The Digital Revolution Revisited:

Artificial Intelligence & Employment

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Abstract

Artificial intelligence (AI) is a quickly advancing technology that has the potential to displace a great deal of workers. Unlike past automation based technologies, I find that high skilled labor is more impacted by AI than lower skilled labor. In order to analyze the impact that AI will have on the labor market, I utilize a fixed effects model for a historical case of automation's impact on employment and a fitted parameter methodology to analyze the careers most and least exposed to artificial intelligence. My results suggest that an increase in exposure to automation technologies by one percentile leads to a .049% decrease in industry-occupation share of the labor market.

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I. Introduction and Motivation

Throughout modern economic history, automation technologies have almost strictly been substitutes for low skilled labor and complements to high skilled labor; however, as human innovation and technological advancements have progressed, there now exists a technology that has the potential to displace high skilled labor. Artificial intelligence (AI) refers to technologies that utilize machine learning, in which computers analyze data using algorithms, establish statistical patterns, and use these patterns to make decisions. Differing from past technology, AI completes tasks with no human instruction (outside of the development of AI itself), and atop this fact, AI achieves these tasks with superhuman performance (Webb, 2020). As such, artificial intelligence is causing a great deal of anxiety over the future of human work and employment. The aim of this paper is to analyze the potential impact that artificial intelligence will have on employment (by industry and occupation).

The impact of automation on the labor market has been a concern for economists since the organization of modern work arose. The motivation for a plethora of economic papers on automation, including this one, comes from John Maynard Keynes's idea of technological unemployment, which is "unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour" (Keynes, 1930). When technological advancements significantly outpace new job creation, there is a significant disconnect between the amount of available jobs and the amount of individuals in the labor force. Changes in the labor market are slow to occur for a multitude of reasons: investing in human capital takes a great deal of time and effort, new industries are slow to develop, occupations remaining may not be suitable for certain demographics, etc. However, historically these changes do occur over time, and standards of living are improved for virtually everyone in the economy. This evolution in the labor market was understood and predictable. Artificial intelligence has the potential to change technological expectations; therefore, the implications of AI on employment and demographic equality and inequality ought to be analyzed.

Currently, there exists a “false dichotomy” in the debate on artificial intelligence and its implications on the labor market: AI means the end of human work versus AI, regardless of its capabilities, will contribute to an increase in labor demand like automation technologies have always done in the past (Acemoglu and Restrepo, 2018). Those who are more pessimistic have an understandable viewpoint. Artificial intelligence is capable and will advance to be more capable of doing something that was previously exclusive to the human aspect of the labor market: the ability to learn, adapt, and make decisions. Atop this, because artificial intelligence tends to target high skilled labor that requires more of an investment in human capital (Webb, 2020), the previous “cure” of investing in more human capital will not be nearly as effective as it was in the past. However, the past normally and somewhat accurately, tends to provide insight into what the future holds. This paper will analyze historical technological forms of automation (robots and software) on employment and use these parameters to estimate the potential impact of artificial intelligence and machine learning on employment.

II. Literature Review

Artificial intelligence is cutting edge technology and its potential impact on the future of human work is just being realized. As such, the economic literature on artificial intelligence is in the early phases and relatively scarce. However, the study of general automation of work and its impact on labor is extensive. Publications of this sort will assist in guiding the historical analysis necessary to examine artificial intelligence, and any paper that analyzes artificial intelligence first examines historical cases. The most common first step among existing literature is defining and providing a numerical score for some sort of a "technology" variable. This entails matching common tasks found in various occupations to tasks that patented technologies are capable of performing. Patented technology is defined as any and all products, processes, and methods registered with the US Patent Office. Multiple sources (Brynjolfsson, Mitchell, and Rock, 2018; Frey and Osborne, 2013; Webb, 2020) utilize data from O*NET, which is a database provided by the US Department of Labor that explains the tasks performed in occupations in the United States. If a patented technology has the capability to perform a task within an occupation, then its technology score increases. However, though the goal is the same, there are different methodologies in establishing these scores. Frey and Osborne utilize a Gaussian process classifier in order to establish a "probability of computerisation" for 702 detailed occupations. Brynjolfsson, Mitchell, and Rock construct a variable entitled the "suitability for machine learning" or SML, which takes 964 occupations in the economy and matches them to 18,156 specific tasks at the occupation level. The authors then use a rubric developed in a past paper written by Brynjolfsson to determine the SML. Because all occupations have a multitude of different tasks, virtually no occupation has tasks that are all 'SML'. Similarly, Webb (2020) develops a technological exposure score for occupations collected through the American Community Survey. Task descriptions from O*NET are cross referenced with public patent data, which is gathered through Google Patents. Verb-noun pairs from each dataset are matched with the use of WordNet, a program commonly used in natural language processing for literature. Based on the frequency of verb-noun pairs, Webb establishes a numerical exposure score and exposure percentile for each occupation. Upon the creation of this variable, all of these authors are able to analyze and run models on technology's (and more particularly artificial intelligence) impact on the labor market. Various other papers, including Bessen, et. al, 2019 and Graetz and Michaels, 2018, examine technology's impact differently. In *Automatic Reaction – What Happens to Workers at Firms that Automate?,* the authors examine firm level data after the introduction of automation technology, while in *Robots at Work,* the authors utilize data from the International Federation of Robotics. Despite having different focuses, these papers share a similar theme: to examine the impact of modern automation on the labor market.

