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A Deep Dive into Technological Unemployment: A State-Level Analysis on the Employment Effect of Technological Innovations

Yuqing "Jenny" Cang
Claremont McKenna College

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Professor Ananda Ganguly

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Yuqing "Jenny" Cang

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Abstract

Ever since the first Industrial Revolution, during which many textile artisans lost their jobs to weaving machines, the relationship between technological progress and unemployment has been explored and examined by researchers and policy makers. Existing empirical research, mostly at the microeconomic level, has presented ambiguous results. Procuring data on 51 U.S. states for a period of 19 years and a large number of controls, this paper studies the employment effect of technological innovations with a novel state-level macroeconomic analysis. Using commercially-supplied Research and Development expenditure as a proxy, this paper finds that although technological innovations have a non-significant effect on employment at the general state level, there are a few factors that determine how well each state's labor market responds to technological changes. More specifically, non-urbanized, non-tech-savvy, or states with a large number of workers employed in Manufacturing or Accommodation and Food Services industry experience a more severe unemployment effect than the other states. The results also suggest that unemployment rate is more negatively affected by technological innovations during the Obama Administration, compared with the Clinton and Bush Administration. This paper adds to the limited, macroeconomic literature on technological unemployment, and provides policy makers with important implications on how to prepare citizens for the imminent waves of technological changes.

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I. Introduction

As technological innovations, such as artificial intelligence, nanotechnology and robotics advance, the workforce faces the prospect of being completely revolutionized. In 1942, Economist Joseph Schumpeter introduced the term “creative destruction,” articulating that disruptive transformation resulting from technological innovations might stall economic growth. Since then, an extensive literature has been dedicated to the potential impact of technological innovations, which were often developed with the intention of cost-saving, through reducing waste, developing by-products, and increasing the capacity of equipment relative to its price (Gold 1964). Some economists raise concerns about the labor impact of technological innovations, which include massive human labor job displacement, and a resulting rise in unemployment (Ricardo 1951). Clark (2007) famously argues that the advancement of technology will “leave behind some people,” just as the horses were replaced due to “the arrival of the internal combustion engine” in the early twentieth century. Others argue that technological innovations will lead to more middle-skill jobs that combine routine technical tasks and non-routine tasks that require interpersonal interaction, problem solving, and adaptability, as they replace the traditional labor-intensive, solely routine tasks (D. H. Autor 2015).

While previous researchers have mostly investigated the relationship between unemployment and technological innovations on the microeconomic-level (i.e. firm and industry level), there is a need for macroeconomic analysis yet to be fulfilled by existing literature. Macroeconomic research can help government agencies and policy makers better understand the aggregate employment effect of technological innovations, and provide insights on how to best respond to technological changes without unnecessarily disrupting the labor market. This paper contributes to the discussion by conducting a novel state-level macroeconomic analysis on the employment effect of technological innovations. Using commercially supplied Research & Development expenditures as a proxy for technological innovations, and data on 51 U.S. states (including District of Columbia) over the period of 19 years and a large number of controls, I hypothesize that technological innovations have a labor-friendly nature on the overall state-level. Moreover, I investigate how different presidential administrations, as well as certain state characteristics such as urbanization level, and major industry of employment, impact the extent to which state labor markets are affected by technological changes.

I find that although technological innovations have a non-significant effect on employment at the aggregate state level, there are a few factors that determine how well each state's labor market responds to technological changes. I find that non-urbanized, non-tech-savvy, or states with a large number of workers employed in Manufacturing or Accommodation and Food Services industry experience a more severe unemployment effect than the other states. In addition, the results suggest that unemployment rate is more negatively affected by technological innovations during the Obama Administration, compared with the Clinton and Bush Administration.

The remainder of the paper is organized as follows: The next section summarizes relevant past literature on both the theoretical background and empirical findings. Section III describes the methodology used and three main hypotheses behind my research, and explains the control variables employed in the model. Section IV describes data sources. Section V presents and interprets the regression results. Finally, Section VI concludes and discusses the limitations of my research.

II. Literature Review

A. Theoretical Background

Unemployment has always been a focus area in labor economics research. Researchers in the past have attempted to find the determinants of unemployment through various methodologies. For example, Maqbool et al. (2017) find that population, foreign direct investment, and inflation have significant effect on unemployment in the long run. In addition, they find an inverse relationship between unemployment and inflation, suggesting the existence of Phillips curve at play both in the short- and long-run. Maki and Spindler (2017) look at the post-1966 increase in measured unemployment rates in the United States and find that a large part of unemployment changes is due to the changes in unemployment benefits. Political factors come into play as well. Wood et al. (2005) find that certain chactertistics of U.S. presidents, such as the sentiment with which they deliver their presidential remarks, significantly affect people's perception of the economy, and the overall economic performance, which includes employment.

One significant area of research on the determinants of unemployment has revolved around technological progress and development. More specifically, economists have examined the effect of technological progress on the labor market, particularly the efficiency of the existing labor force, and the demand for labor. Two of the most prominent economists who have studied this topic are Joseph Schumpeter and David Ricardo. Schumpeter (1911) famously argues that technological innovation, as reflected by productivity growth, will spur a temporary increase in demand for primary factors to produce new goods. This will be followed by a reduction in labor demand as process innovation provides 'a saving effect,' and competes with the primary factors, leading to higher unemployment. This issue is also addressed by Ricardo in his book "On Machinery," where he proposes "...the opinion, entertained by the laboring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy" (Ricardo, 1951). Following Schumpeter and Ricardo, many others have contributed to the discussion on the relationship between productivity growth and unemployment. Under a theoretical model, there have mainly been two employment effects of technology-incurred productivity growth in tension. First, technological progress leads to job creation through the 'capitalization effect.' Pissarides (1990) suggests that since the costs of job creation are paid initially, faster technological progress "means a lower effective discount rate on future profits and hence higher present value for profits." If variations in the rate of job destruction are assumed to be constant across various business cycles, the effect of faster growth is to increase jobs and reduce unemployment. The second employment effect, coined by Schumpeter as 'creative destruction effect,' captures a positive relationship between technological progress and unemployment (Aghion and Howitt 1994). It highlights that the new capital will only be employed by newly created jobs, and therefore suggests that technological progress requires a transition of workers to new firms, creating lower job creation and higher job destruction flows resulted from labor reallocation (Boianovsky and Trautwein 2007). Which one of the abovementioned theoretical effects will dominate is unclear, and will be explored further in later sections through empirical research. With the inconclusive effects presented by theoretical models aside, however, the media has frequently reported and portrayed the direct, often destructive effect of technological advancement on workers ever since the first Industrial Revolution, during which spinning machines became a competitive force to human labor. As a prominent example, the Luddite movement in the 19th century was centered around a group of English textile artisans and weavers, who feared being replaced in the industry, and protested the automation of textile production by destroying weaving machines (Skidelsky 2014).

