The Influence of Information and Communication Technology Investments on Productivity:
A Panel Data Analysis

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Abstract

In recent decades, new technologies have made tremendous progress, radically altering the way businesses produce and provide products and services. Information and communication technologies (ICT) are an important part of these technological innovations. Nowadays, it is difficult to imagine most businesses without them, particularly in manufacturing, where ICT is used extensively. As a necessary consequence, the impact of different technologies on productivity is of great importance for researchers. In this thesis, I examine the impact of ICT equipment investments on total factor productivity (TFP) and labor productivity in the United States manufacturing sector.
For this purpose, I use data from the United States Bureau of Labor Statistics from 1987 until 2020 to conduct a panel data analysis in R.
The findings of this thesis demonstrate that capital investments in ICT have, in general, a positive impact on productivity over the studied period. The impact, however, is highly dependent on the respective subsector. ICT investments in high R&D-intensive subsectors have a greater positive impact than investments in low R&D-intensive subsectors. Furthermore, the COVID-19 pandemic in 2020 had no significant impact on the relationship between ICT and productivity.
Consequently, this thesis contributes to a better understanding of the relationship between capital investments in ICT and productivity, as well as how new emerging technologies are affecting our economy.

Title: The Influence of Information and Communication Technology Investments on Productivity: A Panel Data Analysis

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Keywords: ICT, Information and Communication Technology, Productivity, Technology, TFP, Total Factor Productivity, Labor Productivity, Manufacturing

Sumário

Nas últimas décadas, as novas tecnologias fizeram enormes progressos, alterando radicalmente a forma como as empresas produzem e fornecem produtos e serviços. As tecnologias de informação e comunicação (TIC) são uma parte importante destas inovações tecnológicas. Hoje em dia, é difícil imaginar a maioria das empresas sem elas, particularmente no fabrico, onde as TIC são amplamente utilizadas. Como consequência necessária, o impacto das diferentes tecnologias na produtividade é de grande importância para os investigadores. Nesta tese, examino o impacto dos investimentos em equipamento TIC na produtividade total dos factores (PFT) e na produtividade do trabalho no sector transformador dos Estados Unidos.

Para este fim, utilizo dados do Bureau of Labor Statistics dos Estados Unidos de 1987 até 2020 para realizar uma análise de dados de painel em R.

Os resultados desta tese demonstram que os investimentos de capital em TIC têm, em geral, um impacto positivo na produtividade durante o período estudado. O impacto, no entanto, é altamente dependente do respectivo subsector. Os investimentos em TIC em subsectores de alta intensidade de I&D têm um impacto positivo maior do que os investimentos em subsectores de baixa intensidade de I&D. Além disso, a pandemia COVID-19 em 2020 não teve um impacto significativo na relação entre as TIC e a produtividade.

Consequentemente, esta tese contribui para uma melhor compreensão da relação entre investimentos de capital em TIC e produtividade, bem como da forma como as novas tecnologias emergentes estão a afectar a nossa economia.

Título: A Influência dos Investimentos em Tecnologias de Informação e Comunicação na Produtividade: Um painel de análise de dados

Author: Sebastian Christian Sieber

Palavras-chave: TIC, Tecnologia da Informação e Comunicação, Produtividade, Tecnologia, TFP, Produtividade Total dos Factores, Produtividade Laboral, Fabrico

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Glossary

α	Probability of Making Type I Error
β	Regression Coefficient
Δ	Delta
AI	Artificial Intelligence
BLS	U.S. Bureau of Labor Statistics
FD	First Differences
FE	Fixed Effects
H1	Hypothesis 1 (2-7 respectively)
ICT	Information and Communication Technology
IT	Information Technology
LLC	Levin-Lin-Chu Unit Root Test
M	Mean
Max.	Maximum Value
Min.	Minimum Value
n	Sample Size
NAICS	North American Industry Classification System
OLS	Ordinary Least Squares
OPT	Office of Productivity and Technology
p	*p*-value
R&D	Research and Development
SD	Standard Deviation
SE	Standard Error
TFP	Total Factor Productivity
VIF	Variance Inflation Factor

1. Introduction

"You can see the computer age everywhere but in the productivity statistics." – Robert M. Solow (1987)

This 35-year-old quote from Robert M. Solow (1987) is cited in the literature on productivity extremely often. It raises the question of whether it is still relevant today and what might have changed in the past 35 years. In contrast to 1987, there has been a multitude of technological innovations. First and foremost, robots and artificial intelligence (AI) have become incredibly widespread in a variety of economic sectors in recent decades. As a result, robots and intelligent machines are taking over tasks previously performed by humans (Atack et al., 2019). Moreover, automation costs have decreased in recent years, and machines' ability to handle more advanced tasks has improved. Robots have become easier to program and thus to use in a variety of manufacturing industries. Besides that, innovation is critical to global competitiveness. To stay competitive, the development and use of innovative technology, such as industry 4.0, AI, sensors, and other information technology-based manufacturing technologies are essential (Kromann et al., 2020). Although this has resulted in the replacement of labor in some jobs, it has also led to the creation of several new ones (Acemoglu & Restrepo, 2019; Cohen et al., 2019; Kromann et al., 2020; Stiroh, 2002). Furthermore, as competition from low-wage countries has increased, many manufacturing firms in the developed world have closed or outsourced parts of the manufacturing process (Kromann et al., 2020).

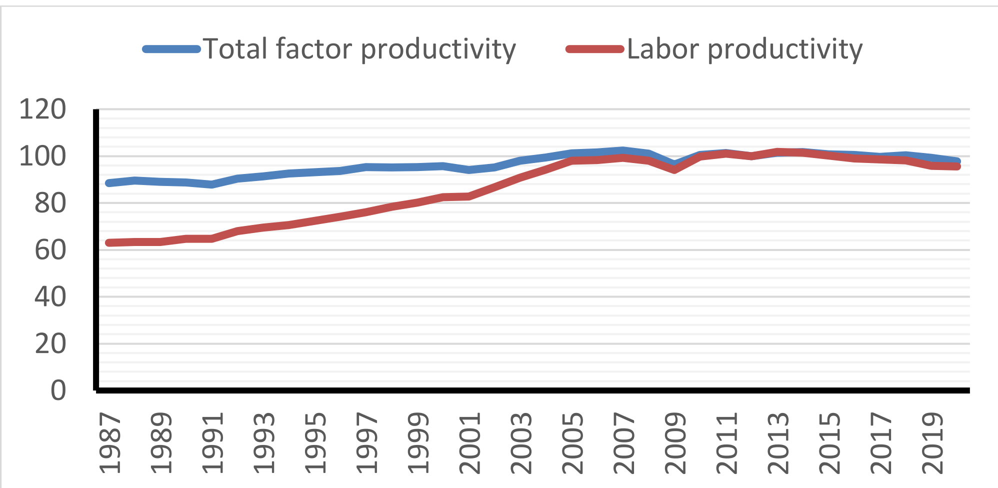
All these different trends over the last 35 years must somehow be reflected by the labor market and productivity statistics. Information Technology (IT) has automated and transformed US workplaces and will continue to do so (Acemoglu et al., 2014), while productivity (total factor productivity [TFP] and labor productivity) in the United States manufacturing sector has increased from 1987 to 2020 (see Figure 1). In line with this trend, the rapid progress of the technological revolution and continuous transformations across nations and sectors call for studies concerning productivity to be conducted on a regular basis (Vu et al., 2020). The question now is whether and exactly how productivity statistics reflect differences based on investments in new technologies. Can the investments in new technologies create productivity growth? Do any of these effects differ in different subsectors of the manufacturing sector? Did the COVID-19 pandemic have a noticeable effect on productivity statistics? And finally, what is the impact of the investments in technology on the total number of jobs in the manufacturing sector (employment), the number of labor hours worked by all workers to produce goods and services (hours worked), and the payments made as compensation for labor (labor compensation)?