Like with any economic analysis of future trends, there are limitations. Predicting and even explaining the impact of technology is no easy feat. Virtually any author of empirical papers on automation based technologies discuss the limitations of their research in their conclusion section. However, compelling results that are logically sound are possible and given in the existing literature. There are variations in the results ranging from a conclusion that areas in which automation is a factor, incumbent workers are more likely to be displaced (Bessen, et. al, 2019) to an increase in the use of industrial robots and other forms of technology contribute to a significant increase in labor productivity (Graetz and Michaels, 2018). Papers that look exclusively at AI or machine learning find that these forms of automation have the potential to displace highly educated, high skilled labor, which is a historical first (Brynjolfsson, Mitchell, and Rock, 2018; Webb, 2020). Frey and Osborne have more pessimistic results, which suggest that 47% of total employment in the United States is considered at "high risk," meaning that these jobs could potentially be fully automated within the next two decades. Regardless, all of these results suggest that the current technological boom should be studied and understood.

In *The Impact of Artificial Intelligence on the Labor Market,* Michael Webb examines the impact of AI further by running a simulation to predict the future of income inequality. He finds that AI has the potential to decrease income inequality by displacing high skilled workers who tend to be paid more. His paper also examines various descriptive statistics of demographics, including age, gender, education, and wage percentile. However, the authors of the existing literature do not predict the displacement effect on employment as Webb did for two historical cases. As such, this paper will explore the potential changes in employment for artificial intelligence explicitly.

III. Theoretical Model

The theoretical model for this paper is guided by the historical tendency for capital or technology to substitute for labor when it performs the same or comparable tasks better than its human counterpart. In the past, automation in all its forms, whether advanced farming equipment of the Industrial Revolution or robots that have taken over the manufacturing industry, initially reduced the demand for labor and put downward pressure on wages. Labor and wage reduction is counteracted by a productivity effect, which leads to cost savings, which leads to an increase in the labor demand for occupations not impacted by AI (Acemoglu and Restrepo, 2018). However, artificial intelligence can have an ambiguous effect on labor because there may or may not be a mismatch of skills between remaining occupations and displaced high skilled workers. Another potential problem arises with the rate at which artificial intelligence is being introduced and developed. This exorbitant rate can further the divide between displacing workers and the counter effect discussed above. The employment and wage reduction (displacement effect) does not necessarily fade in a timely fashion: the negative impact from the introduction of robots and software are still measurable and significant after 10 years (Webb, 2020). As such, the detrimental aspects of artificial intelligence will more than likely be observable well into the future; therefore, examining and predicting the severity of the impact on employment is necessary.

In the publication *Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction,* Argawal, et al. (2019) layout theoretical models and scrutinize all necessary economic intuition for analyzing artificial intelligence and the labor market. Artificial intelligence causes displacement anxiety for good reason: computers have advanced at an alarming rate over the past decade and their use for economically valuable tasks is developing just as quickly. Currently, AI is more than sufficient in making predictions, which are a major component of decision making. AI performed predictions tasks are perfect substitutes to human performed prediction tasks and are perfect complements to decision tasks. AI will directly disrupt prediction task based jobs and may indirectly impact decision task based jobs by changing the relative returns of labor versus capital (Argaway, et al., 2019). The authors continue to suggest that occupations that were not previously thought of as prediction based will be transformed and reconfigured in order to minimize costs for firms. Regardless of the occupation, the authors suggest thinking of occupations in terms of prediction and decision tasks, due to the substitutionary and complementary relationship. Similarly to all historical cases of automation displacing workers, artificial intelligence will likely "lead to increases in labor tasks upstream or downstream" (Argaway, et al., 2019). Chin et al. (2005) found this to be the case during the Second Industrial Revolution, as the automation in the sailing and shipping industry initially decreased demand for sailors. This was counteracted by the creation of a new demand for engineers aboard ships and an increase in productivity for merchants. Because of the cyclical nature of the economy and the similarities between past technology and artificial intelligence, history will provide insight on the future. This leads to the hypothesis for this paper that higher exposure to technology (and artificial intelligence specifically) will lead to a decrease in industry-occupational employment. In other words, after substitutionary technology is introduced in an industry-occupation the relative number of individuals within that industry-occupation will decrease, as shown through a decrease in the industry-occupation's share of the labor market.

