Senior Project

Department of Economics

The Effect of Adaptation of Information Processing Equipment on Employment Rate

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Abstract

Technological unemployment is a phenomenon that presents itself when a certain new technology dramatically influences the way people work and hence productivity. The same way an innovation may wipe out an older, less convenient way of doing things; a new technology could potentially make some jobs obsolete. The rapid development of technologies such as artificial intelligence raises concerns about its potential consequences on employment. There are ambivalent feelings on technology adoption because there are both benefits and drawbacks to its widespread adoption. The benefits technology brings to the workplace include greater productivity and efficiency. On the other hand, the unemployment aspect is a drawback that should be considered. Technology helps employees, but the increasing adoption as well as its improvement changes employment opportunities. This study will contribute to the discussion of unemployment caused by technological development through empirical research studying the effect of information processing equipment adoption on the number of jobs available. The main result is that the increased adoption of information processing equipment correlates with an increase in the number of jobs available by a small percentage.

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I. Introduction

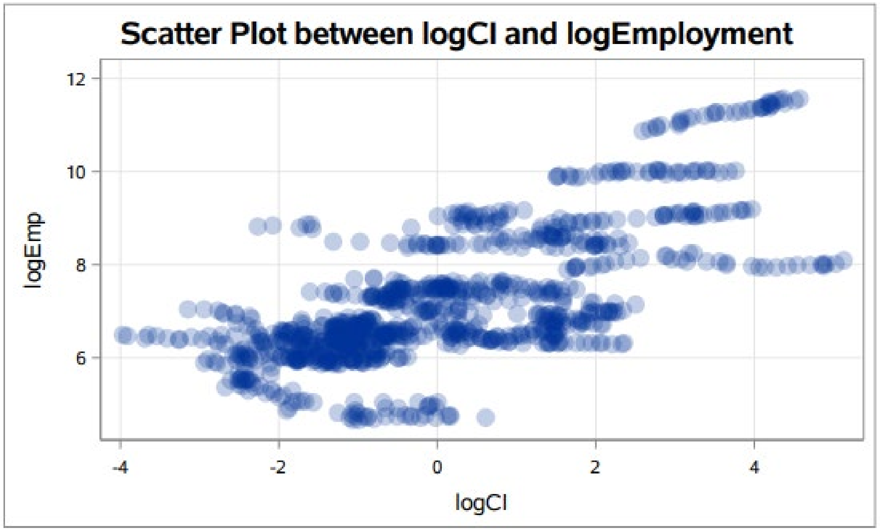
This paper analyzes the effect of information processing equipment technology's adaptation across firms on employment levels. Whenever there comes a new type of technology, the danger of lower employment presents itself. As fewer people are needed for firms to do the same amount of work, the competition for jobs is more severe. However, many technologies can also create jobs which would employ more people. An example of that could be the introduction of different apps that employ people as independent contractors such as Uber, Doordash, and Knack Tutoring. These types of apps could employ more people as they offer more flexibility in where and when they work. Therefore, this study aims to contribute to existing knowledge by determining whether information processing equipment negatively influences employment rate.

Since 1983, with the introduction of personal computers which rapidly become present in offices, companies, factories, and later in almost every home, there is already research on this topic. Several researchers have concerns about the effect of the process of computerization on unemployment. Thacker (1983) writes an article about "The impact of computerization on work and society" as computers become more common. After that, Wolff (2005), Autor and Dorn (2013), Jordan (2015), and Bessen (2016) write on this topic to discuss different aspects of computerization that impacts the labor force, especially its effect on unemployment. There were two camps on this discussion, some researchers like Wolff points out that computerization would have a negative effect on employment while researchers like Autor and Dorn (2013) analyze the shift of the work force where the process of computerization causes the polarization phenomenon in the labor market, but indeed it did not contribute to the increase of the unemployment rate. Lately, with the development of AI, this discussion is currently a relevant issue again, and several research papers address this question on how AI is going to affect the labor force. If robots are smarter and more productive compared to human, then will humans be in danger of losing jobs to them? Writers like Walsh (2018), Badiuzzaman & Rafiquzzaman (2020), Lima (2021), and lately Brynjolfsson & Wang (2023) discuss these questions, but the discussion divides into two directions, and the real answer is still unknown. This paper adds an answer to this question: with updated data sets to the present and the analysis on coefficients of the two-way fixed effect model, this paper can contribute up-to-date and reliable results. Nonetheless, the data sets which are used for this work are entirely from the U.S. Bureau of Labor Statistics, and so this paper totally relies on the accuracy of their data sets and is limited as such.

This paper uses data on the employment rate by different sectors and the asset values of information processing equipment by different sectors from the Bureau of Labor Statistics data archive. The data are useful in providing an analysis of the effect of asset size of information processing systems on employment rates by industry sectors in a semester's limited time frame. This study uses a two-way fixed effects model, and the result it gives is that increased adoption of information processing equipment increases employment opportunities.

Figure 1 below graphs a scatterplot of the relationship between $log(Emp_{it)}$ and $B_1\log(CI_{it})$. It shows a steady increase in the percentage changes of employment as the percentage changes of capital investment in information processing equipment increase.

Figure 1. Number of Jobs and Productive Capital Stock



Source: U.S. Bureau of Labor Statistics.
Notes: This figure shows the relatively upward trend in employment with percentage increases in capital investment in information processing equipment.

Today's rapid technological change makes it more important to understand the impact of technology on employment. With the advent of technologies such as AI and machine learning, many people are afraid that jobs will be replaced by robots. A gap in existing literature that this paper fills in is the analysis of a specific technology, information processing equipment, and its effect on employment across different sectors. This will contribute to existing research on technological unemployment.

Technology is both a benefit and a problem. AI could make the economy stronger, but this would only be the case if people can still find jobs to support their livelihoods. The government's intervention in regulating technology use can produce favorable outcomes. Different industries are affected differently by technology. The problem of technological unemployment is therefore an issue that this paper describes using information processing equipment.

