The Gettysburg Economic Review

Volume 10 Article 3

2017

The Rise of Technology and its Influence on Labor Market Outcomes

Maja K. Thomas
Gettysburg College
Class of 2017

The Rise of Technology and its Influence on Labor Market Outcomes

Abstract
Technological progress has significantly changed the inputs and production processes utilized by firms. Such shifts have led to warnings throughout the past few decades that substantial numbers of jobs, particularly things belonging to the middle class, would be eliminated and replaced by technology. This paper examines the validity of this argument by estimating the impact of technology investment on local labor markets during that period. I find evidence for a positive, rather than negative, relationship between technology and employment. Furthermore, my estimates suggest there exists a complementary relationship between technology investment and growth in labor opportunities, rather than a substitution effect of workers moving from technology-intensive industries to non-technology intensive sectors.

Keywords
technology, technological development, labor markets, employment, labor opportunities, robotics, computerization

The Rise of Technology and its Influence on Labor Market Outcomes

Maja Thomas

Abstract: Technological progress has significantly changed the inputs and production processes utilized by firms. Such shifts have led to warnings throughout the past few decades that substantial numbers of jobs, particularly things belonging to the middle class, would be eliminated and replaced by technology. This paper examines the validity of this argument by estimating the impact of technology investment on local labor markets during that period. I find evidence for a positive, rather than negative, relationship between technology and employment. Furthermore, my estimates suggest there exists a complementary relationship between technology investment and growth in labor opportunities, rather than a substitution effect of workers moving from technology-intensive industries to non-technology intensive sectors

Introduction

The rise of technology, specifically robotics and computerization, has dramatically shifted the inputs available to businesses over the past several decades. This rapid development has transformed the production processes for many different industries. Many fear that this technological development has increased automation while not adding enough jobs to offset the drop in opportunities. If true, this decrease in the employment capacity would negatively impact the wages and incomes of many workers, namely middle skill white collar and blue collar labors performing easily codifiable tasks (Autor 2011).

The subject of automation and its expansion in recent decades has ignited fears and frustrations over its threat of making many traditional jobs obsolete. Automation has been used as anecdotal evidence to explain claims of declining productivity, employment, and the current economic slow growth. The impact of automation has discriminately hit certain industries and job types, most of which are middle-paying and moderate-skilled, while straying away from others (Autor 2011). Much of this is because automation is only viable for certain job types, most of which are middle-paying and moderate-skilled. The core tasks of these positions often require employees to follow precise methodical procedures which machines are well equipped to perform. But is the rise in technology to blame for labor market perils or has it simply provided a digestible narrative?

Per neoclassical theory, investment would actually increase labor demand due to the complementary nature of labor and capital. However, many economists consider ICT capital differently, worrying that investment would decrease the demand for labor by increasing productivity of labor. Nevertheless, with spillover effects on other industries, incomes, or aggregate demand (and thus output), the impact of ICT investment is difficult to assess per traditional theory.

Thus, this paper answers this question empirically, examining the impact of technology investment on local labor markets. In the next section, I discuss the influence of robotics and job automation on employment dynamics. In section III, I develop an econometric model to analyze the relationship between increases the level of information and communications technology investment within a commuting zone and the expected level of employment in that county. In section IV, I discuss the data collected to test my hypothesis, and in section V, I use that data to test my hypothesis and find evidence for a positive relationship between investment and employment.

I. Job Automation and Labor Market Demand

The interaction between job automation and labor market dynamics has attracted significant attention from both economists and scholars alike. With vast technological advances occurring in computing and robotics, machines have now become as or more efficient than human workers in various environments. Without a clear consensus, economists continue to question automation's bearing on the labor market while the public remains largely in fear.

A negative relationship between the levels of ICT investment and employment would hardly be surprising. Since the rise of machines and machine learning, many have feared that robots would replace human labor, leading to employment losses. Straying from traditional neoclassical framework, economists tend to view ICT investment as a substitute for labor rather than a compliment. In this case, demand for labor would decrease, thereby reducing employment. Furthermore, while decreases in job opportunities due to automation could hypothetically be made up by increases in job opportunities in other industries, labor may not be able to shift into these new opportunities due to a lack of experience or other structural problems, thus leading to structural unemployment and an overall decline in employment. These findings would uphold implications from the Solow growth model, where an increase in technological investment increases labor productivity (i.e. output per worker). Ceteris paribus, firms would need less employees and would be incentivized to cut jobs.