In this thesis, I focused primarily on the manufacturing sector as in this sector automation and technological innovation are very intense and widespread. To measure automation, I will use the total investments in Information and Communication Technology (ICT) equipment and to measure productivity I focused on TFP and labor productivity. To provide a comprehensive understanding of the manufacturing industry, I observed the impact of ICT on productivity in general, and then for each subsector individually.

This thesis is structured as follows. In Section 2, the literature on technological advancements and productivity in the manufacturing sector is investigated to understand the current state of the art in this research field. Beyond that, the hypotheses for this thesis are derived from the literature. Section 3 describes the methodology used and includes a detailed description of the data and variables as well as the statistical methods. Section 4 presents the thesis' descriptive and empirical findings. Section 5 wraps up by discussing the main contributions and implications of this thesis. Furthermore, the limitations and possible future research opportunities are provided. Section 6 provides a short conclusion of this thesis.

Figure 1:

Mean of Total Factor Productivity and Labor Productivity in the United States (1987-2020)



Source: U.S. Bureau of Labor Statistics

2. Literature Review

2.1 Technological Advancements in the Manufacturing Sector

Today we are experiencing a time of rapid automation. The rise of industrial robots and other automated machinery is disrupting the jobs of production workers (Acemoglu & Restrepo, 2020; Atack et al., 2019; Cardona et al., 2013; Kromann et al., 2020; Vu et al., 2020), while workers in other occupations like accounting, sales, logistics, and trading have been replaced in some of their former tasks by specialized software and AI (Graetz & Michaels, 2018). This recent development is called industry 4.0. The fourth industrial revolution relies on the global connection of people, things, and machines. While previous industrial revolutions focused on mechanization (industry 1.0), electricity (industry 2.0), and information technology (industry 3.0). Industry 4.0 refers to digital transformation (Wójcicki et al., 2022). It is driven by new digital technologies that are implemented in the production process. The key technologies can be divided into software and hardware. Software technologies are the internet of things (IoT), big data, cloud computing, cyber-physical systems, machine learning, and real-time optimization. Hardware technologies are augmented reality, cobot, and additive manufacturing. These technologies are connected and communicate with each other to gather data via sensors installed on traditional machines, devices, and products, which results in smart and self-learning devices and the creation of smart factories (Cohen et al., 2019). The IoT lays the foundation for the improved manufacturing process. It enables real-time performance and quality dashboards and provides a high level of responsiveness and flexibility. Therefore, at the industrial level, IoT and other new technologies lead to entirely automated manufacturing systems through the connection of organizations, the generation of data, the implementation of automation and intelligent decision-making based on data. In conclusion, industry 4.0 is driven by information technology and leads to the transformation of manufacturing towards digital and connected manufacturing (Wójcicki et al., 2022). This apparent process is affecting all kinds of different industries. However, especially the manufacturing sector is heavily disrupted because of the huge number of simple tasks that can be transferred to machines and the amount of data that can be evaluated to improve processes (Atack et al., 2019). The manufacturing sector can be divided into 21 subsectors, all of which have different characteristics and react to technological innovations at different paces. The subsectors can be classified according to their technology R&D-intensity into high-tech, medium-high-tech, medium-low-tech, and low-tech (OECD, 2011). Table 1 in Section 3.1 contains the specifications for the various subsectors and their related classification.

There has been considerable focus on automation as a source of higher productivity in manufacturing. The typical measure of automation used in empirical studies is often R&D expenditures, the number of patents, the number of industrial robots, survey questions about innovation activities, or the number of ICT investments (Acemoglu & Restrepo, 2020; Becchetti et al., 2003; Cardona et al., 2013; Kromann et al., 2020; Schwabe & Castellacci, 2020; Stiroh, 2002; Vu et al., 2020). Investments in ICT enable faster information processing and allow firms to consider new ways of communicating with suppliers and customers, as well as arranging new distribution systems. Processes can be streamlined and automated, lowering capital requirements by better utilizing equipment and decreasing inventories and thus space requirements (Becchetti et al., 2003; Vu et al., 2020). ICT equipment is considered a subset of emerging technologies that serve as enablers for future innovation. Computers, mobile communication devices, and the internet are increasingly being incorporated into people's daily lives, altering how businesses and markets operate in a variety of ways. It is hardly surprising then, that this is attracting academics who want to investigate how ICT is transforming the economy. However, while some studies include communication technology in their ICT measures, this is rarely explicitly addressed (Cardona et al., 2013; Stiroh, 2002). In this study, I focused on the effects of capital investments in ICT as a proxy for technological advancement, which include among others automation and AI.

The following section defines and summarizes what is known about productivity in the manufacturing sector.

2.2 Productivity in the Manufacturing Sector

Productivity is defined as a measure of economic efficiency that shows how effectively economic inputs are converted into goods and services (Syverson, 2011). Ultimately, productivity is what drives a country's wealth and economic power. This is the case since a more efficient employee receives a greater salary and thereof has a higher standard of living. In particular, since Europe's productivity grew slower than in the United States from the mid-1990s to the mid-2000s, determining the driving factors of productivity has become a critical issue for researchers and policymakers (Cardona et al., 2013). The most commonly used macroeconomic concepts of productivity consist of multi-factor measurements (TFP) or single-factor productivity measures, as in the case of labor productivity. Both have been used as indicators to assess the competitiveness of various countries and industries.

First, let's consider the single-factor productivity measure. Labor productivity reflects the ratio of labor hours to the physical output of goods. Labor productivity is often calculated by using hours worked or the number of employees as labor input. Using hours worked provides a more realistic picture of the actual economic activity. Labor productivity is the most prevalent productivity indicator and can be based on gross output or value added as the applicable output measure (Cardona et al., 2013). The level of single-factor productivity is influenced by the intensity of use of the excluded inputs (Goodrum & Haas, 2002; Syverson, 2011). Therefore, researchers frequently employ a productivity concept that is insensitive to the intensity with which observable factor inputs are used. The most common multifactor measurement is TFP, which is defined as the efficiency at which combined inputs are used to produce output of goods and services. Inputs can be a combination of labor, capital, energy, materials, and purchased services. Manufacturers with higher TFP will produce more output with the same set of observable inputs than manufacturers with lower TFP (Syverson, 2011). This concept was used in many studies conducted in research on productivity in the manufacturing sector (Cardona et al., 2013; Graetz & Michaels, 2018; Kromann et al., 2020; Stiroh, 2002; Vu et al., 2020). Researchers have long been concerned about the impact of technological progress on productivity and employment. Numerous academic articles address this issue from various perspectives. Therefore, the following section provides an overview of the existing literature that focused on the influence of automation on productivity and employment.