This paper will first provide an overview of the literature on technological unemployment. After that, a description of the data and theories in this study helps to provide insight into what this paper's research is about. Next, the empirical methodology and the results of the study will contribute to the current knowledge on the relationship between technological growth and employment. The conclusion section of this paper discusses the results of the study as well as potential implications of the results. Finally, at the end of this paper includes the reference section, appendix, and SAS codes.

II. Literature Review

Many researchers study technology to see the impacts of its advancement on different aspects of society. Just like how different inventions change people's way of life, technology changes the way people work. Technologies such as computers, automation, IT, and AI have tremendous prospects in increasing people's productivity in work. Technology also changes firm structure and occupational responsibilities. Taking the far-reaching impacts technology has on the workplace into account, researchers diverge on whether the ubiquitous adaptation of technologies such as computer and IT affect employment negatively or positively.

The first approach, and the majority opinion of researchers, is that technology raises concerns about unemployment. Some studies assert that increased usage of computing significantly influences unemployment duration (Wolff, 2005). Not only does the duration of unemployment increase, but employment also stagnates when technologies such as IT increase firm size and productivity (Brynjolfsson et al., 2023). The effect that technology has on employment is viewed as a threat to people's jobs since many of these technologies such as computers and IT tools can do better jobs than humans can. Artificial intelligence automation is also a newly developed tool that many employees fear will replace their jobs. This is especially true in highly populated areas where competition for jobs is fierce. In fact, a study by Badiuzzaman and Rafiquzzaman (2020) shows that automation has replaced almost 60% of garment workers in Bangladesh, an industry that feeds many Bangladeshi families. One study connects values of innovation of digital assets to employment and shows that higher values of innovation lead to increased productivity but also higher unemployment levels (Filippo et al. 2020).

On the other hand, the second approach is more optimistic about technology's adaptation and contends that technology does not influence employment levels as adversely. These researchers claim that besides technology's contribution to revenue growth of many firms across different sectors, technology also creates new opportunities for people. With the advent of information technology, many disabled individuals were able to find jobs where before they were not able to do so (Thacker 1987). This transition from a workplace without technologies such as computers to a workplace that fully integrates its use allows for a new diverse workforce to emerge with people having different disabilities. Bigger companies can also have a bigger workforce. Bessen (2016) affirms a causal relationship between computer adoption and increased employment using Granger causality tests.

As industries embrace new emerging technologies such as AI, the importance of AI-related competencies also become relevant when deciding whom to hire (Dawson et al., 2021). This becomes a threat to places where most workers are unskilled or lower-skilled. Some reveal expectations that AI will surpass humans in various tasks such as self-diving cars over the next few decades (Grace et al., 2018). Older employees worry that with new technologies, their employment will be at risk. This trend leads to public concerns about job loss and its associated negative social impacts. The research on the impact of ICT (Information and Communication

Technology) adaptation on employment aligns closely with the findings of the study on the growth of low-skill service jobs and the polarization of the U.S. labor market (Autor & Dorn, 2013). As technological advancements reduce the cost of routine tasks, they lead to the displacement of routine labor, especially among non-college workers. The adaptation of ICT also contributes to the polarization of employment, with significant growth observed in both high-skill occupations and low-skill service occupations. This growth underscores the importance of understanding the intricate relationship between technological progress and labor market dynamics in shaping employment trends and economic outcomes.

AI brings up a technology that makes many people tremble, and that is of human-level machine intelligence (HLMI). These AI are assumed to be able to do everything a human can. That means HLMI will potentially replace all works of professionals such as engineers, doctors, and artists. But Walsh notices that we should also consider other factors which might affect employment besides automation like the economic growth from productivity gains, new jobs created by technology, globalization effects, and changes such as in demographics, retirement, and migration (Walsh, 2018). Badiuzzaman and Rafiquzzaman (2020) agree with Walsh on these points and further emphasize that the effect of job loss on unskilled and lower-skilled labor imposes a greater threat on higher populated countries when compared to other parts of the world.

Experts who are concerned with a future of uncontrolled technological growth propose different theories to prevent and address unemployment caused by adaptation of technology. Lima and his colleagues (2021) offer several solutions to address technological unemployment: this includes augmenting workers' skills, sharing work through reduced working hours, reviving traditional occupations, creating new economic sectors, and international tax cooperation; it also discusses measures like basic income guarantees, charitable donations, and changes to the social safety net to mitigate the consequences of unemployment.

With all these research studies in mind, the threat of technology replacing peoples' work and causing unemployment is a concern among many. Some studies point out that there is a negative relationship between technological advancement and employment levels while others a positive relationship. Most of these studies, however, fail to report the direct relationship between information processing equipment adoption and employment levels. Analysis of this will help to fill a current gap in this discussion. With that background knowledge, this study will further provide analysis on the relationship between the adaptation of a technology, information processing equipment, on employment levels.

III. Data

There are two databases that will be used in this empirical analysis. Data is extracted from the Bureau of Labor Statistics website. Information processing equipment (IPE) data from 1987-2021 on measures of ICT (Information and Communication Technology) capital details for major sectors and industries were extracted. This variable lists information processing equipment's capital investment, productive capital stock, and wealth stock worth in billions of 2017 dollars of information processing equipment by different industries. The second variable extracted is hours worked and employment data. This data lists employment levels from 1987-2021 using the number of jobs by sectors. The main regressor is capital investment while the controls are productive capital stock and wealth stock.