More recently, scholars have been concerned with the popularity of computers and their potential ability to replace a significant portion of existing jobs. For example, Brynjolfsson and McAfee (2016) predict that rapid digitization brings economic disruption by eliminating companies' needs for some kinds of workers. Acemoglu and Restrpo (2016) propose the relationship to be a "stable balanced growth path in which the two types of innovations go hand-in-hand; an increase in automation reduced the cost of producing using labor, and thus discourages further automation and encourages the faster creation of new complex tasks." A more quantitative study is brought about by Frey and Osborne (2013), who estimate the probability of computerization for 702 detailed occupations, and find 47% of total U. S. employment to be at risk of being computerized.

But to what extent are technological advancement and innovations taking away human jobs? How concerned should one be about the future of employment? Extensive empirical research has attempted to shed light on these questions by looking at employment data from different industries and countries, and its relationship with workforce characteristics.

B. Empirical Research

Most of the existing research examines the employment effect of technological innovations at the firm level, and suggests a labor-friendly nature of technological innovations. For example, Bogliacino et al. (2012) apply the dynamic LSDVC estimator to a longitudinal dataset that covers 677 European companies over the period of 1990 to 2008, and find that business R&D has a significant, although small in magnitude, job creation effect. Based on data on 20,000 firms chosen as random samples of manufacturing and services from 4 European countries covering from 1998 to 2000, Harrison et al. (2014) find that the growth of demand, spurred by product innovation, is a strong contributing force to employment creation. They also observe a weak effect of process innovation on the number of workers hired, or the demand for labor. This conclusion is supported by other research such as Hall et al. (2008). They find a lack of evidence that links employment displacement to process innovation, based on microdata of over 9000 Italian manufacturing firms. However, they do recognize a significant contribution of product innovation to employment growth. Lachenmaier and Rottman (2007) find positive effects of both product and process innovation on employment. Interestingly, they find the effect of process innovation to be higher than that of product innovation. Using data from Argentina, Chile, Costa Rica and Uruguay, Crespi and Tacsir (2012) further test the Harrison et al. (1998) model, and find a strong compensation effect of introduction of new products.

Using a sample of 15,186 French manufacturing firms over the 1986-1990 period, Greenan and Guellec (2000) find that process innovation has a stronger job creating effect than product innovation at the firm level, but the contrary is true at the sector level. They also find that innovative firms, firms that have high level of innovative activity according to the French Innovative Survey (EAE), tend to create more jobs. This finding is consistent with other research such as Smolny (1998), which uses microeconomic data from West German manufacturing firms, and finds that innovative firms are more successful, and show higher employment growth than non-innovative firms.

Similar patterns are observed with British firm-level panel data. Controlling for fixed effects, endogeneity, and dynamics, Reenen (1997) utilizes data on headcounts of innovation in 598 British firms, and finds that higher technological innovation activity was associated with higher number of employees hired at the firm-level.

Coad and Rao (2011) focus on the patenting and R&D expenditure histories of four manufacturing industries, and use Weighted Least Square analysis to find that firm innovations have a positive effect on the total number of jobs, not just limited to firm-specific behavior.

Looking at the effect of computerization on a firm's output growth and labor productivity, Brynjolfsson and Hitt (2003) use computer stock data from 527 large US firms over 8 years, and find a positive short-term effect of computerization on measured productivity. In addition, they find that over longer periods of time, the productivity contribution made by computerization might even be greater, reaching up to five times.

Pellegrino et al. (2017) employ data of Spanish firms over the period of 2002-2013 to test the employment impact of different types of innovative investments. They find that the statistically significant, and positive impact of innovation can only be observed in high-tech firms.

However, not all firm-level research finds the employment effect of technological innovations positive. For example, Brouwer et al. (1993) examine a data set of 859 Dutch manufacturing firms over the period 1983-1988, and find that the growth of firm's R&D intensity has in fact a negative impact on employment. In addition, they observe no significant impact of R&D cooperation on employment growth.

A lot of researchers have also studied the employment effect of technological innovation at the industry level. In contrary to the generally consistent results from firm-level research, industry-level literature has recorded very mixed results. For example, Evangelista and Savona (2010) utilize data from the Italian Innovation Survey from 1993 to 1995, and find an overall negative impact of innovation on employment across service industries. More specifically, they find that firm size and service sector play significant roles: small firms tend to experience positive employment effect with higher level of innovation activity, whereas larger firms and capital-intensive industries observe negative employment impact of innovation.

Piva and Vivarelli (2017) utilize longitudinal data from manufacturing and service sectors for 11 European countries over a period of 14 years and conclude that the positive employment effect seems to be entirely from the medium- and high-tech sectors. They also find a negative correlation between employment and capital formation, which suggests that technological progress could potentially be labor-saving given that process innovation is often incorporated in investment. Their result is complemented by other research, such as Moretti (2010), who highlights the multiplier effect of jobs, and finds that with each additional skilled job in high tech industries, more than two jobs are created in the non-tradable sector in the same city.

Based on panel data from 15 European countries that covers the 1996-2005 period and 25 service sectors, Bogliacino and Vivarelli (2010) find a job-creating effect of product innovation, proxied by R&D expenditure. They also observe the labor-friendly nature of R&D emerge in both the flow and stock specifications.

Mincer and Danninger (2000) utilize microdata from the PSID (Panel Study of Income Dynamics) and find that although in the short run, technological progress seems to have unclear effects on aggregate unemployment, it reduces unemployment in the longer run.

One other significant employment impact of technological progress observed at the industry level is job polarization. Goos et al. (2014) document the strong contributing effect of routine-based technological change to the pervasive job polarization in 16 European countries over the period of 1993 to 2010. Michaels et al. (2014) look at Information and Communication

Technologies (ICT) data from 11 countries, and conclude that industries with faster ICT growth have observed a shift in demand from middle-educated workers to highly-educated workers.

Despite the benefits of using microeconomic data to study the employment effect of technological progress, as it allows for precise capture of product innovation, and overall mapping of innovation variables, there are considerable limitations associated with firm-level or industry-level analysis. For example, the microeconomic approach may not fully account for the indirect compensation effect, which operates largely through aggregate dynamics. In addition, as suggested by Vivarelli (2012), firm-level research often exhibits a "positive bias" and suggests job creation by technological innovations, failing to acknowledge the potential crowd-out by innovative firms or industries in the broader labor market.