IV. Data and Empirical Methodology

My primary source of data comes from the American Community Survey. I use individuals' race, gender, level of education, age, and income as control variables. I restrict these controls to 2010. These (excluding age and income, which are quantitative) are first constructed as dummy variables. Race is divided by white, African American, and other; levels of education is measured by Low Education (less than high school) Medium Education (diploma or GED, some college) and High Education (Bachelor's degree or Higher). I then utilize the means procedure to find the demographic makeup of each industry-occupation cell. My occupation and industry variables are standardized using titles and descriptions from 1990. Using David Dorn's offshorability by occ1990 variable, I control for global occupational relocation.

In order to create my employment variable, I follow the literature and first establish an industry-occupation variable, in which the first three digits are the industry (1990 basis) code and the last three digits are the occupation (1990 basis) code. Rather than strictly looking at occupations, the industry-occupation provides a deeper level of insight into occupations that span across multiple industries (and allow for many more observations). I then utilized the DHS method which was created by Davis, Haltiwanger, and Schuh in 1996. This effectively creates an "arc percentage" or percent change related to the midpoint and calculates the change in share of employment. I do this by finding each industry-occupation's change in share of the labor market from 1980 to 2010 and dividing by an average of the two years. The DHS percent change between 1980 and 2010 (which I multiply by 100 so that all parameter estimates make more sense) is my dependent variable.

The proxy variable for technology comes from Michael Webb (2020). Each occupation with a 1990 basis from the ACS data is given an exposure score to various types of technology including software and artificial intelligence. Webb assigns this score by analyzing the text of task descriptions found in patents (pulled from Google Patents) and matching that to that of task description for each occupation (pulled from O*NET). By matching verb-noun pairs found in both patents and job descriptions, Webb is able to quantify the extent to which each job may be automated. It is important to note that the exposure score to AI does not describe the extent to which occupations have already been automated, but how these tasks have the potential to be automated, while the exposure score to software gives a better insight into how careers have already been automated. Furthermore, this exposure score is then measured as a percentile in order to make comparisons between occupations more simple. In order to assign an exposure score percentile to each individual in the American Community Survey data, I merge the datasets by the occupation code present in both datasets. I utilize the exposure score to software as my main independent variable in empirical methods and the exposure score to artificial intelligence for the fitted parameter analysis of the industry-occupations most and least exposed to artificial intelligence. Michael Webb also utilized the fitted parameter methodology. The Digital Revolution of the 1990s contributed to similar societal anxieties over employment as the AI revolution of today is doing, making software a valid benchmark in analyzing AI.

In order to gain initial results, I use a simple ordinary least squares regression, and later run the same model controlled for occupational fixed effect. In the following model, *i* represents the occupation:

$$DHSPctChange_i = \beta_0 + \beta_1\, pct\_software_i + \beta_2\, task\_offshorability_i + \beta_3\, Female_i + \beta_4\, African\_American_i + \beta_5\, Other\_Race_i + \beta_6\, Age_i + \beta_7\, Medium\_Education_i + \beta_8\, High\_Education_i + \beta_9\, LogIncome_i + \varepsilon_i$$