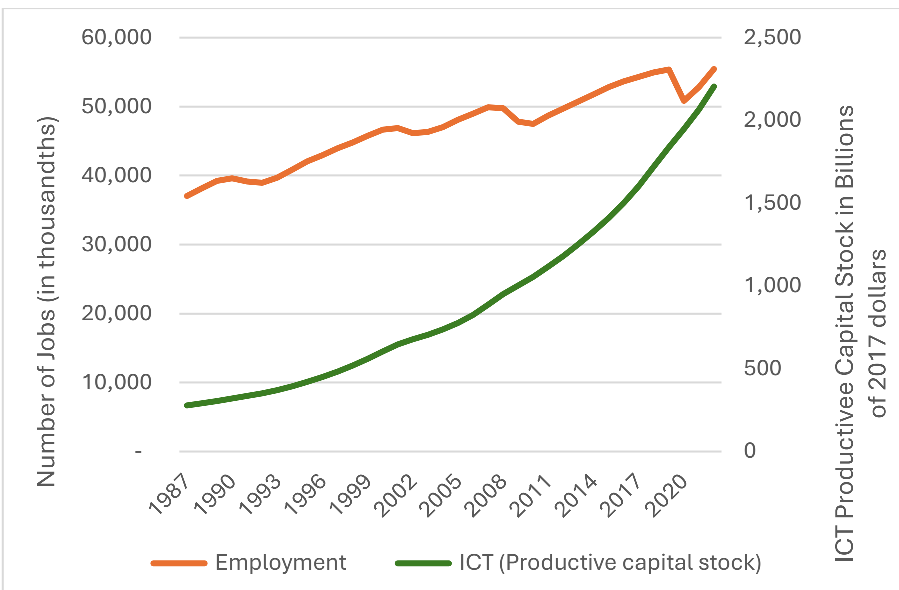
The data is then organized by sorting and cleaning. Both "Information processing equipment (IPE)" and "Hours worked and employment" is cleaned and modified by NAICS digits. This research selects 2-digit and 3-digit level coding for the NAICS industries, and some closely related industries are manually combined for ease of analysis. [1] Table 4 in the appendix lists out all the specific industry sectors by NAICS codes. These codes are manually sorted to ensure alignment between the industry classifications in both datasets so that the corresponding industries between employment and ICT related values are appropriately matched. This allows for an examination of the relationship between ICT investment and employment levels across various sectors of the economy.

Another note is categories of information processing equipment values. The studied value is capital investment which is the value that firms invest in to buy more ICT equipment. The other two, productive capital stock and wealth stock, are control variables. Total productive capital stock and total capital investment are used to give a picture of how ICT values are growing when compared to other growths in capital such as of land or factories. Six panels below graph relationships of ICT values with employment. Figure two and three show these trends with thousands of jobs in orange, total values in blue, and ICT values in green from years 1987-2020. Figure four shows the percentage changes of employment in orange, of productive capital stock in blue, and of capital investment in green.

[1] To provide an example, NAICS 11 (Agriculture, forestry, fishing, and hunting) combines 111 (Crop production), 112 (Animal production), 113 (Forestry and logging), 114 (Fishing, hunting and trapping), and 115 (Support activities for agriculture and forestry).

Figure 2. Number of Jobs and Productive Capital Stock
Panel A: Number of Jobs & Total Productive Capital Stock

Panel B: Number of Jobs & ICT Productive Capital Stock



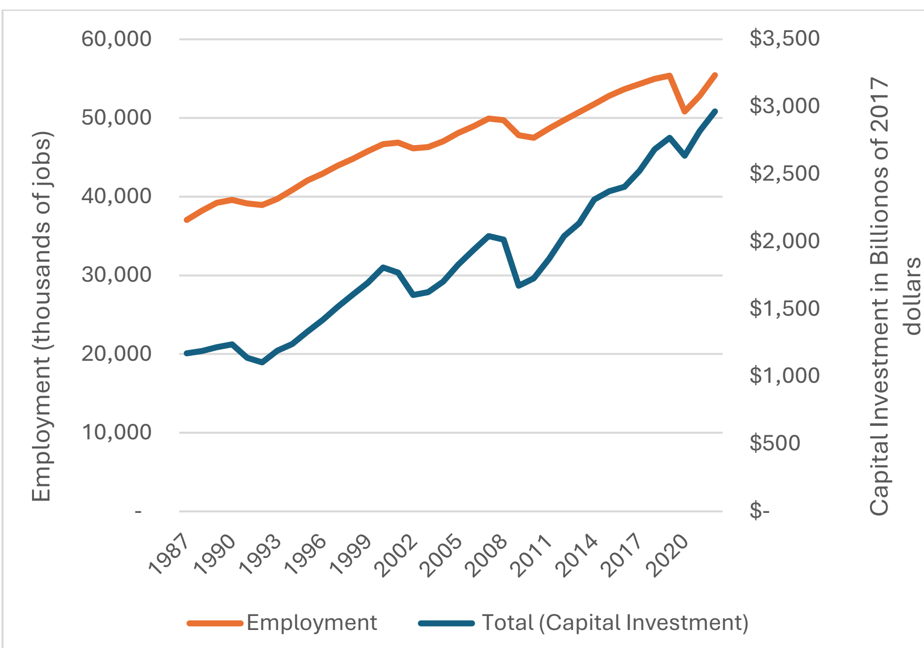
Source: U.S. Bureau of Labor Statistics.
Notes: The graph shows the trend in the total number of jobs and information processing equipment-productive capital stock across U.S. industries.