2.3. Influence of Automation on Productivity

The influence of automation and technological improvements on productivity or employment was addressed by many articles and the findings have resulted in a wide range of different opinions. Adam Smith (1776) contributed to the early stages of this research, believing that incremental improvements in technology, such as the plough and the corn mill at the time, could lead to significant increases in productivity and employment. In the following, the literature about productivity and employment will be investigated, and provide the basis for the hypotheses of this thesis.

Between the 1980s and the 1990s, the literature was outweighed by explanations and discussions of the "Solow Paradox" by Robert M. Solow (1987), before moving to the question of causes for the late-1990s productivity recovery in the United States (Cardona et al., 2013). Studies at that time found no evidence of an impact of ICT on productivity, which was attributed to the amount of ICT capital being too small to be identified in large-scale studies (Berndt & Morrison, 1995; Brynjolfsson, 1996). In the early stages of the 21st century, Goodrum and Haas (2002) investigated the impact of different types of equipment technology for five technology factors (energy, control, functional range, information processing, and ergonomics) on partial factor productivity. They analysed data from the construction industry over 22 years. Hence, they discovered that equipment technology factors that underwent a significant change produced greater long-term improvements in partial factor productivity than those that did not. More recently, Bartel et al. (2007) conducted research at the micro-level that addressed automation and firm performance. They discovered that using more advanced technologies and machines in the valve manufacturing industry in the United States increased productivity by reducing setup time, production time, and inspection time. Cardona et al. (2013) conducted a study that summarized the findings of 150 empirical studies and concluded that ICT capital does indeed play an important role in productivity statistics, but that the evidence is most pronounced for the United States, while the evidence for European countries is more ambiguous. In addition, Kromann et al. (2020) found that increased robot-intensity is associated with increased TFP.

Therefore, considering the previous literature with a focus on the latest results, I hypothesize the following:

H1: Total investments in ICT equipment have a positive influence on the productivity (TFP and labor productivity) of the manufacturing sector in the United States.

While several studies have focused on TFP as their measurement of productivity (Cardona et al., 2013; Graetz & Michaels, 2018; Kromann et al., 2020; Venturini, 2015; Vu et al., 2020), other studies have used the single-factor measurement of labor productivity (Goodrum & Haas, 2002; Stiroh, 2002; Waldman, 2016). The influence on labor productivity is usually slightly higher than on TFP. To the best of my knowledge, only a few other researchers have compared the impact of ICT equipment investments on both productivity variables, and none of them has concluded that there are significant differences between those measures. Thus, my second hypothesis is:

H2: Investments in ICT equipment have a similar impact on TFP and labor productivity.

Despite the focus on the influence of capital investments in ICT on productivity it is important to observe how the recent economic event of the COVID-19 pandemic influenced the relationship between the investments in ICT and productivity. The COVID-19 pandemic has had an impact on productivity in several ways. One major factor is the disruption of global supply chains caused by the pandemic, which has affected the availability of raw materials, components, and other inputs for manufacturing processes. This has resulted in delays and other disruptions to production schedules, which could have reduced overall productivity (Pujawan & Bah, 2022). In addition, the pandemic has led to widespread shifts to remote work and other measures to protect the health and safety of workers, which may have required manufacturers to invest in new technologies and infrastructure to support remote collaboration and communication. These ICT investments have been necessary to maintain productivity and business continuity. However, the transition to remote work and the use of new technologies has not been without challenges, and some workers may have experienced difficulties adapting to these changes, which could have affected productivity.and the effectiveness of the ICT investment (Ardolino et al., 2022). Beyond that, a negative effect of past deep recessions on TFP is elaborated by Furceri et al. (2021). They predicted a negative effect of the COVID-19 pandemic on TFP, like it was observed in the UK private industry sector (Bloom et al., 2020).

Consequently, I will investigate how the relationship between the dependent and independent variable changed during the COVID-19 pandemic. In addition, I examine how the pandemic in the year 2020 influenced the productivity variables in the United States manufacturing sector, therefore I hypothesize that:

H3: The COVID-19 pandemic in 2020 changed the relationship between total capital investments in ICT and productivity.

H4: The COVID-19 pandemic in 2020 had a negative influence on productivity in the United States manufacturing sector.

Moreover, manufacturing is not a homogeneous field, encompassing several subsectors that differ greatly from each other (e.g., wood products and computer & electronic products). These different manufacturing subsectors may show different productivity levels and may invest in ICT differently.

According to Gordon (2000) the new economy, driven by changes in technology and the internet, resulted in an explosion of productivity growth in the durable manufacturing sector but no visible productivity growth in other sectors, despite large investments in computers and other technologies. Moreover, Stiroh (2002) explored the link between IT capital accumulation and productivity growth in various industries of the United States. His result showed that industries with higher IT investments in the early 1990s achieved higher productivity gains in the late 1990s. In addition, he found that IT-related differences across industries are large and that the differences are an important factor when investigating productivity. Furthermore, the framework for productivity-enhancing policy making developed by Waldman (2016) was based on an industry-level analysis of the evolution of manufacturing productivity. His findings revealed that investments in innovation and equipment are important for productivity growth and that the drivers depend on the respective subsector. Beyond that, Acemoglu et al. (2014) discovered that there is some evidence of differential productivity growth in IT-intensive manufacturing industries. However, this is dependent on the measure of IT intensity and is not visible after the late 1990s. More importantly, when it occurs, it is accompanied by declining relative output and even faster declines in employment. Therefore, the authors argued that the evidence suggests that Solow Paradox resolutions should be critically examined and that more direct evidence of the technological discontinuity of the IT-induced transformation in the United States economy is required. It follows, that different subsectors have different characteristics, and thus the effect should be estimated in each subsector individually, which leads to my next hypothesis.

H5: The extent of the influence of investments in ICT on productivity depends on the subsectors of the manufacturing sector and there are strong differences between the subsectors.

In addition, the manufacturing subsectors can be differentiated according to their technology R&D-intensity (OECD, 2011). Subsectors with high R&D-intensity tend to be more reliant on advanced technologies and are therefore more likely to benefit from investments in ICT. Apart from that R&D-intensity potentially leads to knowledge spillovers from research conducted to produce IT, which positively influences TFP in the long run. In contrast, subsectors with lower R&D intensity may have less room for improvement in productivity through ICT investments, as they may be less reliant on advanced technologies (Han et al., 2011; Venturini, 2015). Therefore, the effect of ICT investments could differ in the R&D-intensity classifications.

