement effect is larger than the productivity effect, so technology is directly displacing labor. It is important to note, however, that the relationship during the period studied was small. Although I cannot conclude this from the evidence I gathered, I do hypothesize that the displacement effect will only get larger as artificial intelligence advances. The labor force should start preparing for the possibility that robots will replace their jobs.

References

Acemoglu, Daron, and Pascual Restrepo. 2017. "Robots and Jobs: Evidence from U.S. Labor Markets." NBER Working Paper No. 23285 (March).

Acemoglu, Daron, and Pascual Restrepo. 2018. "Artificial Intelligence, Automation and Work." NBER Working Paper No. 24196 (January).

Aguilera, Andrés, María Gabriela, and Ramos Barrera. 2016. "Technological Unemployment: An Approximation to the Latin American Case." *AD-Minister*, no. 29 (September): 59-78.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2016. "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis." *OECD Social, Employment and Migration Working Papers*, no. 189 (May).

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29, no. 3: 3-30.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York and London: W. W. Norton & Company.

Cang, Yuqing. 2017. "A Deep Dive into Technological Unemployment: A State-Level Analysis on the Employment Effect of Technological Innovations." Senior Thesis, Claremont McKenna College.

Chui, Michael, James Manyika, and Mehdi Miremadi. 2015. "Four Fundamentals of Workplace Automation." *McKinsey Quarterly* (November)

Clague, Ewan. 1935. "The Problem of Unemployment and the Changing Structure of Industry." *Journal of the American Statistical Association* 30, no. 189 (March): 209-214.

Dobbs, Richard, James Manyika, and Jonathan Woetzel. 2015. *The Four Global Forces Breaking All The Trends*. McKinsey Global Institute.

Economist, The. 2016. "Automation and anxiety." *The Economist*, June 25.

Feldmann, Horst. 2013. "Technological Unemployment in Industrial Countries." *Journal of Evolutionary Economics* 23, no. 5 (April): 1099-1126.

Frey, Carl B., and Michael A. Osborne. 2013. "The Future of Employment: How Susceptible Are Jobs To Computerisation." Oxford Martin School.

Loi, Michele. 2015. "Technological Unemployment and Human Disenhancement." *Ethics and Information Technology* 17, no. 3: 201-210.

Lonigan, Edna. 1939. "The Effect of Modern Technological Conditions upon the Employment of Labor." *The American Economic Review* 29, no. 2 (June): 246-259.

Matuzeviciute, Kristina, Mindaugas Butkus, and Akvile Karaliute. 2017. "Do Technological Innovations Affect Unemployment? Some Empirical Evidence from European Countries." *Economies* 5, no. 48.

McCloskey, Dierdre. 2017. "The Myth of Technological Unemployment." *Reason*.

Montgomery, Edward. 1989. "Employment and Unemployment Effects of Unions." *Journal of Labor Economics* 7, no. 2 (April): 170-190.

Mortimer, Thomas. 1772. *The Elements of Commerce, Politics and Finance*. London: Hooper.

Nordhaus, William. 2007. "Two Centuries of Productivity Growth in Computing." *The Journal of Economic History* 67, no. 1 (March): 128-159.

Pew Research Center. 2014. "AI, Robotics, and the Future of Jobs."

Steuart, James. 1767. *An Inquiry into the Nature and Causes of the Wealth of Nations.* New Rochelle: Arlington House.

Terleckyj, Nestor. 1980. "Direct and Indirect Effects of Industrial Research and Development on the Productivity Growth of Industries." In *New Developments in Productivity Measurement*, by eds. John W. Kendrick and Beatrice N. Vaccara, 357-386. Chicago: University of Chicago Press.