The second figure graphs the relationship between employment and ICT productive stock capital. Looking at the graph, it is obvious that the number of jobs increases from around

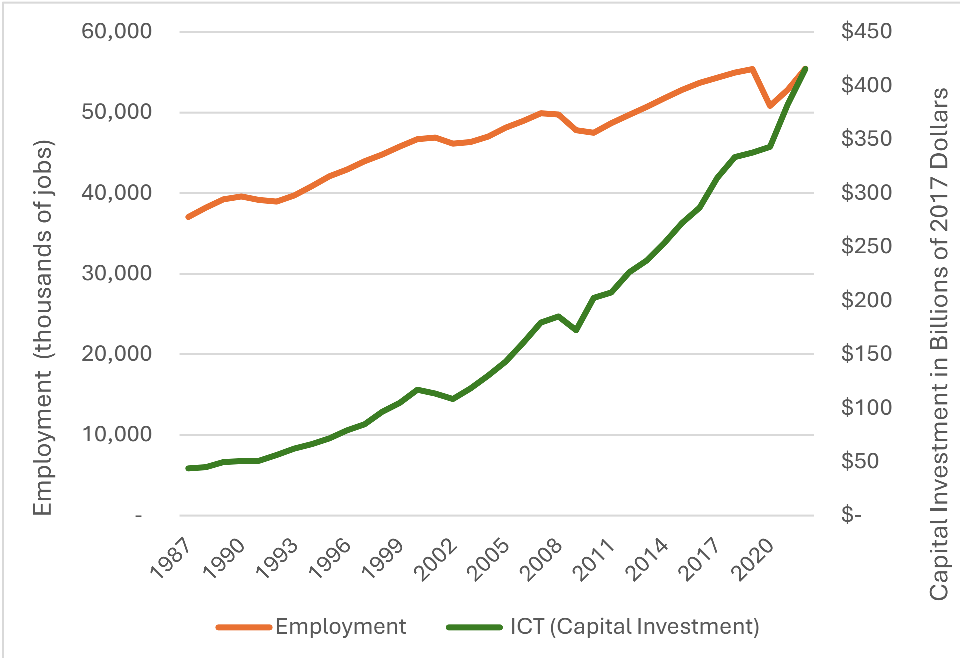
40,000,000 in 1987 to around 55,000,000 in 2021 with a slight dip in 2019 most likely caused by the pandemic. The capital stock of total information processing equipment also grows steadily from years 1987-2021 where the ICT portion's trendline is steeper when compared to the total portion of all productive stock capital.

The third figure graphs the relationship between employment and ICT capital investment. Looking at the graph, the number of jobs increases from around 40 million in 1987 to around 55 million in 2021 with a slight dip in 2019 most likely caused by the pandemic. The capital investment of total information processing equipment also grows steadily from years 1987-2021 with the same trend of the ICT portion increasing steeper when compared to the total portion of all capital investment.

Figure 3. Employment and Capital Investment
Panel A: Employment-Total Capital Investment



Panel B: Employment-ICT Capital Investment

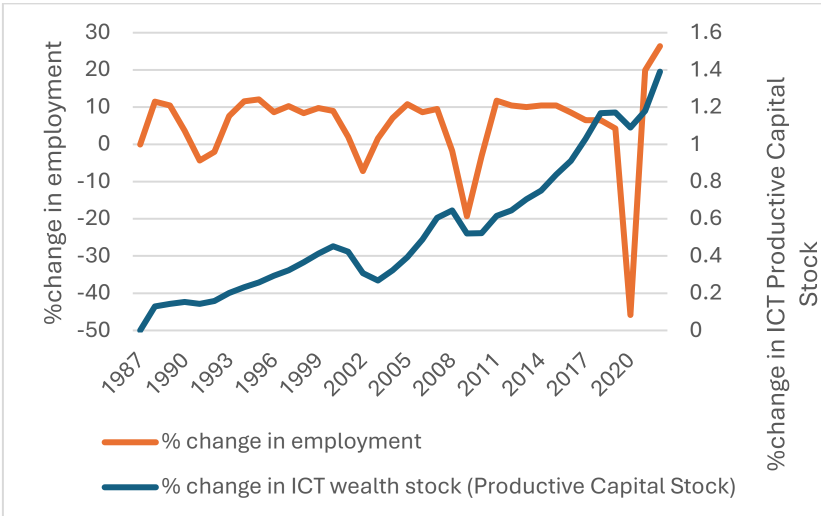


Source: U.S. Bureau of Labor Statistics.
Notes: This graph is created by graphing the linear growth of the number of jobs and the trend of information processing equipment- capital investment expansion together.

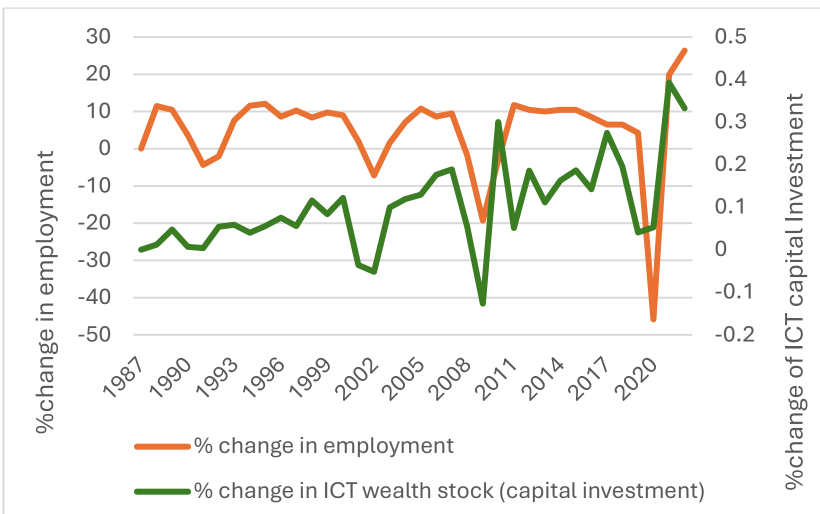
The fourth figure graphs the percentage change of employment to percentage change of ICT productive stock capital, and the percentage change of employment to percentage change of ICT capital investment. Panel A compares the relationship between employment percentage changes throughout the years with percentage changes in ICT productive capital stock. Panel B compares of the relationship between employment percentage changes throughout the years with percentage changes in ICT capital investment. It can be observed that employment had relative stable changes around zero except for the sharp negative 2019 dip. The percentage change in ICT wealth stock of productive capital investment increased over the years from 1987-2021. This indicates a continuous, larger growth in ICT's productive role in firms. ICT wealth stock of capital investment, on the other hand, shows a more fluctuating and modest increase, but is still trending towards growth.