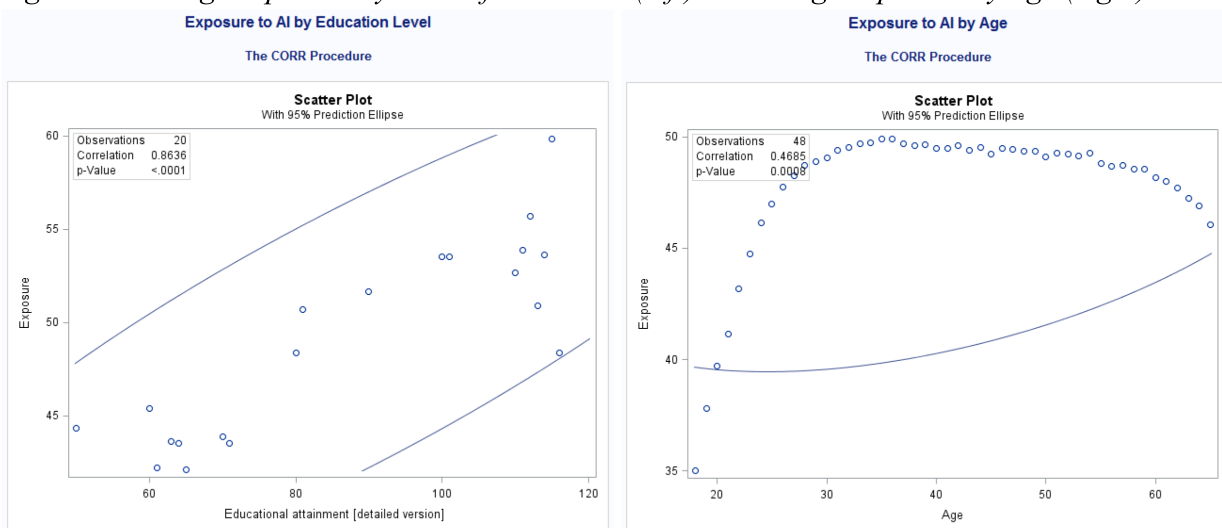
The independent variable of interest is pct_software, which ranks each industry-occupation's exposure to software based technologies on a percentile level. Using the reasoning that technology is a substitute for labor, I expect that this coefficient will be negative. I expect a similar phenomena to occur for the task_offshorabilty variable, as occupations that are more likely to be sent to other countries will lose share of the domestic labor market.

My expectations for the demographic control variables are mainly rooted in trends and generalizations. The female coefficient will likely be positive because of an increase in females in the labor market. African American labor force participants tend to be in lower skilled occupations, and as such I predict that the African_American variable will have a negative coefficient. The Other_Race variable may be a little more ambiguous, as individuals of other races are more heterogeneous with both high and low skilled individuals. As such, I expect the other race variable to be slightly positive, albeit closer to zero. The Age variable will likely be negative due to older people being more exposed to technology than younger people. Human capital attainment has a positive relationship with employment, so I expect Medium and High levels of education to have a positive coefficient. I expect LogIncome, which is a log measure of individuals' yearly earnings, to be positive because of a trend of the labor market moving towards higher wages.

V. Descriptive Results

Descriptive statistics are crucial for understanding who will be most impacted by the artificial intelligence movement and increasing levels of automation. To measure this, I correlated occupational demographics to Exposure to AI. Because I restricted the level of education down to three broad categories, I rather looked at the IPUMS detailed education level for more observations in this correlation. A higher x-value corresponds to a higher level of education. For the age correlation, I found the average level of exposure for each age, such that there is one observation for each year old (18-65) age group. My results fell in line with existing literature:

Figure 1: Average exposure by level of education (left) & Average exposure by age (right)



Unlike past trends, one gains more exposure to this form of automation technology as they invest more into human capital. In other words, higher educated people are more likely to work with (or be substituted) by artificial intelligence. The correlation coefficient of .86 suggests a strong relationship between education and AI exposure. Generally speaking, older people are more likely to be exposed to AI than those first entering the labor market. This relationship has a great deal of importance: older workers are more "immobile," both geographically and occupationally, and because they have fewer years left in the labor market, retraining is less appealing to them (Webb, 2020). The relationship between gender and exposure to AI was not as clear (or as visually appealing) as the other two demographics. Females are less likely to be exposed to AI, with a relatively weak correlation coefficient of -.26. An exhaustive list of more descriptive statistics can be found in Tables 1 & 2 of the Appendix.

VI. Empirical Results

i. Historical Analysis (Software)

In order to examine whether or not technological exposure has a negative relationship with employment, I utilized both an Ordinary Least Squares and a one-way fixed effects model. Within the OLS model (See model 2 in Table 3), my independent variable of interest (pct_software) is negative and significant, just as I hypothesized. The results suggest that an increase from the 25th to the 75th percentile in technological exposure results in a 5.5% decrease in industry-occupation share in the labor market, all other things being equal. Though this percentage may seem small, the labor market was over 150 million people in 2010, making every hundredth of a percent have a profound impact. Although this is the historical technological impact on employment, with the fitted parameter methodology, this has a great deal of impact for the future of the labor market as the artificial intelligence movement continues. The task offshorability parameter estimate is negative, as expected. If tasks in a particular occupation have a high tendency to be relocated to other countries, then these occupations would be expected to have a lesser share of the labor market domestically. As for the control / demographic results, education parameters became increasingly more positive at each level. From 1980 to 2010, careers became more and more dependent on higher levels of human capital attainment which suggests that those who achieved a high school diploma or higher would see their occupation's share of the labor market increase. Similarly, the female coefficient is positive such that an increase of 1 % in the female ratio of each industry-occupation results in a .19 % increase in an industry-occupation's share of the labor market. This is likely due to the female labor force participation rate increasing from 1980 to 2010 as well as a high female participation rate in service based industries, which are not as impacted by technology. The coefficient for age is negative as expected, with an increase in average age by 1 year leading to a .97 % decrease in industry-occupation's share of the labor market. This is likely due to the aging labor market: the Baby Boomer generation (which is larger than other generations) reached retirement age by 2010, and as such industry-occupation's with an older average age shrank. In terms of race, industry-occupations with a higher percentage of African American individuals saw their share of the labor market actually increase, which was opposite of what was expected. For every additional percentage of African American individuals, the industry-occupation's share of the labor market increases by .095%, and for every additional percentage of other races, the industry-occupation's share of the labor market increases by .1319%.