H6: The impact of investments in ICT is higher for subsectors with high technology R&D-intensity than for subsectors with lower R&D-intensity.

2.4 Influence of Automation on Employment

The influence of automation on employment is a controversial and important topic for researchers. John Maynard Keynes (1931) predicted that the rapid spread of automation technologies would result in technological unemployment. In the recent literature, opinions and findings on the influence of automation on employment differ. Becchetti et al. (2003) discovered in their firm-level study that ICT investments positively influenced the demand for highly skilled workers and the creation of new products and processes. Kromann et al. (2020) detected that automation is followed by higher wages and stable, or even increased employment. They concluded that automation could be used to reintroduce production in developed countries. Acemoglu and Restrepo (2020) investigated the long-term effects of increased industrial robot use on the United States labor market. However, they found that a robust negative impact of robotic automation on employment and wages persisted between 1990 and 2007. As a result, according to their analysis, adding one robot to every thousand workers reduces the employment-to-population ratio by about 0.2% points and wages by 0.37%.

Later, Shuai et al. (2022) emphasized the importance of labor type in their study of the effect of AI on employment in China. The researchers found that AI increased the demand for high-skilled labor and reduced the relative demand for low-skilled labor. In consequence, the increased investments in R&D, as well as the expansion of the scale, increased the overall labor demand. Beyond that, Acemoglu and Restrepo (2019) developed a task-based model to investigate the effects of various technologies on labor demand. They measured the allocation of tasks to production factors and found that the automation of production changes the tasks to be performed by workers. The introduction of new tasks in which labor has a comparative advantage remains to be performed by production workers. The main implication of this study is that the recent stagnation of labor demand can be explained by an increase in automation and a decrease in the creation of new tasks. Furthermore, the economy experienced a slowdown in productivity growth, contributing to declining labor demand.

Consequently, according to all the previous considerations, my final hypothesis is:

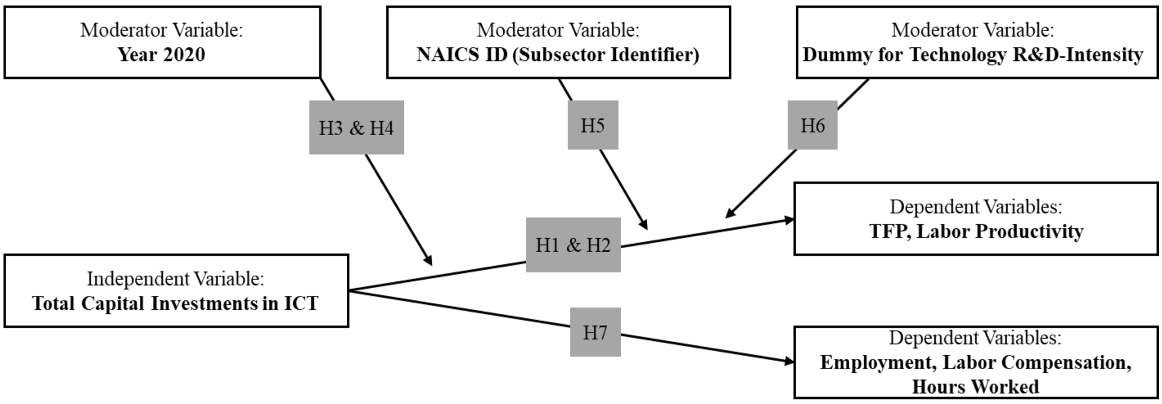
H7: ICT equipment investments have a negative effect on other productivity related variables, specifically employment, labor compensation, and hours worked.

2.5 Research Gap and Conceptual Model

As the relevant reviewed research in this field suggests, there is room to add to the question of the connection between ICT investments and productivity. This paper attempts to analyse the influence of investments in ICT equipment, which is used as a proxy for automation on the productivity of the United States manufacturing sector. It does so by considering two productivity variables, which adds robustness to the conclusions. Moreover, it looks at potential differences resulting from different subsectors in manufacturing and acknowledges the effect of the COVID-19 pandemic on these variables. To the best of my knowledge, this is the first study that addresses this relationship between ICT investments and productivity with a long time series of over three decades until the year 2020, which includes a pandemic year, and a special focus on different subsectors. Therefore, I will try to close this knowledge gap. Figure 2 depicts the conceptual model for this study and connects the hypotheses to the variables. Subsequently, the methodological approach of the work is described in detail.

Figure 2:

Conceptual Model



3. Methodology

3.1 Data Sources and Data Treatment

The data used in this analysis was published by the U.S. Bureau of Labor Statistics (BLS). This is the primary source of labor and workplace data in the United States and was used in many research articles about productivity (Acemoglu & Restrepo, 2019; Berndt & Morrison, 1995; Cardona et al., 2013; Stiroh, 2002; Vu et al., 2020). The Office of Productivity and Technology (OPT), which is a part of the BLS, processed the data concerning this specific field of research about productivity and capital investments. This department closely monitors how efficiently the United States converts inputs into outputs of goods and services. To test my hypotheses and investigate the impact of ICT equipment investments on productivity, I used two panel data sets from the productivity tables relating to TFP and related measures. The first dataset entailed productivity information and measures about different industries inside of manufacturing, air transportation, and line-haul railroads sectors. This dataset consists of data from 1987 until 2021 and is based on all workers in the United States. The second dataset entails capital details for major sectors and industries for information processing equipment and includes data from 1987 to 2020. The information in this dataset is based on all companies operating in the respective manufacturing subsectors in the United States.

In order to gain a comprehensive database, I merged the above-mentioned datasets into one according to their 3-digit North American Industry Classification System (NAICS) number. The subsectors of food manufacturing (NAICS 311) and beverage and tobacco product manufacturing (NAICS 312) were combined because no data for the subsectors separately were available in the capital details dataset. The same procedure had to be done for textile mills (NAICS 313) and textile product mills (NAICS 314), as well as for apparel manufacturing (NAICS 315) and leather and allied product manufacturing (NAICS 316). The subsector of transportation equipment manufacturing produces equipment for transporting people and goods. For this analysis it is split into two subsectors, due to extremely high differences in the values of the data. On the one side, NAICS 3361, 3362, and 3363 include the production of motor vehicles, motor vehicle bodies and trailers, and motor vehicle parts, on the other side NAICS 3364, 3365, 3366, and 3369 encompass the manufacturing of aerospace products and parts, railroad rolling stock, ship, boat, and other transportation equipment.

Due to missing values, I excluded the year 2021 from the analysis. The final database for the analysis consists of 646 observations and 14 variables from 19 subsectors within the manufacturing area. Table 1 provides a brief overview of the subsectors under investigation. The variables of interest are described in detail in the following section.