Figure 4. Percentage Changes

Panel A: % change employment - % change in productive capital stock



Panel B: % change employment - % change in capital investment



Source: U.S. Bureau of Labor Statistics.

Notes: These graphs are created by first calculating the percentage changes of employment, ICT productive capital stock and ICT capital investment separately.

Additionally, Table 1 shows the summary statistics of important variables in this paper. Data on individual sectors is available and so analyzing variations in employment and technology adoption across sectors can help identify some helpful patterns and trends across all sectors. The first summary statistic table analyses all the values of ICT capital investment by different sectors. The second summary statistic table analyses all value of ICT productive capital stock by different sectors. The Private business sector in Table 1 accounts for almost all the sectors in the database. Nonfarm nonmanufacturing sector and the two manufacturing sectors are further breakdowns of the industries for analysis. An interesting statistic to note is that the capital investment of private business sector has a positive average value at 169.59 billion.

Table 1. Summary Statistics

Variable	# of obs.	Mean	Std Dev	Min	Max
Capital Investment					
Private Business sector (PG)	36	169.59	108.42	43.88	415.48
Nonfarm Nonmanufacturing Sector (WG)	36	145.31	98.62	36.42	378.56
Durable Manufacturing Sector (DM)	36	12.01	5.70	3.10	20.56
Nondurable Manufacturing Sector (ND)	36	8.11	2.08	3.61	12.87
Productive Capital Stock					
Private Business Sector (PG)	36	919.92	561.66	278.37	2204.47
Nonfarm Nonmanufacturing Sector (WG)	36	758.72	486.22	220.06	1911.72
Durable Manufacturing Sector (DM)	36	76.69	38.46	27.61	140.02
Nondurable Manufacturing Sector (ND)	36	57.88	13.04	30.54	79.58

Source: U.S. Bureau of Labor Statistics.

Notes: Above is a summary statistics table of the ICT capital investment and productive capital stock wealth of specific sectors given all the entries from years 1987-2021. The values are given in units of billions of 2017 dollars.

IV. Theoretical Discussion

Relevant economic theories that apply to this topic is that of the capital replacing theory and the positive productivity theory. The theory of capital replacing labor suggests that as technology advances and capital becomes more efficient, firms tend to substitute capital for labor in the production process which decreases employment. Positive productivity theory asserts that technological advancements and efficiency gains lead to increased output per employee, driving employment levels upward. These two economic theories help to explain how employment is affected by the expansion of information processing equipment across different sectors.

The expected relationship between the variables of information processing equipment and employment level is that of a positive relationship. In other words, it is expected that the increased productivity theory plays a bigger role than the capital-labor substitution theory on employment. Therefore, the more information processing equipment the higher the employment level. This study aims to provide a piece of empirical analysis on this relationship by providing evidence-based insights into the potential outcomes of technology adaptation. Empirical analysis helps to confirm using real-world data whether more of the capital replacing labor theory or the positive productivity theory impacts employment.

V. Empirical Methodology

This research utilizes the two-way fixed effects model that accounts for the effects of time and industries to provide empirical analysis on the effect of information processing equipment on employment levels. Time and industry fixed effects can absorb such shocks to the regression as Covid-19. A two-way fixed effects model in this empirical analysis serves as a robust statistical approach to control both time-invariant individual heterogeneity and time-varying factors that do not vary across industries simultaneously. The model below is used to determine the relationship between employment and the expansion of information processing equipment.

$$log(Emp_{it)} = B_0 + B_1 \log\left(CI_{it}\right) + \mathrm{X}_{it} + Sector_i + Year_t + \varepsilon_{it}$$

The dependent variable, log $(Emp_{it)}$, represents the natural log of employment of the number of jobs in thousands in industry *i* and year *t*. $B_1 \log\left(CI_{it}\right)$ stands for the natural log of capital investment in billions of 2017 dollars in industry *i* and year *t* of information processing equipment. X_{it} represents two control variables including productive capital stock and wealth stock. Productive capital stock is the value of information processing equipment that is used in business production while wealth stock is the overall asset value of a sector's information processing equipment. $Sector_i$ and $Year_t$ are sector and year fixed effects, respectively. Lastly, ϵ is the white noise. By incorporating fixed effects for both individual sectors and time periods, the two-way fixed effects model effectively controls for sources of heterogeneity and temporal variation. This control is crucial for mitigating omitted variable biases which can distort estimates and lead to false conclusions in empirical analysis.

Although this model tries to capture an unbiased relationship between ICT capital investment and employment, endogeneity concerns still could arise when the independent variable in a regression model is correlated with the error term. In this empirical model, potential endogeneity issues could emerge due to omitted variables or reverse causality. Omitted variables, such as technological advancements or shifts in market demand, may affect both employment levels and capital investment, leading to biased coefficient estimates. Additionally, reverse causality might occur if changes in employment levels influence investment decisions, rather than the other way around as assumed in this model. These endogeneity problems can undermine the reliability of results and weaken the argument on the relationship the model gives between ICT capital investment and employment.

The results of the analysis provide insights into the impact of information processing equipment expansion on employment levels across industries. A statistically significant negative coefficient on measures of technology expansion would suggest that information processing equipment expansion correlates to a reduction in employment levels. Conversely, a statistically significant positive coefficient would indicate that information processing equipment expansion is associated with increased employment, potentially due to job creation in complementary sectors or productivity gains leading to overall economic growth.

VI. Results

Looking at the results table. The results are in line with a priori expectations discussed in the theoretical section. The observed relationship between the variables aligns with the hypothesized effects of the positive productivity theory where information processing equipment expansion increases employment levels. Looking at Table 2, model 3 shows that a 10 percent increase in the capital investment of information processing equipment correlates with a 1.3 percent increase in the percentage of the number of jobs available. The appendix also has Table 3 to show the levels data alongside the log data. The results in Table 3 in the appendix are in line with Table 2.