With 19,836 industry-occupations as observations, all variables except for African American were statistically significant beyond the 99 percent level. The model has a weak adjusted r-squared value of .0559 which suggests this model can only explain about 5% of the variation. However, this likely stems from the fact that this is a simple OLS without controlling for endogeneity or any other problems.

The F-Value of 23.11 (Model 4 in Table 3) suggests that I can reject the null hypothesis of no fixed effects, thus indicating that a fixed effects model is more suited for my research question than an OLS. After controlling for occupation fixed effects, the coefficient for technological exposure remains robust; however, it weakens slightly, such that an increase from the 25th to the 75th percentile in technological exposure results in a 2.45% decrease in industry-occupation share in the labor market. This coefficient also became slightly less statistically significant, dropping from the 99% level to 95% level. Most other coefficients remain similar to those in the OLS. The biggest difference comes from the log of yearly income variable, as it was negative and significant in the OLS model but positive and significant in the fixed effects, such that a one percent increase in yearly income leads to a .0466% increase in labor market share by industry-occupation.

The explanatory power of the fixed effects model is much greater than that of the OLS model, with an adjusted r-squared value of .2413. This is comparable to the adjusted r-squared that Michael Webb (2020) found with his fixed effects model. When the fixed effects methodology is implemented, the chance of omitted variable bias is greatly reduced and validity is added to the results.

ii. Prediction Analysis (AI)

Following the literature, I use fitted parameters in order to predict the future of artificial intelligence's impact on employment. This Digital Revolution is often considered the Third Industrial Revolution and shares a great deal of similarities with the technological advancements of today, which is often referred to as the Fourth Industrial Revolution. Within the later part of the twentieth century, technology became a staple of everyday life. The rise of the internet and personal computers, average individuals were able to utilize relatively advanced technology in their homes. However, in the workplace, digitization and software caused a great deal of socio-economic anxieties over the future of work (and as my results suggest, these anxieties were valid since software exposure did decrease share of employment). Political leaders and innovators of AI are voicing some of the same concerns today. Since the Digital Revolution of the late twentieth century can be used as a benchmark, I can utilize the parameters found in model 4, but substitute my exposure percentile for software with the exposure score for artificial intelligence. This requires me to make the strong assumption that software will have the same impact as AI, just on different occupations. Utilizing the fitted parameters I found the predicted impact for the five industry-occupations most and least exposed to Artificial Intelligence:

Figure 2: Examining the most and least exposed industry-occupations. Most exposed have an exposure percentile of 100 and least exposed have an exposure percentile of 1.

Prediction for Artificial Intelligence **Fitted Parameters**			
Most Exposed to AI		**Least Exposed to AI**	
Occupation **(Industry)**	**Predicted DHS Δ**	**Occupation** **(Industry)**	**Predicted DHS Δ**
Clinical Laboratory Technicians (Health Services)	8.97	Funeral Directors (Funerals & Crematories)	-.781
Chemical Engineers (Industrial Chemicals)	18.82	Food Preparation (Restaurant)	-5.06
Optometrists (Optometry)	-3.84	Mail Carriers (US Postal Service)	-3.38
Power Plant Operators (Electric Light and Power)	-4.26	Subject Instructors (Colleges & Universities)	34.16
Dispatchers (Public Order)	-1.05	Art/Entertainment Performers (Misc. Personal Services)	-5.07

Notes: Predicted change in DHS is calculated using industry-occupation specific demographics and the parameters found in the detailed Fixed Effect Model (1).