This negative relationship between technology investment and labor has been documented by different parts of the literature. Robots and automated systems have negatively impacted several occupations, almost entirely eliminating elevator operators, highway toll collectors, parking attendants, and other similar roles (Quereshi and Syed 2014). Qureshi and Syed found that in the health care industry, 19 Aethon TUG robots can perform $1 million in human labor each year for $350,000, saving the industry 65% in labor costs. Robots such as these, in working two shifts seven days per week, save the labor of 2.8 full time equivalent (FTE) employees while costing less than one. Ebel (1986) also noted the labor costs savings by employing robots. Robots in the automotive industry costs around $6 per hour including depreciation and maintenance costs, compared with between $23 and $24 an hour in wages and benefits for an employee.

Contradicting evidence would demonstrate either no significant relationship or a positive relationship between the commuting zone levels of ICT investment and employment. If there were no significant relationship between the dependent and independent variables, job losses would either not result from automation or losses would be made up by gains in other sectors or occupations. If there were a significant and positive relationship, commuting zone job growth would result from ICT investment due to aggregate demand effects. This would align with neoclassical theory, which states that an increase in ITC investment would increase labor demand because capital and labor are complements. Higher investment would increase production, leading to an increase in income and increase the demand for goods and services, overall employing more individuals to produce these goods and services. Additionally, if demand for output increased because of the technological investment, a decrease in employment resulting from increases in labor productivity would be offset by an increase in labor demanded to increase total output. Even if ICT investment and labor were substitutes, there could be spillover effects (i.e. increases in demand for labor in related industries, impacts of increased income or aggregate demand, etc.) which could increase employment overall.

Other parts of the literature have found ICT investment to have had a non-negative impact on the labor market, largely due to spillover effects of ICT investment. Autor (2015) found that automation had not led to significant job losses, citing that the interaction between technology and employment required ingenuity and creative thinking that cannot be adequately computerized. Autor (2011) detailed growing labor market opportunities for both high skill, high-wage and low skill, low-wage white and blue collar industries, as a result of automation-led wage-level occupational shifts. As computer and robotics technologies progressed, machines were well equipped to perform core job tasks of middle skilled industries. However, this has caused various spillover effects and led to increases in opportunities in other sectors, and likely triggered dramatic growth in service occupations as detailed by Autor and Dorn (2013). Such also appeared the case during the early 2000s, where Charles, Hurst, and Notowidigo (2016) found that the declines in the manufacturing industry were propped up by the growth in the housing sector, which benefitted from the decreases in construction costs and increases in building efficiency. Leontif and Duchin (1984) forecasted the intensive use of automation the twenty years following 1985, estimating it would conserve about 10% of the labor force required to produce the same goods. However, their models predicted an increase in the output level which would offset the effects of job displacement, finding a complementary relationship between investment and employment as would the neoclassical framework. Furthermore, they argued the impacts would involve a significant increase in professional employees and a steep decline in the relative number of clerical workers as a proportion of the labor force.

An even smaller proportion of the literature has found no relationship between ICT investment and the labor market. Doms, Dunne, and Troske (1997) found that time series results demonstrated little correlation between the adoption of technology and changes in workforce characteristics. The adoption of new technologies did not appear to impact a factory's relative share of non-production labor or high wage workers, as compared to plants which did not adopt new technologies. This relationship between factory automation technologies and employment of highly paid workers was further established by Dunne and Schmitz (1995) and Siegel (1995).

Thus, the impact of ICT investment on labor markets could reasonably be either positive or negative. This paper aims to answer the empirical question of ICT investment's impact on the change in employment, differing from the above literature which addresses similar questions utilizing historical data and qualitative methods. Further information on the model is detailed in the next section.

II. Modeling

I test whether information and communications technology investment in a commuting zone affects the level of employment in that commuting zone using methods similar to those of Autor et al (2015). Commuting zones are clusters of US counties characterized by strong within-cluster and weak between-cluster ties that have been compiled by the Economic Research Service in 1990. The average level of information and communications technology investment is computed annually over the course of two eight year periods: 1992-1999 and 2000-2007.