Comparing the four models in the results table yields insights into the nuanced effects of information and communication technology (ICT) capital investment on employment, considering various control variables and fixed effects. Model one, which regresses the log of employment solely on the log of ICT capital investment without industry and year fixed effects, offers a basic understanding of the relationship between these two variables but overlooks potential industry-specific or time-related influences as well as control variables. Model 2 introduces additional controls by including ICT productive capital stock and ICT wealth stock alongside ICT capital investment but still lacks industry and year fixed effects. This expanded model allows for a more comprehensive assessment of the impact of ICT-related factors on employment levels. Moving to model 3, which includes industry and year fixed effects but retains only ICT capital investment as the independent variable, provides insights into how industry-specific and time-related factors shape the relationship between ICT investment and employment, albeit without considering other ICT-related variables. Finally, model 4 incorporates both industry and year fixed effects while accounting for ICT productive capital stock and ICT wealth stock alongside ICT capital investment. This comprehensive approach offers a robust analysis, capturing the combined effects of ICT investment, ICT productive capital stock and ICT wealth stock on employment while controlling for industry-specific and temporal variations.

Table 2. Number of Jobs and Capital Investment (Log-Log model)

Regressors	Model1	Model2	Model3	Model4
logCI	0.56***	0.84***	0.13***	0.04*
	(0.02)	(0.09)	(0.01)	(0.02)
logPCS		0.01		0.20***
		(0.05)		(0.07)
logWS		-0.31***		-0.07
		(0.10)		(0.08)
Intercept	7.15***	7.64***	8.53***	8.28***
	(0.03)	(0.16)	(0.05)	(0.07)
Industry and Year Fixed Effect	no	no	yes	yes
Number of Observations	972	972	972	972
Adjusted R-Square	0.5086	0.5124	0.9818	0.9825
Overall Significance	661.70***	246.40***	2,188.62***	2,243.21***

Source: U.S. Bureau of Labor Statistics.
Notes: This table shows percentage changes in employment caused by one percent increase in variables of capital investment (CI), productive capital stock (PCS), and wealth stock (WS). Using Model 3, it is concluded that a 10 percent increase in the value of capital investment in information processing equipment in a sector correlates with a 1.3 percent increase in the number of jobs in that sector.

The size of coefficients in Table 2 are plausible. The signs of these coefficients are expected and is not surprising. A percentage increase in 0.13 of jobs is a reasonable result associated with more information equipment technology adaptation.

Interpreting coefficients in regression analysis also involves assessing both statistical significance and economic significance. Model 3's results in Table 2 have a high level of statistical significance in the regression analysis. The result is statistically significant at the 99% confidence level. This means that there is a very low probability (less than 1%) that the observed relationship occurred by chance alone. The results also show economic significance because the size of the coefficient of logCI has practical importance in terms of the percentage change in jobs available.

VII. Conclusion

In conclusion, the adoption of information processing equipment increases the number of jobs available in the job market. The data used in this study only includes the technology of information processing equipment, and so it cannot represent the whole scope of technology's impact on employment. Only the private sector data is measured and so this study's results are limited to what is happening in the private sector. However, an R-squared value of 0.9818 indicates a strong fit that 98.18% of the variability in the employment can be explained by the adoption of information processing equipment using model 3's coefficient in table 2. A policy recommended based on the knowledge gained in this study is to encourage technological development to spur productivity as well as employment. Future research to improve this research can focus on other technologies such as AI adaptation and its impact on employment. This study's findings offer an example with information processing equipment adaptation and its impact on employment.

VIII. References

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IX. Appendix

Table 3. Number of Jobs and Productive Capital Investment (Levels)

Regressors	Model1	Model2	Model3	Model4
CI	521.72***	-2,427.91***	107.88***	-508.22***
	(110.73)	(237.43)	(30.99)	(120.92)
PCS		8.05		21.17**
		(10.12)		(9.95)
WS		711.38***		130.41***
		(72.11)		(40.24)
Intercept	2,224.08***	914.93**	3,490.74***	2,664.96***
	(438.46)	(444.97)	(941.43)	(912.74)
Industry and Year Fixed Effect	No	No	Yes	Yes
Number of Observations	972	972	972	972
Adjusted R-Square	0.3155	0.556	0.9679	0.9749
Overall Significance	22.20***	51.28***	577.32***	399.27***

Source: U.S. Bureau of Labor Statistics.

Notes: This table shows the changes in employment caused by changes in variables of capital investment (CI), productive capital stock (PCS), and wealth stock (WS). Using Model 3, it is concluded that increase in the value of capital investment in information processing equipment increases employment ($B_1 = 107.88$).

Table 4. Industry List for Data Merger

NAICS Code	Description
11	Agriculture, forestry, fishing, and hunting
21	Mining
22	Utilities
23	Construction
321	Wood products
327	Nonmetallic mineral products
331	Primary metal products
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
337	Furniture and related products
339	Miscellaneous manufacturing
311-312	Food and beverage and tobacco products
313-314	Textile mills and textile product mills
315-316	Apparel and leather and applied products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
42,44-45	Trade
48-49	Transportation and warehousing
51	Information
52-53	Finance, insurance, real estate, and leasing
54-81	Services

Source: U.S. Bureau of Labor Statistics.

Notes: This table shows the different industries and its corresponding codes. Some codes are combined so that employment data and ICT data are accurately merged. The data section on page 10 discusses the process and reason for the need to combine certain codes. Regression analysis uses ICT and employment values on all the sectors listed.