The most exposed industry-occupations are all within the 100th percentile for exposure to artificial intelligence whilst the least exposed industry-occupations are within the 1st percentile. Because the historical analysis examined a change over 30 years, the numbers above estimate the change from 2010 to 2040. There are some pretty clear trends, with the highly exposed careers mainly losing labor market share. However, there are quite a few discrepancies, which come as a result of technological exposure not having the only role in determining changes in employment. Most notably, chemical engineers and clinical technicians are highly exposed to AI, but the fields are expected to grow quite significantly. An overwhelming majority of individuals in these occupations have medium or high levels of education. Similarly, industry-occupations that are minimally exposed and have lower average levels of education, such as art performers and food workers, actually decrease in their share of the labor market. This suggests that gains from higher levels of human capital investment can outweigh the losses that come from being exposed to automation (and vice versa). In a broader sense, the highest amounts of investment in education may offer job security against automation. There exists a plethora of other variables that play a role in determining the shape of the labor market, many of which are impossible to capture manually. However, when controlling for fixed effects between occupations, exposure to technology is most definitely influential in how industry-occupations change over time.

VII. Conclusions and Limitations

Higher technological exposure was shown to historically decrease occupational labor market share / employment, which confirms my hypothesis. I make rather strong assumptions by utilizing the fitted parameter methodology, and truthfully, I do not believe AI and software will have the same exact economic impact. Though my research finds that the impact of an artificial intelligence revolution may not be as extreme as others suggest, there are a great deal of policy and societal implications. Firstly, individuals (especially those entering college and the labor force) should be aware of the potential their field has for being automated. This will undoubtedly impact the types of degrees college students obtain as AI becomes more and more prevalent in the workforce. Secondly, state and national governments should be aware of the potential for structural unemployment and the welfare safety nets for these individuals.

Industry leaders and government leaders alike have warned about the future of artificial intelligence. Elon Musk, founder of SpaceX and Tesla, often warns about what the future of AI has in store. Because of his familiarity with the powerful technology, he has stated that he believes AI is a “fundamental threat to the existence of human civilization,” and as such regulation from the government should be “proactive rather than reactive.” Similarly, Russian President Vladimir Putin says that the nation that leads in AI “will be the ruler of the world.” These public statements contribute to societal anxieties, but also suggest that AI holds more potential (economically) than any past technologies.

Because artificial intelligence is continuously advancing and has only recently started being used to perform humanlike tasks, the general public may not see the direct impacts for upwards of 5 or so years. Measuring phenomena that have not yet occured is difficult because data simply does not exist, which is why I utilized past data to provide an insight into the future. However, as the above literature suggests, artificial intelligence may not necessarily lead to some of the same economic consequences as software. The reality that stems from artificial intelligence may be much more ambiguous than my model suggests. A displacement effect may occur much faster than in previous cases as software requires constant human instruction, while artificial intelligence does not. However, artificial intelligence also requires a great deal of investing in complementary capital (Webb, 2020), which may slow down a possible displacement effect. Because of the uncertainty surrounding the future of artificial intelligence, future econometric analysis is needed as the data applicable to AI becomes available.

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IX. Appendix

Table 1.

Descriptive Statistics n=19,836			
Variable	**Description**	**Mean**	**Source**
task_offshorability	Score for outsourcing by OCC1990	.431	David Dorn
pct_ai	Exposure percentile to AI by OCC1990	54.402	Michael Webb
pct_software	Exposure percentile to software by OCC1990	52.75	Michael Webb
Female	Average percentage of women across industry-occupations (2010 basis)	.399	ACS
White	Average percentage of white individuals across industry-occupations (2010 basis)	.802	ACS
African_American	Average percentage of African American individuals across industry-occupations (2010 basis)	.09	ACS
Other_Race	Average percentage of individuals of a different race across industry-occupations (2010 basis)	.108	ACS
Low_Education	Average percentage of individuals with a low level of education across industry-occupations (2010 basis)	.087	ACS
Medium_Education	Average percentage of individuals with a medium level of education across industry-occupations (2010 basis)	.63	ACS
High_Education	Average percentage of individuals with a high level of education across industry-occupations	.283	ACS
DHS	Average arc percentage change in share of the labor market across industry-occupations times 100	.705	ACS
LogIncome	Average log of annual income ($) across industry-occupations in 2010	9.18	ACS

Table 2.