To date, there has been limited macroeconomic research on the employment effect of technological innovations. Vivarelli (1995) uses aggregate time-series data from Italy and the United States, and finds mixed results: the labor saving effect of process innovation seems to have affected the Italian economy more negatively whereas product innovation has benefited the U.S. labor market with employment growth. Based on data from 9 OECD countries over the period 1960-1990, Pini (1995) finds no evidence to support a job creation effect of technological innovations. Instead, he observes a negative effect on employment, and some equally significant compensation effects such as export dynamics and the process of production of new physical capital, both of which linked to the innovation process.

Feldmann (2013) analyzes the impact of technological unemployment empirically by examining annual data of 21 industrial countries from 1985 to 2009. He finds that the ratio of triadic patent families to population, as a proxy for technological change, is negatively correlated with employment in the short term (3 years). However, he finds no long-term effect, suggesting that the adverse effect on unemployment is more transitory than permanent. Notably, Feldmann employs a wide range of macroeconomic control variables, which are selectively adopted in this paper.

C. Proxy for Technological Innovations

There have been four main approaches in existing literature that attempt to capture and document technological innovation quantitatively. The first one, proposed by Gali (1999) and further developed by Francis and Ramey (2005), is to use long-run restrictions in a Vector Autoregression (VAR), assuming that only technology affects long-run productivity. The second approach is from Basu et al. (2006). They create a measure of aggregate technology change with an augmented Solow-Hall approach, controlling for aggregate, non-technological effects such as non-constant returns and imperfect competition. The third method, initially developed by Shea (1999), takes a more direct approach, and employs observable indicators such as Research and Development (R&D) spending, and number of patent applications. The fourth approach, constructed by Alexopoulos (2011), looks at the number of new titles published in the fields of technology and computer science to reflect technological progress, which turns out to be consistent with R&D expenditure data.

This paper adopts the third approach and utilizes company-supplied R&D expenditure as a proxy for technological innovation. The reasons are as follows: First, R&D activity accurately measures the input invested in innovative activity. As Shea (1999) suggests, variation in perceived marginal product of knowledge should at least be partly reflected by the fluctuations in R&D expenditures if technological change is truly stochastic. Second, direct measures, such as R&D expenditures, do not rely on the assumption that only technology affects long-run productivity, which is subject to violation if technological growth is endogenous. Third, existing studies using data from European countries have established that R&D expenditures are closely related to product innovation (Conte and Vivarelli, 2005; Parisi et al., 2006). Despite the benefits of using direct measures, I acknowledge the limitations of using R&D expenditures as a proxy. In particular, since R&D only measures the input in innovation, the output is unlikely to be perfectly correlated with the input. In addition, it takes time to develop a product or service and bring it to market, resulting in an indeterminate lag between the input and output (Alexopoulos and Cohen 2011).

This paper contributes to existing literature by presenting state-level evidence on the employment effect of technological innovations in the United States, which, to the author's knowledge, has never been studied before. State-level analysis is important due to the following reasons: First, using macroeconomic data, rather than microeconomic data, allows for a more accurate and comprehensive mapping of the overall employment effect, as it takes into account of potential spillover between industries, and compensation/saving effect of variables that are stimulated by technological innovation. Second, having different demographic, political and socioeconomic variables in place, different states may absorb and respond to technological shocks differently. For example, following the logic of Robbins et al. (2000), those states that encourage entrepreneurship and adopt a more welcoming attitude towards small businesses and innovative activities might see less technological unemployment, compared with states that tend to protect traditional, corporate, non-innovative businesses. A lack of state-level analysis can hinder state-based efforts to cushion technological shocks, and leave affected states in an economically worse-off situation. A deep dive into the reasons behind states' various responses to technological progress provides important policy and regulatory implications, and informs state-level efforts to reduce unemployment. The results also provide insights for state government on how to best educate, protect and prepare citizens for the imminent waves of technological innovations.

III. Methodology

A. Hypothesis Development

To find the state-level impact of technological innovations, and the determinants of the extent to which each state is affected, I develop 3 hypotheses, and test each hypothesis with an adjusted model. The models used in my research are largely built upon a previous model from Feldmann (2013), where he examines the country-level effect of technological changes, proxied by the number of triadic patent families, on unemployment, and runs two-stage least squares regressions. The second stage of his regression model is as follows:

$$U_{i,t} = \beta_1 P_{i,t} + \beta_2 X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t}$$

($U_{i,t}$ - unemployment rate of country i at year t, $P_{i,t}$ - ‘patent’ variable, $X_{i,t}$ - vector of control variables, α_i - country fixed effects, λ_t - year fixed effects, $\varepsilon_{i,t}$ - error term)

Expanded upon Feldmann (2013)’s model, the regression models I employ in this research adopt the same dependent variable at the state level, and most of the control variables, with some country-level control variables substituted by state-level equivalents.

Hypothesis 1: Other things being equal, one should expect to observe that higher level of technological innovation, proxied by privately-financed R&D expenditure, leads to lower unemployment rate at the state level.

In reference of existing firm-level and industry-level research, I theorize that on the state-level, R&D expenditures will have a labor-friendly nature. In order to test this hypothesis, I estimate the following specification:

$$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \theta_s + \varepsilon_{s,t}$$

The dependent variable in this regression is unemployment rate of 50 U.S. states plus District of Columbia for a period of 19 years (1993, 1995, 1997-2013). Thus, $U_{s,t}$ is unemployment rate of state *s* at year *t*. β_0 captures the constant. Different from Feldmann (2013), my main independent variable of interest is 'Domestic Research & Development expenditures paid for by company and others, and performed by company,' or commercial R&D, represented as *Com_rd*. I choose to use commercial R&D expenditures as a proxy for technological innovations, instead of total R&D, or government-financed R&D, based on research findings from Terleckyj (1980), which suggests that privately-financed R&D has a significant impact on total factor productivity, whereas government-financed R&D as a proxy has insignificant effect and thus should be omitted. $X_{s,t}$ is a vector of my state-level control variables across the entire 19-year period. Y_t is a vector of control variables that are measured at the country-level across 19 years (i.e. same value for each state in a certain year). I control for state fixed effects through generating dummy variables for each state (with state Alabama as the baseline). State fixed effects are captured by θ_s, controlling for the effect of unobserved state-specific characteristics (e.g. dominant culture and religious attitudes towards employment). I include t and t^2 to account for linear and quadratic time trend. Since my research covers a span of 19 years, and does not focus on specific effects of certain years, time trend works sufficiently to control for the process that generates changes extending across years. $\varepsilon_{s,t}$ denotes the error term.

Hypothesis 2: Other things being equal, the extent to which state-level unemployment is affected by technological innovations varies by presidential administration.