X. SAS Codes

```
proc import datafile="/home/u63046968/Senior Project/IPE.CI.xlsx" out=work.CI
		dbms=xlsx replace;
	sheet="CI";
	getnames=yes;
run;

proc sort Data=CI;
	by NAICS;
run;

proc Transpose data=CI Out=CI2;
	by NAICS;
	Var "1987"n-"2021"n "2022"n;
run;

Data CI3;
	Set CI2;
	Year=input(_Name_, 4.);
	CI=Col1;
	keep NAICS Year CI;
Run;


proc import datafile="/home/u63046968/Senior Project/Employment.xlsx" out=work.emply
		dbms=xlsx replace;
	sheet="Sheet1";
	getnames=yes;
run;
```

```
proc Transpose data=emply Out=employ;
	by NAICS;
	Var "1987"n-"2021"n "2022"n;
run;

Data emp;
	Set employ;
	Year=input(_Name_, 4.);
	employment=Col1;
	keep NAICS Year employment;
Run;

proc import datafile="/home/u63046968/Senior Project/IPE.PCS.xlsx" out=work.PCS
		dbms=xlsx replace;
	sheet="Sheet1";
	getnames=yes;
run;

proc Transpose data=PCS Out=PCS2;
	by NAICS;
	Var "1987"n-"2021"n "2022"n;
run;

Data PCS3;
	Set PCS2;
	Year=input(_Name_, 4.);
	PCS=Col1;
```

```
        keep NAICS Year PCS;
Run;

proc import datafile="/home/u63046968/Senior Project/IPE.WS.xlsx" out=work.WS
                dbms=xlsx replace;
        sheet="WS";
        getnames=yes;
run;

proc sort Data=WS;
        by NAICS;
run;

proc Transpose data=WS Out=WS2;
        by NAICS;
        Var "1987"n-"2021"n "2022"n;
run;

Data WS3;
        Set WS2;
        Year=input(_Name_, 4.);
        WS=Col1;
        keep NAICS Year WS;
Run;

Data SeniorProj;
        merge CI3 PCS3 WS3 emp;
        by NAICS;
```

```
	keep NAICS employment CI PCS WS year log:;
	logEmp=log(employment);
	logCI=log(CI);
	logPCS=log(PCS);
	logWS=log(WS);
run;


ods graphics / reset width=5in height=3in imagemap;

proc sgplot data=SeniorProj;
	title height=14pt "Scatter Plot between logCI and logEmployment";
	scatter x=logCI y=logEmp / markerattrs=(symbol=circlefilled size=12)
		transparency=0.75;
	xaxis grid;
	yaxis grid;
run;

ods graphics / reset;
title;

ods output ParameterEstimates=PEforModel1 DataSummary=ObsModel1
	FitStatistics=AdjRsqModel1 Effects=OverallSigModel1;

/*Outcome=main regressor*/
proc surveyreg Data=SeniorProj;
	Class NAICS year /ref=First;
	*Model1:Model employment= CI PCS NAICS year / Solution AdjRsq;
```

```
	Model1: Model logEmp=logCI /Solution AdjRsq;
Run;



/*Outcome=main regressor, controls*/

ods output ParameterEstimates=PEforModel2 DataSummary=ObsModel2
			FitStatistics=AdjRsqModel2 Effects=OverallSigModel2;

/*without Fixed Effects*/

proc surveyreg Data=SeniorProj;
	*Model1:Model employment= CI PCS / Solution AdjRsq;
	Model2: Model logEmp=logCI logPCS logWS /Solution AdjRsq;
Run;



ods output ParameterEstimates=PEforModel3 DataSummary=ObsModel3
			FitStatistics=AdjRsqModel3 Effects=OverallSigModel3;

/*Outcome=main regressor, FE*/
/*with Fixed Effects*/
proc surveyreg Data=SeniorProj;
	Class NAICS year /ref=First;
	*Model1:Model employment= CI PCS NAICS year / Solution AdjRsq;
	Model3: Model logEmp=logCI NAICS year/Solution AdjRsq;
Run;
```

```
ods output ParameterEstimates=PEforModel4 DataSummary=ObsModel4
                              FitStatistics=AdjRsqModel4 Effects=OverallSigModel4;
/*Outcome=main regressor, controls, FE*/
/*with Fixed Effects*/
proc surveyreg Data=SeniorProj;
          Class NAICS year /ref=First;
          *Model1:Model employment= CI PCS NAICS year / Solution AdjRsq;
          Model4: Model logEmp=logCI logPCS logWS NAICS year/Solution AdjRsq;
Run;


******************************;
/* Build the results table */
******************************;


/* Step 1: clean-up the output of the regression analysis you have saved */
Data Table_Long;
          length Model $10; /* Makes sure the variable Model has the right length and its values
are not truncated */
          length parameter $30; /* Makes sure the variable id has the right length and its values are
not truncated */
          set PEforModel1 PEforModel2 PEforModel3 PEforModel4 indsname=M; /*"indsname"
creates an indicator variable (here I call it "M") that tracks the name of databases use in the "set"
statement */
          *THisISM=M;


          if M="WORK.PEFORMODEL1" then Model="Model1";
          else if M="WORK.PEFORMODEL2" then Model="Model2";
```

```
        else if M="WORK.PEFORMODEL3" then Model="Model3";
                else if M="WORK.PEFORMODEL4" then Model="Model4";

                where stderr ne 0;

        if Probt le 0.01 then Star="***";
                else if Probt le 0.05 then Star="**";
                else if Probt le 0.1 then Star="*";

if parameter="Chwkswork" then parameter="wkswork";

        EditedResults=cats(Put(Estimate,comma16.2),star);
        output;

        EditedResults=cats("(",put(StdErr,comma16.2),")");
        output;

run;

/* We sometimes need this sorting step when we have multiple regression models */
proc sort data=Table_Long out=Table_Long_Sorted;
        by Model Parameter;
run;

/* Step 2: Create separate results columns (in the form of separate databases) corresponding to
each model */
data    Model1Results(rename=(EditedResults=Model1))
Model2Results(rename=(EditedResults=Model2))
Model3Results(rename=(EditedResults=Model3))
```

```