Table 1:

Manufacturing Subsectors Overview and Classification

NAICS	*Subsector*	*Classification According to R&D-Intensity* (OECD, 2011)	*naics_id*
311-312	Food, beverage, & tobacco	Low-tech	1
313-314	Textile mills & textile product mills	Low-tech	2
315-316	Apparel, leather & allied products	Low-tech	3
321	Wood products	Low-tech	4
322	Paper products	Low-tech	5
323	Printing & related support activities	Low-tech	6
324	Petroleum & coal products	Medium-low-tech	7
325	Chemical products	Medium-high-tech	8
326	Plastics & rubber products	Medium-low-tech	9
327	Non-metallic mineral products	Medium-low-tech	10
331	Primary metal products	Medium-low-tech	11
332	Fabricated metal products	Medium-low-tech	12
333	Machinery	Medium-high-tech	13
334	Computer & electronic products	High-tech	14
335	Electrical equipment & components	Medium-high-tech	15
3361-3363	Motor vehicles, bodies, trailers & parts	Medium-high-tech	16
3364-3369	Aerospace, railroad, ship, boat & other transportation equipment	High-tech	17
337	Furniture & related products	Low-tech	18
339	Miscellaneous manufacturing (incl. medical equipment and supplies)	High-tech	19

3.2 Description of Variables

3.2.1 Independent Variable

The main explanatory variable under consideration in this study is the variable for total capital investments in ICT equipment (cap_inv_index), which can be defined as payments made to acquire ICT equipment to support the production process of goods and services. It encompasses information technology equipment (computers and related hardware), communications equipment, and software (U.S. Bureau of Labor Statistics, n.d.). All numerical variables (except for year and the dummy variables) are measured in the unit of an index with 2012 as the base year with a value of 100. The unit of index was selected to keep the values comparable between subsectors with different sizes and characteristics. In this study, the correlation between the independent and dependent variable will be observed. Based on this, I will try to investigate the causal relationship.

3.2.2 Dependent Variables

The main target variables in this study are TFP and labor productivity. Total factor productivity is a multi-factor measurement and is defined as the efficiency at which combined inputs like labor, capital, energy, materials, and purchased services are used to produce output of goods and services. In contrast, labor productivity is a single-factor measurement and is characterized as the efficiency at which labor hours are used to produce output of goods and services (Syverson, 2011; U.S. Bureau of Labor Statistics, n.d.). Moreover, to investigate in more detail how the independent variable total capital investments in ICT changed the productivity statistics, I included other productivity related variables into the dataset and used them as dependent variables to investigate H7. These additional productivity variables are total employment, labor compensation, and hours worked.

3.2.3 Moderator Variables

To investigate the influence of ICT investments on the different subsectors of the United States manufacturing sector, I included naics_id as a moderator variable. This variable distinguished between the various subsectors through an identification number from 1-19 (see Table 1).

In addition, dummy variables for R&D-intensity were created as moderator variables and assigned to the respective subsectors according to the OECD (2011) criteria (see Table 1).

Beyond that, the dataset contains the variable year to hold changes over time constant. Also, the dummy variable for the year 2020 (y2020) was added as a moderator variable to observe if the specific year 2020 and the COVID-19 pandemic had a major impact on productivity.

3.3 Procedure and Statistical Methods

This research presents a macroeconomic perspective on the interaction of productivity and investments in ICT equipment and employs an observational approach to investigate the variables' correlation. Therefore, I constructed a regression analysis in R based on the procedures and statistical methods of previous researchers (Cardona et al., 2013; Stiroh, 2002; Vu et al., 2020). In the utilized dataset the variables were observed every year from the year 1987 until 2020. According to this, it was processed using panel data procedures

(Wooldridge, 2010). As a first step, descriptive statistics were created to better understand the data. Afterwards, panel data-specific tests, like the variance inflation factor (VIF), the Shapiro-Wilk normality test, the studentized Breusch-Pagan, Breusch-Godfrey/Wooldridge test, Hausmann test, F-test, the Levin-Lin-Chu (LLC) unit root test and finally the Granger Causality test were run to ensure that the appropriate functions were used for the regression analysis (for more details, see Section 4.2).

In the next step, I created empirical estimation models with the first differences (FD) estimator for panel data. Using FD removes the unit-specific error and all time-invariant regressors (Wooldridge, 2010). A more detailed explanation of why the FD estimator was used here follows in 4.2. First, I constructed an FD model including time-fixed effects with TFP as the dependent variable and capital investments in ICT as the independent variable to show the effect of ICT investments on productivity for the overall manufacturing sector (H1). The variable year and naics_id were used as an index and omitted from the stargazer in all models. In addition, the same model was constructed with labor productivity as the dependent variable. The statistical functions used are the following, where Δv is the error term that changes over time:

$$\Delta \log(\text{tfp}) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta factor(year) + \Delta v_i$$
$$\Delta \log(labor\_prod) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta factor(year) + \Delta v_i$$

Moreover, robustness tests were performed with three different covariates (employment, labor compensation, and hours worked by production workers to assess the model's robustness to omitted variables. Due to multicollinearity, adding more than one covariate at the same time was not possible.

In the next model, the dummy variable for the year 2020 (y2020) and the interaction term between capital investments in ICT (log_cap_inv) and y2020 was added to the above presented statistical functions to investigate the impact of the COVID-19 pandemic on the TFP and labor productivity in the manufacturing sector (H3 & H4). The statistical functions used here are:

$$\Delta \log(\text{tfp}) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta y2020 + \beta_3 \Delta \log(cap\_inv) * y2020 + \beta_4 \Delta factor(year) + \Delta v_i$$
$$\Delta \log(\text{labor\_prod}) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta y2020 + \beta_3 \Delta \log(cap\_inv) * y2020 + \beta_4 \Delta factor(year) + \Delta v_i$$

Building on this, the results were further investigated in different subsectors of the manufacturing sector to validate the findings and base the productivity effect on the individual intensity of investments in each subsector. For this purpose, I created subsets for each manufacturing subsector and ran FD regressions for each of the 19 individual time series (H5).

$$\Delta \log(tfp_{1-19}) = \beta_1 \Delta \log(cap\_inv_{1-19}) + \Delta v_i$$
$$\Delta \log(labor\_prod_{1-19}) = \beta_1 \Delta \log(cap\_inv_{1-19}) + \Delta v_i$$

Beyond that, I grouped the subsectors according to their technology R&D-intensity and ran separate FD regressions for each of the groupings (H6). Following are the statistical functions used for this purpose:

$$\Delta \log(tfp_{high-low}) = \beta_1 \Delta \log(cap\_inv_{high-low}) + \Delta v_i$$
$$\Delta \log(labor\_prod_{high-low}) = \beta_1 \Delta \log(cap\_inv_{high-low}) + \Delta v_i$$

The last step of my empirical analysis was to elaborate what effect ICT investments have on other productivity related variables like employment, labor compensation, and hours worked (H7). Therefore, I constructed FD models including time-fixed effects with the following empirical functions:

$$\Delta \log(\text{employment}) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta \log(cap\_inv) * y2020 + \beta_3 \Delta factor(year) + \Delta v_i$$
$$\Delta \log(labor\_comp) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta \log(cap\_inv) * y2020 + \beta_3 \Delta facotr(year) + \Delta v_i$$
$$\Delta \log(hours\_worked) = \beta_1 \Delta \log(cap\_inv) + \beta_2 \Delta \log(cap\_inv) * y2020 + \beta_3 \Delta factor(year) + \Delta v_i$$

Furthermore, a robustness check was performed with the covariate TFP (log_tfp).