My sample data spans across three presidencies: Bill Clinton, George W. Bush, and Barack Obama. Although this research does not cover the entirety of all three presidencies, the data set covers at least five years of each administration, sufficient for one to draw statistical inference from (Clinton: 1993, 1995, 1997 – 2000; Bush: 2001 – 2008; Obama: 2009 – 2013). In addition to the original model examined for Hypothesis 1, I create three presidency dummy variables (i.e., *ClintonDum*, *BushDum*, and *ObamaDum*) and generate interaction terms between the presidency dummy variables and $Com\_rd_{s,t}$ to capture the additional employment effect that technological innovations have as a result of different presidencies. I choose not to include presidency dummy variables as standalone variables in my regression, because the effect of different administration on unemployment will be absorbed by the existing control for linear and quadratic time trend. The regression is as follows:

$$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * ClintonDum + \beta_5 \cdot Com\_rd_{s,t} * BushDum + \beta_6 \cdot Com\_rd_{s,t} * ObamaDum + \theta_s + \varepsilon_{s,t}$$

During the Clinton administration, the US economy observes a long period of expansion and prosperity. In addition, the Clinton administration overlaps with the boom of Personal Computers (PCs) – computers moved from large, expensive workstations to convenient personal computers widely purchased in the households. I suspect that the bright economic prospects and the wide use of PCs are more likely to positively affect the labor market. In light of that, I hypothesize that the coefficient β_4 of the interaction term between *ClintonDum* and $Com\_rd_{s,t}$

will be negative, suggesting that during the Clinton administration, technological shocks are less likely to increase unemployment.

The Bush Administration observes slower economic growth, as well as a financial crisis (2008). However, during the Bush Administration, a few effective economic policies such as Economic Growth and Tax Relief Reconciliation Act (2001) and Job Creation and Worker Assistance Act (2002) were implemented, which seemed to serve as a cushion to economic declines. I suspect that the shock on labor market in response to the 2008 financial crisis and the following recovery phase will take stronger effect during the Obama Administration (starting from 2009) more than the Bush Administration. Thus, I theorize the coefficient β_5 of the interaction term between *BushDum* and $Com\_rd_{s,t}$ to be negative, yet of a smaller value than that of *ClintonDum*. I expect $ObamaDum*Com\_rd_{s,t}$ to have a positive coefficient, meaning that during the Obama Administration, technological shocks to the labor market are more likely to be negatively accentuated, compared with other administrations.

Hypothesis 3: Other things being equal, certain state-level characteristics impact the extent to which unemployment is affected by technological innovation. These state-level characteristics include focus on education, major industry with highest employment in a state, urbanization level, and tech-savviness.

My main motivation behind testing this hypothesis is to examine if certain state characteristics open up local labor market to more severe impacts from technological innovations. Testing results from this hypothesis inform local governments on how to brace their local labor markets from negative impacts of technological innovations. I include 4 main sets of dummy variables of interest, and create interaction terms between them and $Com\_rd_{s,t}$. Due to collinearity between these 4 sets of dummy variables, I test their effects respectively through interaction terms in 4 regressions. However, none of these sets of dummy variables is included as a standalone variable in the regression model, since the explaining power they might have will have been mostly captured by state fixed effects already included in the model.

$$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * HighEduExp + \theta_s + \varepsilon_{s,t}$$

In this regression, I test the effect of state government's focus on education, proxied by per capita state government education expenditure, on the extent to which a state's labor market is affected by technological innovations. I add an interaction term between $Com\_rd_{s,t}$ and a dummy variable *HighEduExp*, developed from 'Rankings of the States' (2005) produced by National Education Association (NEA). This NEA report ranks the 'per capita state government expenditures for all education' by state. In my model, the top 25 ranked states, which have per capita state government education expenditure higher than national average, receive a '1', whereas the rest of the states receive a '0'. I choose 2005 as a reference point, from which I draw inference for the overall focus on education across the 19-year period in my research, since 2005 is the mid-point of my 19-year period of interest, and is a fairly normal year that does not observe drastic economic or political changes. I hypothesize β_4 to be negative, since higher level of education spending is likely to suggest stronger focus on education, which in turn indicates greater level of reactiveness to change, and preparedness towards new technological trends through education.

$$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * Manufacturing + \beta_5 \cdot Com\_rd_{s,t} * HC + \beta_6 \cdot Com\_rd_{s,t} * Accomm + \beta_7 \cdot Com\_rd_{s,t} * Profesh + \theta_s + \varepsilon_{s,t}$$

In this specification, I test the effect of largest industry in a state, as defined by the industry with highest employment, on how well a state's labor market absorbs technological changes. Similar to the model developed for 'focus on education', I use Year 2005 as a reference point, and group 51 states into 5 categories by their largest industry in 2005: Manufacturing (*Manufacturing*), Retail Trade (*RetailTrade*), Health Care and Social Assistance (*HC*), Accommodation and Food Services (*Accomm*), and Professional, Scientific, and Technical Services (*Profesh*). This categorization is based on statistics from the U.S. Department of Labor. Details on the major industry of employment in each state can be found in Table [1]. I choose to omit *RetailTrade* and use it as the baseline of regression due to collinearity reasons.[1] I generate 4 dummy variables for each category other than *RetailTrade*, and interact them with $Com\_rd_{s,t}$. I hypothesize states whose major industries are those with higher probability of being computerized, such as Manufacturing, will have positive coefficients for interaction terms (β_4 >0), whereas industries that are service-intensive, or require higher level of human capital have negative coefficients for interactions terms ((β_5 <0, β_6 <0, β_7 <0).

$$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * Urban + \theta_s + \varepsilon_{s,t}$$

The above specification tests the effect of urbanization. An interaction term is created between $Com\_rd_{s,t}$ and dummy variable *Urban*. Based on Census data (2010), I assign a '1' to the top 25 urbanized states, and '0' to the rest of the states. Due to availability of data, the reference point is taken at Year 2010, instead of 2005. However, since urbanization level

[1] *RetailTrade*Com_rd* exhibits high collinearity with *Com_rd*, my main variable of interest. As a result, I omit *RetailTrade* to be the baseline of comparison.

changes fairly gradually and slowly, I consider 2010 as a fair reference point to draw inference from. I expect β_4 to be negative, because urbanization is often associated with exposure to technology, and thus technological preparedness. I expect that technological innovations will have less impact for citizens in more urbanized areas, because they are more exposed to technology, and have longer time to prepare for and transition to a technologically-demanding labor market.

$$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * Techsavviness + \theta_s + \varepsilon_{s,t}$$

In this specification, I include a new interaction term between $Com\_rd_{s,t}$ and Tech-savviness. Decluttr, an e-commerce platform for tech gadgets, developed a Tech-savviness index using Google search data. I assign a '1' to 25 states with the lowest scores (which means they have the least number of questions asked per person about technology on Google), and a '0' to the rest. I hypothesize that β_4 will be negative due to similar reasons with the previous hypothesis: states that are more tech-savvy are less likely to be negatively affected by technological innovations, since they have higher level of technological familiarity and preparedness.