            Model4Results(rename=(EditedResults=Model4));
    set Table_Long_Sorted;
    if  Model="Model1" then output Model1Results;
     else if Model="Model2" then output Model2Results;
      else if Model="Model3" then output Model3Results;
     else if Model="Model4" then output Model4Results;
    drop Model;
    keep parameter EditedResults;
run;



/* Step 3: Create the final results table that would include all models side-by-side*/
data Table_Wide;
    merge Model1Results Model2Results Model3Results Model4Results;
    by parameter;

    if Parameter="logCI" then Order=1;
 if Parameter="logPCS" then Order=2;
if Parameter="logWS" then Order=3;
 if substr(Parameter,1, 5)="NAICS" then Order=4;
if substr(Parameter, 1,4) ="year" then Order=5;
if Parameter="Intercept" then Order=6;
where substr(Parameter, 1, 5) ne "NAICS" and substr(Parameter, 1, 4) ne "Year";



    if mod(_n_,2)=1 then Regressors=Parameter;


run;
```

```
/* Order the variables in the results table */

proc sort data=Table_Wide out=Table_Wide_Sorted(drop=Order);

	by Order;

run;



/* Step 4: Create the rows for other statistics */

/* The row for the number of observations */

Data NumofObs;

	merge ObsModel1(rename=(Nvalue1=NVModel1) drop=CValue1)
ObsModel2(rename=(Nvalue1=NVModel2) drop=CValue1)
ObsModel3(rename=(Nvalue1=NVModel3) drop=CValue1)
ObsModel4(rename=(Nvalue1=NVModel4) drop=CValue1);

	where Label1="Number of Observations";

	Model1=Put(NVModel1,comma16.);

	Model2=Put(NVModel2,comma16.);

	Model3=Put(NVModel3,comma16.);

	Model4=Put(NVModel4,comma16.);

	keep Label1 Model1 Model2 Model3 Model4;

run;



/* The row for the adjusted R-Squared */

Data AdjRsq;

	merge   AdjRsqModel1(rename=(cvalue1=Model1) drop=nvalue1)

	AdjRsqModel2(rename=(cvalue1=Model2) drop=nvalue1)

	AdjRsqModel3(rename=(cvalue1=Model3) drop=nvalue1)

		AdjRsqModel4(rename=(cvalue1=Model4) drop=nvalue1);
```

```
        Where Label1="Adjusted R-Square";
run;

/* The row for the F-test related to the Overall Significance of the model */
Data OSM1(rename=(EditedValue=Model1)) ;
        set OverallSigModel1 OverallSigModel2 OverallSigModel3 OverallSigModel4
indsname=M;
        where Effect="Model";
        if ProbF le 0.01 then Star="***";
                else if ProbF le 0.05 then Star="**";
                else if ProbF le 0.1 then Star="*";
        ThisIsM=M;

        Label1="Overall Significance";
        EditedValue=cats(put(FValue,comma16.2),Star);

                if  M="WORK.OVERALLSIGMODEL1" then output OSM1;
        keep Label1 EditedValue;
run;

Data OSM2(rename=(EditedValue=Model2)) ;
        set OverallSigModel1 OverallSigModel2 OverallSigModel3 OverallSigModel4
indsname=M;
        where Effect="Model";
        if ProbF le 0.01 then Star="***";
                else if ProbF le 0.05 then Star="**";
                else if ProbF le 0.1 then Star="*";
        ThisIsM=M;
```

```
	Label1="Overall Significance";
	EditedValue=cats(put(FValue,comma16.2),Star);

		if  M="WORK.OVERALLSIGMODEL2" then output OSM2;
	keep Label1 EditedValue;
run;

Data OSM3(rename=(EditedValue=Model3)) ;
	set OverallSigModel1 OverallSigModel2 OverallSigModel3 OverallSigModel4
indsname=M;
	where Effect="Model";
	if ProbF le 0.01 then Star="***";
		else if ProbF le 0.05 then Star="**";
		else if ProbF le 0.1 then Star="*";
	ThisIsM=M;

	Label1="Overall Significance";
	EditedValue=cats(put(FValue,comma16.2),Star);

		if  M="WORK.OVERALLSIGMODEL3" then output OSM3;
	keep Label1 EditedValue;
run;



Data OSM4(rename=(EditedValue=Model4)) ;
	set OverallSigModel1 OverallSigModel2 OverallSigModel3 OverallSigModel4
indsname=M;
	where Effect="Model";
```

```
	if ProbF le 0.01 then Star="***";
		else if ProbF le 0.05 then Star="**";
		else if ProbF le 0.1 then Star="*";
	ThisIsM=M;

	Label1="Overall Significance";
	EditedValue=cats(put(FValue,comma16.2),Star);

		if  M="WORK.OVERALLSIGMODEL4" then output OSM4;
	keep Label1 EditedValue;
run;



Data OverallSig;
	merge OSM1 OSM2 OSM3 OSM4;
	by Label1;
run;


Data Controls;
	Regressors= "Industry and Year Fixed Effects?";
	Model3="yes";
	Model4="yes";
	Model1="no";
	Model2="no";
	Output;
run;
```

```
/* Combine all rows for other statistics */
data OtherStat;
	set NumofObs AdjRsq OverallSig;
	rename Label1=Regressors;
run;


/* Add rows for other statistics to the table */
Data Table_Wide_Sorted_withStat;
length Controls $30;
	set Table_Wide_Sorted Controls OtherStat;
run;
/* Print the clean results table */
ods excel file="/home/u63046968/Tables/logs.xlsx" options(Embedded_Titles="ON"
Embedded_Footnotes="ON"); /*Use the path to your MySAS folder */
Title "Effect of Information Processing Equipment Adoption on Employment";
footnote1 justify=left "Source: Bureau of Labor Statistics";
footnote2 justify=left "Notes: Robust Standard Errors are in Parentheses.
*, **, *** indicate 10%, 5%, and 1% significance levels, respectively.";
proc print data=Table_Wide_Sorted_withStat noobs;
	var regressors;
	var Model1 Model2 Model3 Model4 / style(header)={Just=Center}
style(data)={Just=Center};
	format Regressors $VariableName.;
run;
ods excel close;


/*proc sgplot: scatter*/
```