Pearson Correlation Coefficients
N = 19,836

Variable	DHS	pct_software	pct_ai	task_offshorability
DHS	**1**	**-.079** **<.0001**	**.054** **<.0001**	**-.046** **<.0001**
pct_software	**-.079** **<.0001**	**1**	**.603** **<.0001**	**-.171** **<.0001**
pct_ai	**.054** **<.0001**	**.603** **<.0001**	**1**	**-.144** **<.0001**
task_offshorability	**-.046** **<.0001**	**-.171** **<.0001**	**-.144** **<.0001**	**1**
Female	**.084** **<.0001**	**-.336** **<.0001**	**-.272** **<.0001**	**.335** **<.0001**
African_American	**.007** **.343**	**.006** **.409**	**-.059** **<.0001**	**.002** **.736**
Other_Race	**.029** **<.0001**	**.018** **.011**	**-.008** **.286**	**.038** **<.0001**
Age	**-.092** **<.0001**	**-.005** **.445**	**.057** **<.0001**	**-.051** **<.0001**
Medium_Education	**-.138** **<.0001**	**.117** **<.0001**	**-.164** **<.0001**	**-.103** **<.0001**
High_Education	**.173** **<.0001**	**-.193** **<.0001**	**.190** **<.0001**	**.133** **<.0001**

Table 3.

Technology & Employment **Dependent Variable: DHSPctChange x 100**					
	Model				
Variable	**OLS (1)**	**OLS (2)**	**OLS (3)**	**Fixed Effects (4)**	**Fixed Effects (5)**
Intercept	14.82*** (1.48)	57.36*** (7.38)	64.89*** (6.58)	-14.89 (9.54)	-16.78* (9.05)
Exposure to software	-.264*** (.02)	-.11*** (.03)	-.17*** (.02)	-.049** (.02)	-.06*** (.02)
Task Offshorability		-8.98*** (.59)	-7.44*** (.57)	-5.36*** (.55)	-4.79*** (.53)
Medium Education		15.73*** (3.86)	16.94*** (3.84)	8.65*** (3.63)	8.41** (3.60)
High Education		70.55*** (4.24)	77.82*** (4.19)	43.39*** (3.98)	45.99*** (3.92)
Income (Log)		-7.08*** (.00)	-13.42*** (.99)	4.66*** (1.05)	1.50 (.98)
Female		18.98*** (2.16)		6.41*** (2.03)	
African American		9.50** (3.96)		3.86 (3.79)	
Other Race		13.19*** (3.69)		10.73*** (3.39)	
Age		-.97*** (.09)		-.64*** (.09)	
Adj. R-Squared	.0057	.0559	.0465	.2413	.2384
F-Value	115.19	131.47	194.33	23.11	23.86
# of Observations	19,836	19,836	19,836	19,836	19,836

Notes: Each observation is an industry-occupation cell. The dependent variable is 100x the DHS change for each industry-occupation from 1980 to 2010. Standard errors are shown parenthetically below each estimator. Statistical significance is demonstrated as * (90%), ** (95%), and *** (99%). Fixed Effects Models are one way fixed by occupation, and the F-value refers to the F Test for no Fixed Effects.