B. Control Variables

Referencing Feldmann (2013), I control for the impact of most major factors that have been found to affect unemployment rate. Notably, Feldmann (2013)'s research is done only on a national level, across 21 industrial countries, and therefore cannot be fully applied to this study. This study differentiates itself by incorporating some country-level control variables from Feldmann (2013), some state-level replacements of country-level control variables from

Feldmann (2013), and pure state-level control variables. I include a full list of control variables employed in my research, their definitions, descriptive statistics and sources in Table [2].

Country-Level Control Variables

Drawing upon Feldmann (2013), I include a total of 10 country-level variables: Collective bargaining coverage (*CBC*), Foreign direct investment net inflows (*FI_I*), Foreign direct investment net outflows (*FI_O*), Imports (*Impt*), Inflation rate (*Infl*), Output gap (*Out_gap*), Real effective exchange rate (*REER*), Real interest rate (*RIR*), Trade union density (*TradeUD*), and Trade openness (*Trade*). Their values are consistent across states in a given year, but vary across years. They serve as additional controls to complement time trend control variables, as they might affect macroeconomic performance differently across different years.

Wage bargaining characteristics, as captured by *CBC* and *TradeUD* have been studied extensively and proved to determine unemployment. According to Aidt and Tzannatos (2008), collective bargaining power has a significant impact on macroeconomic performances such as unemployment. Many past empirical studies find that union density has a negative employment effect (e.g., Scarpetta 1996, Nickell and Layard 1999, Nickell 1997).

Foreign direct investment (*FI_O* and *FI_I*) can have different employment effects depending on whether the host country is developing or developed, according to Blomstom et al. (1997). In addition, foreign direct investment can also serve as channels for technological diffusion (Feldmann 2013), and thus ought to be controlled for.

Variables like Imports (*Impt*) and Trade openness (*Trade*) are included to control for the effect of import or trade openness has on unemployment over the years. Empirical research suggests that higher level of trade openness, or globalization, correlates with lower structural unemployment rate (Felbermayr et al. 2009). Similarly, real effective exchange rate is controlled for due to its potential impact on employment through affecting domestic production price competitiveness (Feldmann 2013).

Inflation rate (*Infl*) needs to be controlled for in this study due to its empirically proven impact on unemployment. Akerlof et al. (2000) shows the tradeoff between inflation and unemployment in the United States: inflation rate increasing slightly over zero leads to lower unemployment, yet as soon as inflation rate rises above a certain level, sustainable unemployment starts to rise.

Based on existing literature, I theorize that a country's adoption of technological innovations is positively correlated with a country's economic development. Thus, Output gap (*Out_gap*) is included to control for different levels of macroeconomic performance. Real interest rate (*RIR*) is controlled for because of existing evidence that shows a positive relationship between real interest rate and unemployment (Blanchard and Wolfers 2000).

State-Level Replacements of Country-level Control Variables

Country-level 'GDP per Capita' in Feldmann (2013) is replaced by state-level 'GDP per Capita' (*GDP_pC*) in this study. *GDP_pC* is included to control for the state of business cycle, the effect of a state's economic development on its ability to adopt and develop technological innovations.

Country-level 'Unemployment benefits replacement rate' in Feldmann (2013), denoting gross unemployment benefits as a decimal fraction of previous gross wage earnings, is replaced by state-level unemployment benefits in my research. Unemployment benefits need to be controlled for since they could have various effects on employment during different states of economy (Moffitt 2014, Maki and Spindler 2017).

State-Level Control Variables

I include a few other state-level control variables in addition to the control variables in Feldmann (2013): I control for the impact of union coverage (*Union_Cov*), since high level of unionization is often found to have adverse effect on employment (Montgomery 1986, Layard et al. 2005). I also control for the impact of violent crime and property crime rates (*VioCri* and *PropCri*). Various studies have explored the link between unemployment and crime. Although most research has shown an inconclusive result (e.g., Entorf and Sieger 2014), some present a significant relationship (Melick 2003). I control for them in my model to eliminate any potential explaining power they have on unemployment rate.

Extensive previous studies have found that increase in minimum wage tends to have a negative effect on employment (Kaitz 1970, Wachter and Kim 1979, Brown et al. 1982). In this study, the impact of minimum wage is controlled for with control variable *Min_wage*.

Fixed Effects

To control for state and year fixed effects, I have included dummy variables for each state, as well as linear and quadratic time trends.

Omitted Variables from Feldmann (2013)

I have omitted ‘Wage Bargaining Centralization’ and ‘Wage Bargaining Coordination’ due to lack of statistical significance. Although previous empirical research has shown that both bargaining centralization and coordination seem to lead to lower unemployment (Soskice 1990, Nickell et al. 2005, Feldmann 2011), both country-level variables are not significant for the purpose of this research as the values exhibit little variation throughout the 19-year period of interest. The same reasoning applies to the omission of the indicator of Employment protection legislation for both regular contracts and temporary contracts, as the country level data remains consistent across the 19 years of research interest.

Another control variable from Feldmann (2013) that I choose to omit is ‘Product market regulation’, which indicates the level of regulatory impediment to product market competition in seven non-manufacturing industries. I omit this variable due to a lack of availability of state-level data.

‘Tax wedge’ variable, capturing the effect of tax burden on labor, and ‘Terms of Trade Shock’ variable, denoting the difference between actual and smoothed terms of trade index, are also omitted in this study due to data availability.

The last control variable that I choose to omit from Feldmann (2013)’s model is ‘Active labor market policies,’ denoting the amount of public expenditure on active labor market policies as a percentage of GDP, divided by unemployment rate. In my model, this variable is dropped due to high collinearity with the main independent variable of interest.

IV. Data Sources

To conduct a comprehensive and accurate analysis of the effect in question, this paper utilizes data sets from various sources. I collected data on the main independent variable of interest, *Com_rd*, from the Business R&D and Innovation Survey (BRDIS) (2008-2013), and the annual Survey of Industrial Research and Development (SIRD) (1995-2007). These survey series are developed jointly by the U.S. Census Bureau and National Science Foundation (NSF). BRDIS has served as a replacement to SIRD since 2008, in accommodation to the changes in business innovation environments, as well as the shift from a federal-funding-heavy R&D landscape to a business-supplied-funding-heavy one. In order to maintain data integrity, this paper uses 'Domestic R&D performed by company' data, which has been consistently collected and categorized before and after the implementation of the new survey BRDIS in 2008. This data set contains 839 observations.