4. Results

4.1 Descriptive Statistics

Summary statistics in Table 2 provide the first insights about the dataset and the variables. Table 2 illustrates the main variables of interest, focusing on the central goal of this study, which is to analyse the influence of investments in ICT equipment on productivity. The summary statistic shows that the data consists of 646 observations from 19 different subsectors of the manufacturing sector and the time series is from 1987 until 2020. The variable year reveals that the data was collected across multiple years. Since the number of observations (n = 646) is greater than the number of periods (t = 34), the given data structure is panel data, which consists of multiple statistical units of analysis in several successive periods of time (Wooldridge, 2010). Each of the 19 subsectors has one observation for each of the 34 years of interest. Since no holes (zero or NA) can be found in this structure, this panel is balanced. The mean of the dependent variables tfp_index is 96.43 and labor_prod_index is 86. The mean of the independent variable for total capital investment in ICT (cap_inv_index) is 88.69 and its standard deviation is 49.34, which indicates a very high variance of the residuals.

Table 2:

Summary Statistics (excluding Dummy Variables for the Year 2020 and R&D-Intensity)

Variable	*Description*	*n*	*M*	*SD*	*Min.*	*Max.*
tfp_index	Total factor productivity	646	96.43	11.07	47.77	143.61
labor_prod_index	Labor productivity	646	86.00	18.09	34.22	145.06
cap_inv_index	Total capital investment in ICT equipment	646	88.69	49.34	4.37	306.57
hours_worked_index	Hours worked	646	135.60	52.16	75.41	431.90
employment_index	Employment	646	137.21	53.64	76.62	453.09
labor_comp_index	Labor compensation	646	106.87	43.69	38.79	373.69
year	Year of observation	646	2003.5	9.81	1987	2020
naics_id	Industry identifier number	646	10	5.48	1	19

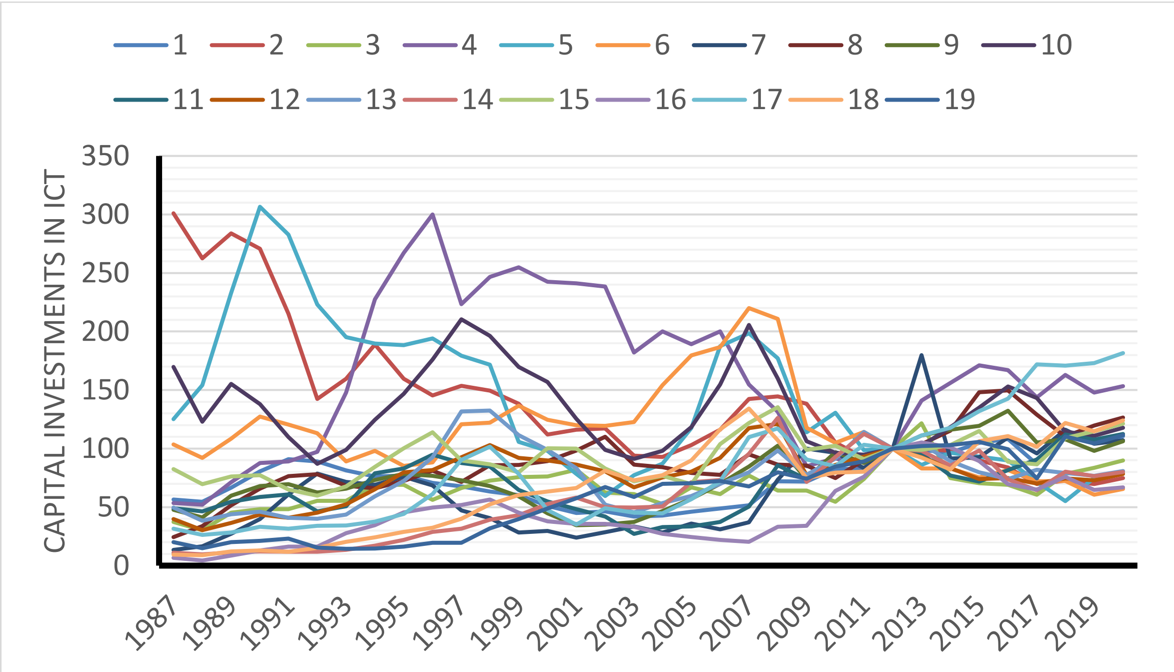
Figure 1, in Section 1, shows that the dependent variables TFP and labor productivity increased over the sample period. The slope of labor productivity is generally steeper than the slope of TFP. This demonstrates that labor productivity grew faster than TFP over time. Figure 3 displays the capital investments in ICT equipment for the sample period. As can be seen, the variation of investments across different manufacturing subsectors is large. Total capital investments in ICT increased over time for all subsectors, except textile mills

& textile product mills (naics_id = 2), printing and related support activities (naics_id = 6), paper products (naics_id = 5) and nonmetallic mineral products (naics_id = 10).

In sum, the table and figures show considerable variation across subsectors and years for the variables of interest. This variation can be caused by many different factors. In the following, I will investigate in more detail if this increase in productivity over the years for the dependent variables TFP and labor productivity is caused by investments in ICT equipment. In the next step, the panel data specific tests to prepare the data are explained.

Figure 3:

Capital Investments in ICT in the 19 Manufacturing Subsectors of the United States (1987-2020)



Source: U.S. Bureau of Labor Statistics

4.2 Panel Data Tests

Before I started to investigate the correlational relationship and constructed regression models, some typical panel data specific tests had to be performed. In the first step, the multicollinearity of the predictor variables was investigated. Highly correlated predictor variables can cause problems when interpreting the regression models. I used the variance inflation factor (VIF) to check for multicollinearity. Since the VIF values (Appendix Table

1) of the independent variable combinations described in Section 3.3 are all close to 1, the results do not indicate multicollinearity (Fox & Monette, 1992).

Afterwards, the normal distribution of the variables was tested with the Shapiro-Wilk normality test (Royston, 1995). The $p < 0.05$ (Appendix Table 2) of the variables tfp_index, labor_prod_index, cap_inv_index, hours_worked_index, labor_comp_index, and employment_index indicates that the data is not normally distributed. Therefore, I created and continued the analysis with the natural logarithm of the variables instead of using the Cobb-Douglas production function, in line with what many researchers did (Cardona et al., 2013).