The benchmark regression can be written as follows:

$$EMPLOY_{i,t} = \beta_0 + \beta_1 INVEST_{\mathrm{it}} + \beta_2 YEAR_{it} + \beta_3\, REGION_{it} + \mu_{it}$$

where;

- EMPLOY measures the level of employment within each commuting zone as a percentage of total employment;
- INVEST represents the average level of information and communications technology investment over two eight year periods, 1992-1999 and 2000-2007, respectively, as a percentage of total investment;
- YEAR is a dummy variablse controlling for differences in employment growth among the two eight-year periods;
- REGION is a vector of dummy variable controlling for differences in employment among census divisions;
- μ is the error term.

From the above regression, the null hypothesis for this model can be written as follows:

H_0: $\beta_1 \geq 0$

An increase in the level of information and communications technology investment within a commuting zone does not negatively impact the level of employment in that commuting zone.

H_A: $\beta_1 < 0$

An increase in the level of information and communications technology investment within a commuting zone negatively impacts the level of employment in that commuting zone.

III. Data

The data in this study comes from the European Union level analysis of Capital, Labor, Energy, Materials, and Service (EU KLEMS) and David Autor, Daron Acemoglu, and David Dorn. The unit of analysis in this data set is commuting zone-year (e.g. commuting zone 100-2007) and the data is compiled in the years 1991-1999 and 2000-2007. The EU KLEMS data measures information and communication technology investment and is part of a larger dataset which includes other variables related to capital, labor, and output from the 1970s to 2007. The Autor et al dataset was the focus of their 2015 paper and includes commuting zone-level data on employment and import penetration in the years 1991, 1999, 2007, and 2011. The data used in this analysis includes their 722 commuting zones and encompasses the entire mainland United States for the years 1999 through 2007. These commuting zones are clusters of counties with strong internal commuting ties (Autor 2014). The data sets utilized in creation of this study are codified by industry and year. Autor employs SIC codes to signify industry type, while EU KLEMS uses broad sector categories. Thus, to combine the data sets, I recode all SIC codes into broad sector categories for ease of merging.

My dependent variable is the change in commuting zone employment. As noted above, commuting zones are clusters of US counties characterized by strong within-cluster and weak between-cluster ties that have been compiled by the Economic Research Service in 1990. Employment is defined as the number of employees who are on payroll in the pay period in

March of each year. Paid employees consist of full time employees, part time employees, employees on sick leave, holidays, or vacations. The data used to construct this variable come from David Autor and the County Business Patterns series from the United States Census. I utilize industry level employment data within each commuter zone and year and manipulate it to construct my dependent variable. I start by finding total employment within each commuting zone by coding a new variable adding each industry together within a commuting zone and removing duplicate observations, leaving only commuter zone and year. This value is then divided by number of working age individuals in each commuter zone to construct an employment-population ratio. I then construct a new variable measuring the change in the employment population ratio for my two years, 1991-1999 and 2000-2007, which will represent 1999 and 2007, respectively. The data includes 1444 observations ranging from -.093% to 2.697% of total employment across all commuting zones.

The independent variable in this study is the percentage of information and communication technology, as a share of total investment, within a commuting zone. Information and communications technology (ICT) is a broad category of technology and can be used as a proxy for robot-type capital. Calculation of ICT capital is based on the database described in Jorgenson, Ho, and Stiroh (2005) and sourced from EU KLEMS. The independent variable is constructed by taking the eight-year average of EU KLEMS' ICT as a percentage of total investment from years 1991-1999 and 2000-2007. Next, I create a variable representing employment share of each industry within each commuting zone by dividing industry employment by total employment within the commuting zone. I then multiply the average ICT investment by employment share. Finally, I sum the industries to create a weighted average of ICT investment in each commuting zone and eight-year period. The finalized variable includes

1444 observations ranging between 9.57% and 23.21% of total investment across all commuting zones. The correlation coefficient between the independent and dependent variables is -0.2718, demonstrating a negative relationship between ICT investment and employment and following the narrative that increases in automation remove jobs from the labor market without adding sufficient new opportunities.

Nine control variables are utilized in this model: one dummy variable accounting for changes in employment level due to time period and eight other dummy variables accounting for changes in employment level due to geographic region (see Figure 1). These variables are coded either '0' or '1'. The year dummy is coded '1' for observations which take place in 1999 and '0' for observations in 2007. Each regional dummy is coded '0' if the commuting zone is not part of that geographic region and '1' if it is. No commuting zone can belong to more than one geographic region. The Mountain region is omitted in the regression analysis, leaving a variable to compare the other regions to. A summary of all variables and their respective descriptive statistics can be seen in the appendix in Table 1.