Data on employment variables (Unemployment rate *Unemp* and Minimum wage rate *Min_wage*) is collected from U.S. Department of Labor, and contains 969 observations, respectively. Data on GDP per capita (*GDP_pC*) and Unemployment benefits (*Ump_Ben*) is collected from U.S. Bureau of Economic Analysis, and contains 969 observations, respectively. Both sets of data are retrieved from FRED, Federal Reserve Bank of St. Louis. Data on Violent Crime rate (*VioCri*) and Property Crime rate (*PropCri*) are collected from Uniform Crime Reporting Statistics, a data repository developed by U.S. Department of Justice (Federal Bureau of Investigation). Crime data sets contain a total of 969 observations, respectively for *VioCri* and *PropCri*.

I collected Union coverage data (*Union_Cov*) from the Union Membership and Coverage Database, constructed by Hirsch and Macpherson (2002, accessed 2017). This online dataset provides private and public sector labor union membership and coverage, compiled from the monthly household Current Population Survey (CPS).

Referencing Feldmann (2013), I collected my country-level macroeconomic data from mainly three sources. Collective bargaining coverage (*CBC)* is calculated based on data from ICTWSS (Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts in 51 countries between 1960 and 2014), developed by Jelle Visser from University of Amsterdam. *CBC* is calculated through dividing the number of workers covered by collective agreements, by the total number of wage and salary earners in employment. Data on output gap (*Out_gap*) and Trade Union Density (*TradeUD*) is collected from OECD (Organization for Economic Co-operation and Development). Data on Foreign direct investment (*FI_I*, *FI_O*), Imports (*Impt*), Inflation rate (*Infl*), Real effective exchange rate (*REER*), and Real interest rate (*RIR*) comes from the World Bank - World Development Indicators dataset.

The data used to test Hypothesis 3 was collected from the following sources: data on per capita state government expenditures for all education comes from 'Rankings & Estimates: Rankings of the States 2005 and Estimates of School Statistics 2006,' an annual report created by National Education Association (NEA). Information on state major industry of employment was collected from Bureau of Labor Statistics. Rankings on state urbanization level were sourced from Census (2010), and accessed from the Priceonomics Data Studio. Finally, I collected rankings on state tech-savviness from research conducted by an e-commerce platform, decluttr, based on Google Search Query data.

V. Results and Discussion

A. Results

In my first specification, I include 16 control variables, in addition to controlling for state fixed effects, and linear and quadratic time trends. Regression results from Table [3] report a negative and non-significant coefficient for the main variable of interest, *Com_rd*. This result indicates that on the state-level, there is no statistically significant correlation between unemployment rate and R&D expenditure, although the coefficient is directionally consistent with my hypothesis. Coefficients of most control variables return expected results. For example, the results suggest that states with higher GDP per capita, and/or higher labor union coverage observe lower level of unemployment rate. In addition, higher unemployment benefits are likely to lead to higher unemployment rate. The only control variable with an unexpected coefficient is Violent Crime Rate (*VioCri*), which shows a negative sign, suggesting that as violent crime rate goes up by one standard deviation, unemployment rate will go down by 0.46.

After testing for the overall state-level effect, I move on to examine the effect of presidential administration. Table [4] reports the results, which are consistent with my hypothesis. To ensure model integrity, I test the model three separate times, each time using a different administration dummy as the baseline. In general, compared with the other two administrations, being under the Obama administration accentuates the unemployment effect of R&D. On the other hand, states experience lessened unemployment effect during the Bush Administration, and receive the least adverse effect on unemployment during the Clinton Administration.

Table [5] reports testing results for my third hypothesis. The results do not support my first sub-hypothesis, and show that there is no statistically significant linear dependence of the extent to which technological innovations affect state unemployment on high education expenditure (*HighEduExp*). However, some of my second sub-hypotheses regarding the effect of major industry of employment are supported. For example, the results indicate that if a state's largest industry of employment is manufacturing, unemployment rate will go up by 0.0000957 with each million dollars of R&D expenditure invested, in addition to the overall employment effect that all states absorb. Notably, when Accommodation and Food Services is the major industry of employment in a state, that state will see an increase of 0.00879 in unemployment rate with each million dollar of R&D expenditure invested, a more substantial effect compared with the manufacturing industry.

The empirical tests also support my hypotheses on urbanization level and tech-savviness as influence factors of how state labor markets react to technological innovations. Results show that in response to technological innovations, or increase in R&D expenditures, urbanized states experience 0.00034 lower unemployment rate than non-urbanized states. On average, states with tech-savvy citizens see 0.000219 lower unemployment rate than states with non-tech-savvy citizens.

B. Implications

The results have meaningful implications with regard to the determinants of how strongly state labor markets are affected by technological shocks. Although I do not find a statistically significant relationship between R&D expenditure and unemployment rate for all states, the results suggest insights that policy makers and state governments should reference when making economic decisions in response to the imminent waves of technology. On the national level, economic prosperity (high GDP per capita) offers a cushioning effect on the labor market when it is hit by technological innovations. However, if technological innovations were to affect the labor market, states that are less urbanized, less technologically informed, or more Manufacturing/Accommodation and Food Services-focused are going to be more negatively affected than other states. Therefore, these states potentially require more compensative labor protection programs and funding from the federal government. In addition, in light of the rapidly growing technological innovations in the past decade, especially on automation, the abovementioned state governments should take action to buffer severe unemployment effect, such as taking precautions against heavy R&D investment, and implementing more job-creating public initiatives. States that receive low ranks for tech-savviness could promote public education that improves the citizens' competitiveness in the labor market, and better prepare them for future technological shocks to employment.

VI. Conclusions and Limitations

The past few years has been rich with new technological breakthroughs. One of the most prominent examples is the development of autonomous vehicles. A stream of companies including Uber and Google has attained their permits to test autonomous vehicles on public roads. It is projected that by 2020, there will be 10 million self-driving cars on the road, replacing the traditional human-driving cars to be the new norm (Garret 2017). Although self-driving cars will bring tremendous benefits such as accident avoidance, their maturity also suggests a bleak career outlook for workers in the transportation industry, such as truck drivers. Despite the buzz and glamor around new technological innovations, some people are inevitably hurt by these new technologies, like the Luddites in the 19^{th} century, or tens of thousands of truck drivers in a few years. The main motivation behind this paper is to closely examine the relationship between technological innovations and unemployment, and provide some implications as to how state governments can help prepare workers to adapt to the new technological era.