In the next step, heteroskedasticity was tested with the studentized Breusch-Pagan test (Breusch & Pagan, 1979). Since the *p*-value for TFP ($p < 0.001$) and labor productivity ($p = 0.025$) is less than 0.05, H0 can be rejected (Appendix Table 3). As a result, the data exhibits heteroskedastic characteristics, implying variability in the observations of the dependent variable. In addition, the Breusch-Godfrey/Wooldridge test (Wooldridge, 2010) for serial correlation in panel models was performed to see if the constructed models have serial correlation. The tests (Appendix Table 14) showed that I can reject the H0 for all the different models ($p < 0.05$). Therefore, the residuals are serially correlated, and robust standard errors must be used. When using the Ordinary Least Squares (OLS) estimator, observations of the same individual are treated as if they originate from other individuals. Important influences, such as serial correlation of observations within the same group are ignored, resulting in biased estimates (Wooldridge, 2010). Hence, a simple OLS model is not the most appropriate for analysing this dataset.

The fixed effects (FE) and FD models estimate changes within a specific group (over time) and control for all time-invariant differences between groups, therefore, leading to unbiased estimates and a better fit to investigate the proposed causal relationships (Wooldridge, 2010).

The Hausmann test was performed to compare the random effects (RE) and FE models. The null hypothesis that the preferred model is RE, can be rejected ($p = 0.002$). Therefore, the preferred model here could be FE. In addition, an *F*-test for time-fixed effects was run. The *p*-value for this test was less than 0.05 ($p = 0.001$), indicating that time-fixed effects are present and should be accounted for.

Beyond that, it is important to test that the time series used to explain the causality between log_tfp or log_labor_prod and log_cap_inv is stationary. To test this assumption, I conducted the Levin-Lin-Chu unit root test (Levin et al., 2002). The null hypothesis of this test is, that the time series is non-stationary (has a unit root), which means it has some time-dependent structure and has means, variances, and covariances that change over time. The LLC test is evaluated at a significance level of 5% ($\alpha = 0.05$). The test was first performed for the entire time series and then for subsets according to their naics_id number. For the test of the entire dataset, I cannot reject the null hypothesis ($p = 0.547$). This shows that at least some of the time-series in my dataset are non-stationary. Thus, in the next step, I performed the LLC test for the different manufacturing subsectors. Accordingly, I cannot reject the null hypothesis for most subsectors ($p > 0.05$), except for the subsectors with the naics_id 2 and 3. Afterwards, I computed the LLC test for the subsets of high-tech, medium-high-tech, medium-low-tech, and low-tech sectors. The test showed that three of the four subsets are non-stationary ($p > 0.05$). Only for the subset of high-tech H0 can be rejected, which indicates that this subsector is already stationary. To build regression models with this dataset, the data must first be transformed to be stationary. Therefore, I used the log-transformed variables and differenced all the variables with a lag of 1 year. In Table 3, the LLC test *p*-values of the log and differenced variables can be compared to the *p*-values of the original dataset. The table showed that for all the different subsectors the *p*-value is less than 0.05, which proves that the data is stationary. Moreover, I retested for heteroskedasticity with the differenced variables. The results in Appendix Table 3 showed that the problem of heteroskedasticity could be eliminated by the performed transformation ($p > 0.05$).

In consequence, the log-transformed variables and the first differences estimator must be used in this regression analysis.

Finally, I tested for causality among the variables with the Granger causality test (Dumitrescu & Hurlin, 2012). Applying this approach showed whether investments in ICT caused productivity and how much of the values in period t are explained by past values. In the second step, I tested whether adding lagged values of higher orders can improve the explanation. With a lag order of 1 year, I can reject the null hypothesis and infer that the time series of capital investments in ICT (log_ cap_inv) granger causes the time series of TFP (log_tfp) ($p = 0.006$) and labor productivity (log_labor_prod) ($p = 0.009$). This showed that knowing the values of log_cap_inv is valuable for forecasting the future values of log_tfp and log_labor_prod. When adding lags of higher order (2-4) there is no statistically significant effect ($p > 0.05$), which showed that adding more lags does not directly improve the explanation of my models. In addition, I performed the reverse causality test. For TFP, reverse causality could be a possible bias, but it is less significant than in the other direction. For labor productivity, no bias could be detected (for more details, see Granger causality test in Appendix Table 4).

In the next sections, I constructed regression models with the derived results from this section.

Table 3:

Levin-Lin-Chu Unit Root Test for Stationarity

Subsectors (naics_id)	Level *p*-value	Log & differenced *p*-value
All	0.5469	< 2.2e-16***
1	0.1596	3.37e-12***
2	0.02555**	2.171e-09***
3	4.804e-09***	0.0003146***
4	0.8137	< 2.2e-16***
5	0.2543	6.864e-11***
6	0.2087	< 2.2e-16***
7	0.6074	< 2.2e-16***
8	0.05562*	< 2.2e-16***
9	0.9649	7.033e-14***
10	0.4638	< 2.2e-16***
11	0.2754	< 2.2e-16***
12	0.4826	< 2.2e-16***
13	0.597	< 2.2e-16***
14	0.4904	5.216e-14***
15	0.3629	< 2.2e-16***
16	0.8	< 2.2e-16***
17	0.6389	< 2.2e-16***
18	0.3165	< 2.2e-16***
19	0.9443	2.383e-08***
High-tech	0.02278**	< 2.2e-16***
Medium-high-tech	0.2335	< 2.2e-16***
Medium-low-tech	0.05356*	< 2.2e-16***
Low-tech	0.0725*	< 2.2e-16***

*Note: *p<0.1, **p<0.05, ***p<0.01*

4.3 Effect of ICT Investments on TFP and Labor Productivity

Hypothesis 1 predicted that capital investments in ICT would positively influence the TFP and labor productivity of the manufacturing sector in the United States. To compare the main effects of investments in ICT on productivity measurements, I ran two separate FD regression models including time fixed-effects and robust standard errors according to the results of the previous section. For more details, see Section 3.4. The constant represents the time fixed effects to capture the trend of the omitted variables over time.

The results in Table 4 show that the independent variable total capital investments in ICT have a positive effect on the dependent variable TFP. Quantifying this impact demonstrates that a 1% increase in the index for capital investments in ICT is associated with a 0.02% increase in the index for TFP, on average ceteris paribus (significant at 5% level, $p = 0.015$).

In comparison to this, the impact on labor productivity is even stronger and significant at 1% level ($p = 0.001$). The outcome for labor productivity is that a 1% increase in the index for capital investments in ICT results in a 0.026% increase in the index for labor productivity, on average (c.p.). This demonstrates that the effect of capital investments in ICT is significant and positive for both productivity variables, which confirms H1. However, it must be considered that the goodness of fit (Adjusted R^2) for labor productivity is greater than for TFP. This shows that 29% of the variation in labor productivity can be explained by this model.

Moreover, the robustness of these models was tested by including the covariates of employment, labor compensation, and hours worked. The log_cap_inv coefficients did not change significantly, and the additional variables had no significant effect on TFP (see Appendix Table 5). For labor productivity as the dependent variable, the log_cap_inv coefficients have not changed much either (see Appendix Table 6). The robustness test revealed that adding covariates did not significantly alter the original results. Therefore, the analysis was carried out without the covariates.