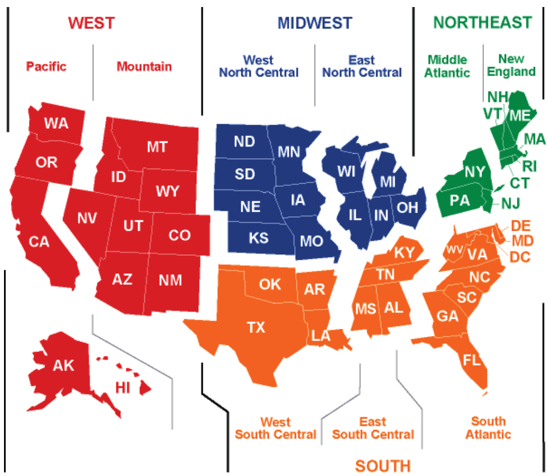


Figure 1: US Census Divisions

Figure courtesy of the US Energy Information Administration (eia.gov)

IV. Findings

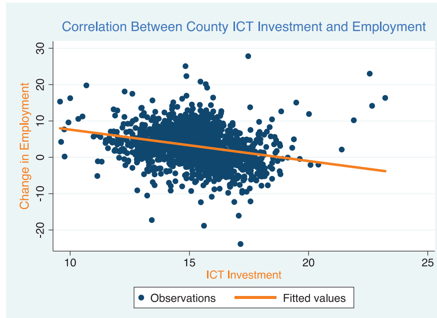
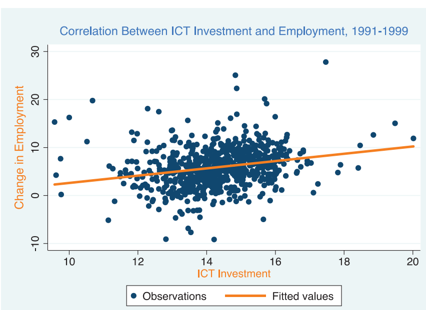


Figure 2: ICT Investment and Employment Relationship

V. Appendix Tables 3 and 4 display the results of the models constructed in this paper; that is, the impact of an increase in the level of ICT investment within a commuting zone on the expected level of employment in that county using an ordinary least squares (OLS) regression. At a first glance, there is a substantially negative relationship between the two, as seen in the scatterplot in Figure 2. The correlation coefficient is -.2718, again demonstrating the negative relationship between the ICT investment and the change in employment. However, as you I add in control variables such as year, there emerges, if anything, a positive relationship. This is supported by the results of the scatterplots on the left in Figures 3 and 4, where the data is separated out by year. In the period from 1991 to 1999, there exists a positive relationship (correlation coefficient of 0.2373) between the level of ICT investment and the change in employment, which is likely due to the economic boom of the 1990s.



Then, through the 2000s the relationship becomes slightly negative (correlation coefficient of -.0809) and less uniform as the market gears up for the Great Recession. Additionally, the summary statistics (see Table 2) show a higher average change in employment during the 1991-1999 period (5.90% versus 0.22%) and lower average ICT investment levels in 1991-1999 than the following eight year period (14.32% versus 16.21%).

While the first glance correlation coefficient supports my hypothesis, the first OLS model does not; I therefore fail to reject the null hypothesis and cannot conclude that there exists a negative relationship between ICT investment and employment. The results of the model (see Table 3a) indicate that there is actually a positive relationship between ICT investment and employment, although they are not significant at the 5% level. But let us not fetishize the 5% level—with a p-value of 0.063 we hold reasonably the same assurance in the coefficient as we would if it were 0.05 or under. These findings suggest that a one-percent increase in the level of ICT investment within a commuting zone, as a percentage of total investment, would lead to a 0.168% increase in the expected change in employment-population ratio in that commuting zone. These findings dispel fears of technological unemployment and the narrative of robots taking human jobs, proving consistent with the complementarities between ICT investment and human labor. However, the small size of the coefficient and borderline

Figure 3: ICT Investment and Employment Relationship, 1991-1999

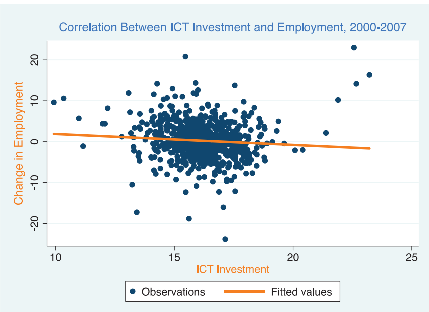


Figure 4: ICT Investment and Employment Relationship, 2000-2007

significance of its p-value may also be in accordance with Autor's (2015) findings that there exists no significant negative relationship between automation and job losses.