Although my research does not find a significant relationship between technological innovations and unemployment on an aggregate level, the results do show that some states are affected by technological changes more so than others. More specifically, states that are less urbanized, less tech-savvy, or have most Manufacturing, or Accommodation Services jobs, are going to suffer more by the job displacement effect, and benefit less from the job creation effect of technological innovations. It is important for us to recognize these determining state characteristics, as they provide insight to which states will be the most vulnerable and thereby require the most legislative protection in facing technological breakthroughs.

Although I control for many factors that might bias the results, I do acknowledge the limitations of this research: One significant factor that state-level analysis is not able to account for is the spillover employment effect of R&D expenditures across states. For example, many corporations have offices in different states. Increased R&D expenditure in one state might result in lay-off of employees residing in other states. The potential spillover is not captured in my study, and thus could result in biased estimates.

I collect data on the main independent variable of interest, Commercial R&D Expenditure, from Business R&D and Innovation Survey (BRDIS), which is a replacement to the old Survey of Industrial Research and Development (SIRD) since 2008. Although the entry of survey that my study focuses on, 'Domestic R&D paid for by company and others, and performed by company' is a consistent entry of interest before and after the adoption of the new survey. If there were a slight change in data collection or categorization method after implementing the new survey, my results in this paper would be affected.

Another limitation of my study is the use of country-level control variables. Although those variables are relevant, and are empirically proven to affect unemployment, they are only able to capture changes across years, since they are the same across states in a certain year. Some of their statistical significance and explaining power might be lost when translated to state-level analysis. Although I attempt to counter this limitation by replacing some of the country-level control variables with state-level equivalents, I was not able to do so for all country-level variables. One direction for future research would be to find more state-level control variables, such as state-level employment protection legislation strictness, and state-level imports. Another avenue for future research is to distinguish product and process innovation at the state level.

Although this paper finds no relationship between high education expenditure and the extent to which state unemployment rate is affected by technological innovations, more research could be done to explore the impact of different types of education expenditure, the results of which will point local governments and policy makers toward the right direction with regard to training workers to be competitive in the labor market in the new technological era.

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Tables

Table [1] List of State Major Industries

This table shows the major industry with highest employment in each state (2005).[2]

State	Industry	State	Industry
Alabama	1	Montana	2
Alaska	2	Nebraska	2
Arizona	2	Nevada	5
Arkansas	1	New Hampshire	2
California	2	New Jersey	2
Colorado	2	New Mexico	2
Connecticut	3	New York	3
Delaware	2	North Carolina	1
District of Columbia	4	North Dakota	3
Florida	2	Ohio	1
Georgia	2	Oklahoma	2
Hawaii	5	Oregon	1
Idaho	2	Pennsylvania	3
Illinois	1	Rhode Island	3
Indiana	1	South Carolina	1
Iowa	1	South Dakota	3
Kansas	1	Tennessee	1
Kentucky	1	Texas	2
Louisiana	2	Utah	2
Maine	3	Vermont	3
Maryland	2	Virginia	2
Massachusetts	3	Washington	2
Michigan	1	West Virginia	3
Minnesota	1	Wisconsin	1
Mississippi	1	Wyoming	2
Missouri	2		

1 – Manufacturing; 2 – Retail Trade; 3 – Health Care and Social Assistance; 4 – Professional, Scientific, and Technical Services; 5 – Accommodation and Food Services.

[2] Source: Bureau of Labor Statistics, United States Department of Labor (2014).

Table [2] List of Variables

This table explains the variables used throughout this paper. [3]

Variable Abbreviation	Full Variable Name	Definition	Mean	Std. Dev.	Min.	Max.	Source
Com_rd	Commercial R&D expenditure	Domestic R&D paid for by company and others, and performed by company	4240.702	8067.947	2	82225	Census and NSF (2013)
Unemp	Unemployment rate	Unemployed as a percentage of the civilian labor force (annual average of non-seasonally adjusted rates), state-level	5.6924	1.9916	2.3	13.7	U.S. Bureau of Labor Statistics (2017)
GDP_pC*	GDP per capita	Gross domestic product per capita, dollar amounts in millions (annual non-seasonally adjusted), state-level	41.5286	17.5206	17.55	173.64	U.S. Bureau of Economic Analysis (2017), author's calculations
Union_Cov*	Union coverage	Employed and covered by labor unions as a percentage of the total number of employed, state-level	339896.3	478665.1	16526	2909494	Hirsch and Macpherson (2014)
VioCri*	Violent crime rate	Number of violent crime incidents per 100,000 population, state-level	446.0768	265.0394	66.9	2921.8	UCR (2017)
PropCri*	Property crime rate	Number of property crime incidents per 100,000 population, state-level	3496.361	1025.29	1724.3	9512.1	UCR (2017)

[3] All control variables are marked with asterisks (*).

Min_wage*	Minimum wage	State minimum wage rate, dollars per hour (annual, non-seasonally adjusted)	5.7366	1.3352	1.6	9.19	U.S. Department of Labor (2017)
Ump_Ben*	Unemployment benefits	State unemployment benefits, dollar amounts in millions (annual, non-seasonally adjusted)	3.04e+07	3.76e+07	1222956	2.82e+08	UBEA (2017)
CBC*	Collective bargaining coverage	Employees covered by collective wage bargaining agreements as a decimal fraction of all wages and salary earners in employment with the right to bargaining, country-level	.137434	.01307	.11923	.17004	Visser (2015), author's calculations
FI_I*	Foreign direct investment net inflows	Foreign direct investment net inflows (new investment inflows less disinvestment) as a percentage of GDP, country-level	1.67271	.70671	.74694	3.4037	World Bank (2017)
FI_O*	Foreign direct investment net outflows	Foreign direct investment net outflows as a percentage of GDP, country-level	2.05004	.71947	.47293	3.6811	World Bank (2017)
Impt*	Imports	Imports of goods and services as a percentage of GDP, country-level	14.4441	2.0407	10.466	17.427	World Bank (2017)
Infl*	Inflation rate	Annual percentage change in the consumer price index, country-level	2.41354	.94069	-.35554	3.8391	World Bank (2017)
Out_gap*	Output gap	The gap between actual and potential output as a decimal fraction of potential output, country-level	-.48184	2.3778	-4.388	3.014	OECD (2017)
REER*	Real effective exchange rate	Weighted average of U.S. currency relative to an index or basket of other major currencies, adjusted for inflation, country-level	107.9954	8.6289	95.09814	124.5618	World Bank (2017)