X. Relevant SAS Code

```
data IPUMS.dum;
set IPUMS.usa_00016;

if sex = 2 then Female = 1;
      else Female =0;

if raced = 100 then White = 1;
      else White= 0;
if raced = 200 then African_American= 1;
      else African_American = 0;
if 110 le raced le 150 then delete;
if 210 le raced le 996 then Other_Race=1;
      else Other_Race = 0;

if 000 le EducD le 061 then Less_than_HS = 1;
      else Less_than_HS = 0;
if 062 le EducD le 064 then Diploma_or_GED = 1;
      else Diploma_or_GED = 0;
if 065 le EducD le 100 then Some_College = 1;
      else Some_College = 0;
if EducD = 101 then Bachelors = 1;
      else Bachelors = 0;
if 110 le EducD le 116 then Masters_Plus = 1;
      else Masters_Plus = 0;
if educd = 999 then delete;

if 000 le EducD le 061 then Low_Education =1;
      else Low_Education = 0;
if 062 le EducD le 100 then Medium_Education = 1;
      else Medium_Education = 0;
if 101 le EducD le 116 then High_Education = 1;
      else High_Education= 0;

if empstat = 1 then Employed = 1;
      else Employed = 0;
if empstat = 2 then Unemployed = 1;
      else Unemployed = 0;
if empstat = 3 then delete;

if occ1990 = . then delete;
if ind1990 = . then delete;
if incwage = . then delete;
if incwage = 0 then delete;

industry= IND1990 *1000;
```

```
indocc = industry + occ1990;
Income = incwage / 52;
LogIncome = log(Income);
run;

proc sort;
      by occ1990;
      run;

libname Exp "D:\Senior_Project\Exp";
filename ai "D:\Senior_Project\Exp\Exposure.csv";

proc sort data = exp.ai;
      by occ1990;
      run;
proc import Datafile = "D:\Senior_Project\Offshore\Offshore.dta" out =
offshoring REPLACE;
      run;
proc sort data = work.offshoring;
      by occ1990dd;
      run;
data offshoring2;
      set work.offshoring;
      rename occ1990dd = occ1990;
      run;

data IPUMS.Good;
      merge IPUMS.dum exp.ai work.offshoring2;
      by occ1990;
      run;

data IPUMS.intermediate;
      set IPUMS.Good;
      run;
proc sort nodupkey;
      by indocc;
      run;

data indoccpct2010;             /*creating employment variable for 2010*/
      merge IPUMS.Good;
      by OCC1990;
      if pct_software = . then delete;
      if year = 2010 then _2010 = 1;
            else delete;
      run;

proc freq;
      tables indocc*(_2010) / out=want outpct;
      run;

data TwentyTen;
      set work.want;
      Rename PCT_COL = Pct2010;
      run;
```

```
data occpct1980;
	merge IPUMS.dum exp.ai;		/*creating employment variable for 1980*/
	by OCC1990;
	if pct_software = . then delete;
	if year = 1980 then _1980 = 1;
		else delete;
	run;

proc freq;
	tables indocc*(_1980) / out=please outpct;
	run;

data NineteenEighty;
	set work.please;
	Rename PCT_COL = Pct1980;
	run;

data pctmerge;
	merge work.TwentyTen work.NineteenEighty;
	by indocc;/*creating main independent variable (change in employment)*/
	if Pct2010 = . then delete;
	if Pct1980 = . then delete;
	PctChange= Pct2010 - Pct1980;
	DHSPctChange = (Pct2010-Pct1980)/((Pct2010+Pct1980)/2);
	PctChangeOCC= (Pct2010 - PctChange) / Pct2010;
	run;

data IPUMS.control;
	set IPUMS.Good;
	if year = 2010 then _2010=1;
		else delete;
	run;
proc sort;
	by indocc;
	run;
proc means noprint;
	by indocc;
	var Female age White African_American Other_Race Less_than_HS
	Diploma_or_GED Some_College Bachelors Masters_Plus LogIncome
	Low_education Medium_Education High_Education;
	output out = control mean(Female age White African_American Other_Race
	Less_Than_HS Diploma_or_GED Some_College Bachelors Masters_plus
	LogIncome Low_education Medium_Education High_Education)=
	Avg_Female Avg_age Avg_White Avg_African_American
		Avg_Other_Race Avg_Less_than_HS Avg_Diploma_or_GED
		Avg_Some_College Avg_Bachelors Avg_Masters_Plus Avg_LogIncome
		Avg_Low_education Avg_Medium_Education Avg_High_Education;
	run;

data IPUMS.FINAL;
	merge work.control work.pctmerge IPUMS.Intermediate;
	by indocc;
	if ind1990 = . then delete;
```

```
	if occ1990 = . then delete;
	if pct_software = . then delete;
	if DHSpctchange = . then delete;
	if task_offshorability = . then delete;
	if female = . then delete;
	if African_American = . then delete;
	if Other_Race = . then delete;
	if Age = . then delete;
	if Medium_Education = . then delete;
	if High_Education = . then delete;
	if LogIncome = . then delete;
	DHS= DHSpctchange*(100);
	run;
proc contents;
	run;
ods pdf;
proc reg;
	model DHS = pct_software;
	run;
proc reg;
	model DHS = pct_software task_offshorability Avg_Female
Avg_African_American Avg_Other_Race Avg_age
 Avg_Medium_Education Avg_High_Education Avg_LogIncome;
	run;
proc reg;
	model DHS = pct_software task_offshorability Avg_Medium_Education
Avg_High_Education Avg_LogIncome;
	run;
proc sort;
	by ind1990 occ1990;
	run;
proc panel data = IPUMS.Final;
	title "Fixed Effects Model 1";
	id ind1990 occ1990;
	model DHS = pct_software task_offshorability Avg_Medium_Education
Avg_High_Education Avg_LogIncome / FIXONE;
	run;
proc panel data = IPUMS.Final;
	title "Fixed Effects Model 2";
	id ind1990 occ1990;
	model DHS =  pct_software task_offshorability Avg_Female
Avg_African_American Avg_Other_Race Avg_age Avg_Medium_Education
Avg_High_Education Avg_LogIncome / FIXONE;
	run;
ods pdf close;
proc means data = IPUMS.Final;
	run;

proc corr data = IPUMS.Final;
	var DHS pct_software pct_ai task_offshorability Avg_Female
Avg_African_American Avg_Other_Race Avg_age Avg_Medium_Education
Avg_High_Education Avg_LogIncome;
	with DHS pct_software pct_ai task_offshorability;
	run;
```