I implement various controls for year and region in the model. The regions are comprised of the following divisions: New England, Mid-Atlantic, south Atlantic, East North Central, West North Central, East South Central, West South Central, and Pacific. Of the nine control variables tested in this model, eight are significant below the 5% level: year, New England, Mid Atlantic, South Atlantic, East North Central, South North Central, West South Central, and Pacific. All control variables hold negative coefficients except year. This relationship between year and employment supports the results of the earlier correlation coefficients and scatter plots, suggesting that employment was expected to be 6% higher in the period from 1991-1999, regardless of region or ICT investment level.

From the results of the first model, I create a second model to include Autor's (2014) import penetration variable to account for differences arising from trade, and assess whether it was an important omitted variable in the first model (see Table 3b). Upon running the mode, I find that the change in import penetration, while significant and negative (as in Autor's findings), does not substantially change the ICT investment coefficient. The coefficient lowers slightly to 0.160 and keeps significance at the 10% level. Thus, I conclude there exists no problem of omitted variables present within the first model.

Next, I construct models which estimate the relationship between the dependent and independent variables in one of the two eight-year periods, to see if the relationships implied by the scatterplots and correlation coefficients hold true that there are differing impacts on the relationship between ICT investment and employment which are dependent on the eight-year period investigated. My first model utilized data only during the 1991-1999, and the results demonstrated a strongly significant and positive correlation between the two variables with a correlation coefficient of 0.566. The results of the 2000-2007 model, however, were negative and insignificant, even at the 10% level. Thus, the models demonstrate that the gains from ICT investment were to be made during the 1990s but did not last not through the 2000s, when the overall employment population ratio tumbled due to the 2001 recession.

Finally, I construct three models to allocate the 27 broad sector industries in each commuting zone into three categories: ICT intensive investment, moderate ICT intensive investment, and non-ICT intensive investment. From the year-commuting zone-industry stage of my data manipulation, I identify the top 9 industries by computing the simple average of the average ICT investment over the two periods, constructing one value from 1991-2007. Then, I compute the total employment in each commuter zone for each bracket, leaving 6,498 observations and three new variables corresponding to each ICT investment level. Finally, I find the change in employment for the two periods and drop the 1991 values from the data set. More information on the industry breakdown and their respective summary statistics can be found in Tables 5-7.

The results of the three ICT models (Table 4a-c) suggest that increased ICT investment positively impacts ICT intensive segments while negatively impacting non-ICT intensive industries. The ICT intensive model demonstrates a positive and strongly significant relationship between the two variables, suggesting that a one percent increase in ICT investment will increase expected employment by .42%. This result further demonstrates the complementarity of ICT investment to the labor market, particularly its addition to ICT intensive industries. On the other hand, the expected relationship between ICT investment in non-ICT intensive industries and employment is significant and negative, with a coefficient of -.21%. This disproves the idea that the increase in employment in the first model was the result of a substitution effect in non-ICT intensive industries. The moderate ICT investment model is insignificant, with a near-zero coefficient that implies no definite relationship between ICT investment and employment. This coefficient is in line with the results of the other two models because of the complementary relationship between intensiveness and employment and substitute relationship between non-intensiveness and employment.

However, the results of the three categorical models may indicate an omitted variables bias problem in the models. If an industry category—ICT intensive, for example—expands, companies may concurrently hire more employees and invest in ICT. In this case, the relationship between ICT investment and change in employment would necessarily be causal, but a response to a third variable which is driving expansion in that sector. Instituting an additional variable to control for this difference would solve this potential problem, but I could not conceive of any measurable instruments to utilize in the model. Thus, further research should attempt to correct for hypothetical bias by using an instrument correlated with ICT investment and not directly linked with employment in those industries.