RIR*	Real interest rate	The lending interest adjusted for inflation as measured by the GDP deflator, decimal fraction, country-level	3.83936	2.0397	1.1613	7.1908	World Bank (2017)
TradeUD*	Trade union density	the ratio of wage and salary earners that are trade union members, divided by the total number of wage and salary earners, country-level	12.4	1.1361	10.8	15.1	OECD (2017)
Trade*	Trade Openness	Exports and imports of goods and services as a percentage of GDP, country-level	25.4418	3.2540	19.985	30.885	World Bank (2017)
Year*	Year	Year variable capturing linear time trend	2003.84	5.7453	1993	2013	
Yearsq*	Year squared	Yearsq variable capturing quadratic time trend	4015416	23020.81	3972049	4052169	
ClitonDum	Clinton Presidency	Dummy variable describing if a year is during the Clinton Presidency (1 if yes, 0 if no)	.368421	.48262	0	1	
BushDum	Bush Presidency	Dummy variable describing if a year is during the Bush Presidency (1 if yes, 0 if no)	.421052	.49398	0	1	
ObamaDum	Obama Presidency	Dummy variable describing if a year is during the Obama Presidency (1 if yes, 0 if no)	.210526	.40789	0	1	
HighEduExp	High Education Expenditure	Dummy variable describing if a state's per capita spending on education exceeds national average in 2005 (1 if yes, 0 if no)	.490196	.50016	0	1	NEA (2006)
RetailTrade	Retail Trade	Dummy variable describing if a state's largest industry of employment is Retail Trade (1 if yes, 0 if no)	.431372	.49552	0	1	U.S. Bureau of Labor Statistics (2014)

Manufacturing	Manufacturing	Dummy variable describing if a state's largest industry of employment is Manufacturing (1 if yes, 0 if no)	.313725	.46424	0	1	U.S. Bureau of Labor Statistics (2014)
HC	Health Care and social assistance	Dummy variable describing if a state's largest industry of employment is Health Care and social assistance (1 if yes, 0 if no)	.196078	.39723	0	1	U.S. Bureau of Labor Statistics (2014)
Profesh	Professional, Scientific, and Technical Services	Dummy variable describing if a state's largest industry of employment is Professional, Scientific, and Technical Services (1 if yes, 0 if no)	.019607	.13872	0	1	U.S. Bureau of Labor Statistics (2014)
Accomm	Accommodation and food services	Dummy variable describing if a state's largest industry of employment is Accommodation and food services (1 if yes, 0 if no)	.039215	.19420	0	1	U.S. Bureau of Labor Statistics (2014)
Urban	Urbanization	Dummy variable describing if a state is highly urbanized (compared with national average, 1 if yes, 0 if no)	.490196	.50016	0	1	Census (2010)
Techsavviness	Tech-savviness	Dummy variable describing if citizens of a state are tech-savvy (compared with national average, 1 if yes, 0 if no)	.490196	.50016	0	1	Decluttr (2016)

Table [3] Regression Results for Hypothesis 1

This table shows results for the following specification:

$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \theta_s + \varepsilon_{s,t}$

Note that there were also 50 state dummy variables, and 10 country-level control variables that were included in the regression but not in this table. None of the coefficients of the abovementioned control variables is significant in an unexpected direction.

Variables	Unemp
Com_rd	-0.00000142
	(-0.0000145)
GDP_pC	-0.0692***
	(-0.00623)
Union_Cov	-0.00000377***
	(-0.000000652)
VioCri	-0.00175***
	(-0.000447)
PropCri	0.00000185
	(-0.000103)
Min_wage	0.0222
	(-0.0577)
Ump_Ben	7.17e-09**
	(-3.20E-09)
Year	36.48***
	(-10.8)
Yearsq	-0.00905***
	(-0.00269)
_cons	-36712.8***
	(-10828)
N	839
adj. R-sq	0.858

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table [4] Regression Results for Hypothesis 2

This table shows results for the following specification:
$U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * ClintonDum + \beta_5 \cdot Com\_rd_{s,t} * BushDum + \beta_6 \cdot Com\_rd_{s,t} * ObamaDum + \theta_s + \varepsilon_{s,t}$
Note that all control variables included in the regression are omitted in this table for brevity reasons. None of the coefficients of the omitted control variables is significant in an unexpected direction.

Variables	(1) Unemp	(2) Unemp	(3) Unemp
Com_rd	-0.0000106	-0.0000732***	-0.0000412**
	(-0.0000148)	(-0.0000242)	(-0.0000176)
Clinton_rd	-0.0000627***		-0.0000321**
	(-0.0000165)		(-0.0000126)
Bush_rd	-0.0000306***	0.0000321**	
	(-0.00000904)	(-0.0000126)	
Obama_rd		0.0000627***	0.0000306***
		(-0.0000165)	(-0.00000904)
_cons	-38820.9***	-38820.9***	-38820.9***
	(-10767.1)	(-10767.1)	(-10767.1)
N	839	839	839
adj. R-sq	0.861	0.861	0.861

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table [5] Regression Results for Hypothesis 3

This table shows results for the following specifications:

(1) $U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * HighEduExp + \theta_s + \varepsilon_{s,t}$

(2) $U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * Manufacturing + \beta_5 \cdot Com\_rd_{s,t} * HC + \beta_6 \cdot Com\_rd_{s,t} * Accomm + \beta_7 \cdot Com\_rd_{s,t} * Profesh + \theta_s + \varepsilon_{s,t}$

(3) $U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * Urban + \theta_s + \varepsilon_{s,t}$

(4) $U_{s,t} = \beta_0 + \beta_1 \cdot Com\_rd_{s,t} + \alpha \cdot X_{s,t} + \gamma \cdot Y_t + \beta_2 \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot Com\_rd_{s,t} * Techsavviness + \theta_s + \varepsilon_{s,t}$

Note that all other variables included in the regression are omitted in this table for brevity reasons. None of the coefficients of the abovementioned omitted variables is significant in an unexpected direction.

Variables	(1) Unemp	(2) Unemp	(3) Unemp	(4) Unemp
HighEduExp~d	0.0000299			
	(-0.0000303)			
Manufactur~d		0.0000957**		
		(-0.0000458)		
HC_rd		0.000025		
		(-0.0000441)		
Accomm_rd		0.00879***		
		(-0.00148)		
Profesh_rd		0.00159		
		(-0.00154)		
Urban_rd			-0.000340***	
			(-0.000075)	
Techsavvin~d				-0.000219***
				(-0.0000767)
_cons	-36469.8***	-35212.4***	-37540.5***	-36667.5***
	(-10831)	(-10616.2)	(-10694.3)	(-10778)
N	839	839	839	839
adj. R-sq	0.858	0.865	0.862	0.86

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01