I was unable to account for all possible influences on level of commuting zone employment which could misconstrue the relationship between the dependent variable and commuter zone ICT investment. Particularly, there is no control for the type of industry employment or the makeup of commuter zone employment in the first model, and the three models which consider industries only do so using intensive, moderately intensive, and non-intensive ICT brackets. However, it is unclear whether the addition of this variable would actually significantly impact the results of the model, and there would exist difficulties in coding this variable for all industries included in the initial dataset. Additionally, research conducted by

Autor et al (2015) did not find industry to have a significant impact in their model. Nevertheless, while the model demonstrates a significant relationship between the dependent and independent variables, there could exist an omitted variable or variables which impact the findings of the model.

As ICT investment is a relatively broad category of technology, further research may be needed to look specifically at the impacts of robotics and possible resulting job automation. In the creation of this model, ICT investment appears to be an adequate proxy for robotics. However, it may be that another indicator of robotics development could have been better served to estimate the model, as it would analyze the funding on specifically technologies which could be used to automate tasks. Additionally, further research should aim to include a larger number of years so as to compute both the change in employment and change in investment. This would allow the model to analyze the impacts of increasing investment in ICT technologies on employment rather than average level. Using an independent variable measuring its change, would, regardless of impact, have more straightforward policy implications.

VI. Concluding Remarks

Job automation and its growth in recent decades have awakened suspicions and frustrations over their risk of making many traditional jobs obsolete and decreasing employment opportunities for the newly jobless. Yet, according to the results of the model, this does not seem to be the case. The findings from this paper challenge my hypothesis of a negative relationship between the dependent and independent variables, instead suggesting that an increase in the level of ICT investment within a commuting zone, as a percentage of total investment, would lead to an increase in the expected employment population ratio in that commuting zone. These results are significant at the 10% level with a p-value of 0.063. Thus, the findings ultimately indicate that ICT investment leads to increased employment.

From these findings, policy recommendations are less than straightforward; the first model dictates that increasing ICT investment would push employment in commuter zones, but due to differences in the two time periods tested and the negative and insignificant coefficient in the third and fourth models, implications for the current slow growth era may be not be effective. However, the differences may be due to the 2001 recession and decrease in growth. Thus, further research is recommended to determine whether periods of slow growth can receive the employment benefits of ICT investment. This paper does not attempt to define the correct limit of spending nor does it serve to understand the optimal distribution of ICT investment by industry. What this paper does, however, is dispel fears of a negative relationship between the two variables.

The US labor market remains a major source of discussion, particularly as the economy has been plagued by slow growth. While the official unemployment rate was 4.9% as of October 2016, the labor force participation rate and employment-population ratio remain far below pre-2007 levels. A struggling labor market in the aftermath of recession and dramatic rise in technology have caused many to couple the two together, and fear that technological developments have contributed to unemployment rates. However, the use of technology appears to be a scapegoat for other issues putting downward pressure on the labor market. The rise of the service sector, as noted by Autor and Dorn (2013) has allowed another outlet for American workers. The results of the models tested in this paper, however, demonstrate a complementary relationship between ICT investment and growth in labor opportunities, rather than a substitution effect of workers moving from ICT-intensive industries to non-ICT intensive sectors. Thus, the public should embrace—rather than fear—information and communication technology investment as a way in which to spur growth and expand labor market opportunities.

VII. Appendix

Table 1: Summary of Variables

Variable	Description	Observations	Source
Employment	Employment within czone as percentage of total employment	1444 observations 1999, 2007	Autor et al.
ICT Investment	Average level of ICT investment as percentage of total investment over eight year periods	1444 observations 1992-1999, 2000-2007	EU KLEMS
Year	Dummy variable representing either 1999 ('0') or 2007 ('1')	1444 observations 1999, 2007	Autor et al/EU KLEMS
New England Division	Dummy variable representing New England czones	1444 observations 1999, 2007	Census Bureau County Business Patterns
Mid-Atlantic Division	Dummy variable representing Mid-Atlantic czones	1444 observations 1999, 2007	Census Bureau County Business Patterns
East North Central Division	Dummy variable representing East North Central czones	1444 observations 1999, 2007	Census Bureau County Business Patterns
West North Central Division	Dummy variable representing West North Central czones	1444 observations 1999, 2007	Census Bureau County Business Patterns
East South Central Division	Dummy variable representing East South Central czones	1444 observations 1999, 2007	Census Bureau County Business Patterns
West South Central Division	Dummy variable representing West South Central czones	1444 observations 1999, 2007	Census Bureau County Business Patterns

Pacific Division	Dummy variable representing Pacific czones.	1444 observations 1999, 2007	Census Bureau County Business Patterns

Table 2: Summary of Independent and Dependent Variables by Year

Variable	Mean	Standard Deviation	Minimum	Maximum
ICT investment 1991-1999	14.32083	.28453	9.5747	20.0174
ICT investment 2000-2007	16.21238	1.396903	9.9275	23.2145
Change in employment, 1991-1999	5.90318	4.114131	-9.162831	27.81029
Change in Employment, 2000-2007	.2150155	4.606847	-23.85641	22.99899

Table 3: Regression Analysis: ICT Investment Across All Levels

Variable	(a) OLS regression Change in commuting zone employment	(b) OLS regression Change in commuting zone employment	(c) OLS regression Change in commuting zone employment in 1999	(d) OLS regression Change in commuting zone employment in 2007

IT investment in commuting zone	.167 (.090)	.160 (.089)	.566*** (.124)	-.116 (.119)
Year	6.01*** (.279)	5.407*** (.287)		
Import penetration		-.971*** (.136)		
New England	-1.67* (.813)	-1.049 (.804)	.833 (1.051)	-4.251*** 1.126
Mid Atlantic	-3.201*** (.678)	-2.389*** (.676)	-3.292*** (.878)	-3.253** (.938)
South Atlantic	-3.152*** (.419)	-2.443*** (.424)	-.732 (.542)	-5.572*** (.580)
East North Central	-2.728*** (.456)	-2.017*** (.459)	.753 (.592)	-6.343*** (.629)
West North Central	-.239 (.400)	.181 (.398)	1.142* (.525)	-1.840** (.548)
East South Central	-2.756*** (.464)	-1.439** (.493)	-.384 (.600)	-5.141*** (.643)
West South Central	-1.471*** (.418)	-1.080** (.415)	-1.317* (.542)	-1.735** (.577)
Pacific	-2.487** (.541)	-2.279*** (.533)	-2.710*** (.701)	-2.307** (.749)
Constant	-0.688** (1.439)	-.213 (1.417)	-1.941 (1.732)	5.224** (1.896)
N	1444	1444	721	722
R^2	.358	.380	0.142	0.218

*p<.05; **p<.01; ***p<.001

Table 4: Regression Analysis: ICT Investment Across All Levels

Variable	(a) OLS regression Change in commuting zone employment for high ICT industries	(b) OLS regression Change in commuting zone employment for mid ICT industries	(c) OLS regression Change in commuting zone employment for low ICT industries
IT investment in commuting zone	.425*** (.060)	-.056 (.041)	-.209*** (.0459)
Year	3.773*** (.185)	1.77*** (.129)	.456*** (.142)
New England	-1.214* (.539)	-.373 (.375)	-.128 (.413)
Mid Atlantic	-1.978*** (.449)	-.965** (.313)	-.317 (.345)
South Atlantic	-.868** (.278)	-.719*** (.193)	-1.560*** (.213)
East North Central	-1.704*** (.302)	-1.106*** (.210)	.115 (.232)
West North Central	-.928*** (.265)	.171 (.185)	.558** (.203)
East South Central	-1.223*** (.308)	-.422* (.214)	-1.098*** (.236)
West South Central	-1.163*** (.277)	-.449* (.193)	.143 (.212)
Pacific	-1.087** (.359)	-.871*** (.250)	-.484 (.274)
Constant	-5.77*** (.953)	1.561* (.664)	3.459 (.731)
N	1444	1444	1444
R^2	.257	.225	0.137

*p<.05; **p<.01; ***p<.001

Table 5: ICT Level Industry Breakdown: ICT Intensive Industries

ICT-Intensive Industry Name	Broad Sector Code	Average ICT Investment, 1991-1999	Average ICT Investment, 2000-2007	Average ICT Investment, 1991-2007
Transport and storage	26	0.229	0.374	0.360
Education	35	0.300	0.349	0.344
Electrical and optical equipment	15	0.238	0.345	0.335
Machinery, nec	14	0.244	0.308	0.302
Financial intermediation	29	0.297	0.248	0.253
Wholesale trade and commission trade	22	0.226	0.246	0.244
Transport equipment	16	0.204	0.239	0.235
Construction	19	0.138	0.205	0.198
Community social and personal services	33	0.165	0.178	0.176

Table 6: ICT Level Industry Breakdown: Moderate ICT Intensive Industries

Moderate ICT Industry Name	**Broad Sector Code**	**Average ICT Investment, 1991-1999**	**Average ICT Investment, 2000-2007**	**Average ICT Investment, 1991-2007**
Pulp, paper, paper, printing and publishing	7	0.132	0.170	0.166
Manufacturing nec; recycling	17	0.163	0.166	0.166
Health and social work	36	0.149	0.153	0.152
Chemicals and chemical products	10	0.135	0.146	0.145
Retail trade, repair of household goods	23	0.124	0.132	0.131
Sale, maintenance and repair of motor vehicles and motorcycles	21	0.129	0.115	0.117
Basic metals and fabricated metal	13	0.101	0.102	0.102
Coke, refined petroleum and nuclear fuel	9	0.097	0.099	0.099
Other non-metallic mineral	12	0.089	0.094	0.093

Table 7:: ICT Level Industry Breakdown: non-ICT Intensive Industries

Non-ICT Intensive Industry Name	**Broad Sector Code**	**Average ICT Investment, 1991-1999**	**Average ICT Investment, 2000-2007**	**Average ICT Investment, 1991-2007**
Food, beverages and tobacco	4	0.076	0.091	0.090
Textiles, textile, leather and footwear	5	0.065	0.091	0.088
Real estate, renting and business activities	30	0.068	0.073	0.072
Electricity, gas and water supply	18	0.062	0.070	0.069
Wood and of wood and cork	6	0.059	0.066	0.065
Rubber and plastics	11	0.045	0.061	0.059
Hotels and restaurants	24	0.044	0.050	0.049
Mining and quarrying	2	0.061	0.040	0.042
Agriculture, hunting, forestry and fishing	1	0.014	0.018	0.018

VIII. References

Autor, David H. "The polarization of job opportunities in the US labor market: Implications for employment and earnings." *Center for American Progress and The Hamilton Project* (2010).

Autor, David H. "Why are there still so many jobs? The history and future of workplace automation." *The Journal of Economic Perspectives* 29.3 (2015): 3-30.

Autor, David H, et al. *Import competition and the Great US Employment Sag of the 2000s*. No. w20395. National Bureau of Economic Research. (2014).

Autor, David H., and David Dorn. "The growth of low-skill service jobs and the polarization of the US labor market." *The American Economic Review* 103.5 (2013): 1553-1597.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. *Computing inequality: have computers changed the labor market?* No. w5956. National Bureau of Economic Research (1997).

Berman, Eli, John Bound, and Zvi Griliches. "Changes in the demand for skilled labor within US manufacturing: Evidence from the annual survey of manufacturers." *The Quarterly Journal of Economics* (1994): 367-397.

Berndt, Ernst R., Catherine J. Morrison, and Larry S. Rosenblum. *High-tech capital formation and labor composition in US manufacturing industries: an exploratory analysis*. No. w4010. National bureau of economic research, 1992.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. "The Masking of the Decline in Manufacturing Employment by the Housing Bubble." *The Journal of Economic Perspectives* 30.2 (2016): 179-200.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske. "Workers, wages, and technology." *The Quarterly Journal of Economics* (1997): 253-290.

Dunne, Timothy, and James A. Schmitz Jr. "Wages, employment structure and employer size-wage premia: their relationship to advanced-technology usage at US manufacturing establishments." *Economica* (1995): 89-107.

Ebel, Karl H. "Impact of Industrial Robots on the World of Work, The." *Int'l Lab. Rev.* 125 (1986): 39.

Leontief, Wassily, and Faye Duchin. "The Impacts of Automation on Employment, 1963-2000. Final Report." (1984).

Qureshi, Mohammed Owais, and Rumaiya Sajjad Syed. "The impact of robotics on employment and motivation of employees in the service sector, with special reference to health care." *Safety and health at work* 5.4 (2014): 198-202.

Siegel, Donald S. "The impact of technological change on employment: evidence from a firm-level survey of Long Island manufacturers." *Economics of Innovation and New Technology* 5.2-4 (1998): 227-246.

Sullivan, Daniel, and Till Von Wachter. "Job displacement and mortality: An analysis using administrative data." *The Quarterly Journal of Economics*(2009): 1265-1306.