Hypothesis 2 stated that the effect of capital investments in ICT is similar for the multi-factor measurement of TFP and the single-factor measurement of labor productivity. The effect is slightly higher for labor productivity compared to the effect for TFP in the entire United States manufacturing sector in Tables 4 and 5.

Table 4:

H1 Analysis with the First Differences Estimator and Robust Standard Errors: Influence of Capital Investment in ICT on Productivity

	Dependent Variable			
	log_tfp		log_labor_prod	
	Estimate	SE	Estimate	SE
log_cap_inv	0.020**	0.008	0.026***	0.008
Constant	0.003**	0.001	0.013***	0.001
Year	yes		yes	
Observations	627		627	
R^2	0.296		0.327	
Adjusted R^2	0.257		0.290	
F-Statistic	7.562***		8.751***	

*Note: *p<0.1, **p<0.05, ***p<0.01*

4.4 Investigation of the Effect of the COVID-19 Pandemic

Hypothesis 3 synthesized that the COVID-19 pandemic, which started in the year 2020, changed the relationship between capital investments in ICT and productivity. To test this, I included an interaction term between log_cap_inv and the dummy variable for the year 2020 in the regression model of Section 4.3. Table 5 shows that the estimate of the independent variable log_cap_inv stayed the same. Additionally, the interaction term between log_cap_inv and y2020 is very small and not significant (log_tfp: $p = 0.983$; labor productivity $p = 0.844$). This proves that the relationship between ICT investments and productivity in the year of the pandemic was not significantly different from other years. Therefore, H3 cannot be confirmed.

In addition, I tested if the COVID-19 pandemic had a major impact on the productivity variables (TFP and labor productivity) in the United States manufacturing sector. The dummy variable of the year 2020 had a negative impact on the dependent variables TFP ($\beta = -0.024$, $p = 0.837$) and labor productivity ($\beta = -0.058$, $p = 0.769$). Surprisingly, this effect is not significant either. Therefore, no clear statement about the effect of the COVID-19 pandemic on productivity can be made due to the very high standard errors. According to this, H4 cannot be supported.

Following that, I investigated the impact of ICT investments in the individual subsectors for both dependent variables.

Table 5:

H3 & H4 Analysis with the First Differences Estimator and Robust Standard Errors: Influence of COVID-19 and Capital Investments in ICT on Productivity

	Dependent Variable			
	log_tfp		log_labor_prod	
	Estimate	SE	Estimate	SE
log_cap_inv	0.020**	0.008	0.026***	0.008
y2020	-0.024	0.115	-0.058	0.196
log_cap_inv*y2020	0.001	0.026	0.008	0.043
Constant	0.004***	0.001	0.013***	0.001
Year	yes		yes	
Observations	627		627	
R^2	0.296		0.328	
Adjusted R^2	0.256		0.289	
F-Statistic	7.327***		8.483***	

*Note: *p<0.1, **p<0.05, ***p<0.01*

4.5 Examination of the Impact of ICT Investments in Different Subsectors

4.5.1 Individual Subsectors

Figure 2 in 4.1 shows a significant deviation in ICT investments across subsectors. The concern that arises is how does this affect productivity in the respective subsectors?

Hypothesis 5 predicted that the effect of ICT investments on productivity depends on the various United States manufacturing subsectors. Therefore, I constructed subsets of data for each of the 19 subsectors and ran two separate FD analyses, first with TFP as the dependent variable and afterward with labor productivity as the dependent variable (for more details, see Section 3.4).

The first analysis shows a highly significant (at the 1% level) and positive effect of investments in ICT on TFP in 11 out of the 19 subsectors. The effect is the highest for the computer & electronic products subsector (naics_id = 14, β = 0.121, $p < 0.001$), where a 1% increase in capital investments in ICT (index) results in a 0.121% increase in TFP (index), on average (c.p.). Other subsectors with a relatively high positive impact are furniture & related products (naics_id = 18, β = 0.119, $p < 0.001$), aerospace, railroad, ship, boat & other transportation equipment (naics_id = 17, β = 0.073, $p < 0.001$) and printing & related support activities (naics_id = 6, β = 0.071, $p < 0.001$). Moreover, in the fabricated metal products (naics_id = 12, β = 0.111, $p = 0.051$) subsector the effect of ICT on TFP is positive and significant at the 10% level.

In contrast to the subsectors where ICT has a positive impact on productivity, ICT has a negative impact in 7 subsectors. In the food, beverages & tobacco subsector, ICT has the greatest negative influence (naics_id = 1, $\beta = -0.069$, $p < 0.001$). A 1% increase in capital investments in ICT (index) in the food, beverages & tobacco subsector results in a 0.069% decrease in TFP (index), on average (c.p.). Moreover, in the subsectors wood products (naics_id = 4, $\beta = -0.030$, $p < 0.001$), petroleum & coal products (naics_id = 7, $\beta = -0.026$, $p < 0.001$), and chemical products (naics_id = 8, $\beta = -0.014$, $p = 0.007$), capital investments in ICT have a significant negative impact at the 1% level. For more detailed information see Appendix Tables 10 and 11.

The second model with labor productivity as dependent variable demonstrates that ICT investments have the largest positive effect on the furniture & related products sector (naics_id = 18, $\beta = 0.153$, $p = 0.01$) and a large positive effect for the computer & electronic products subsector (naics_id = 14, $\beta = 0.117$, $p = 0.049$). The food, beverages & tobacco subsector (naics_id = 1, $\beta = -0.066$, $p < 0.001$) indicates the highest negative effect of ICT investments, like for TFP as the dependent variable. Further differences are that the paper products subsector changed from a significant positive influence of ICT on TFP to a significant negative influence on labor productivity (naics_id = 5, $\beta = -0.005$, $p < 0.001$). In addition, the primary metal products subsector changed from a significant negative influence of ICT on TFP to a significant positive influence on labor productivity (naics_id = 11, $\beta = 0.024$, $p = 0.011$). Beyond that, it is important to mention that in the subsectors of apparel, leather & allied products (naics_id = 3, $\beta = -0.011$, $p = 0.180$), chemical products (naics_id = 8, $\beta = 0.002$, $p = 0.132$), fabricated metal products (naics_id = 12, $\beta = 0.058$, $p = 0.164$) and machinery (naics_id = 13, $\beta = 0.030$, $p = 0.205$) no significant impact of capital investments in ICT on labor productivity could be detected. Appendix Tables 12 and 13 provide additional information.

Referring to H2, the regression models for the individual subsectors showed that in most subsectors the impact is almost similar, but there are subsectors with significant differences as mentioned before. Therefore, capital investments in ICT equipment do not have a similar impact on TFP and labor productivity in each individual subsector.

4.5.2 Subsector Groups According to Technology R&D-Intensity

Hypothesis 6 indicates that the impact of investments in ICT would be higher for subsectors that have high intensity in technology R&D in comparison to subsectors with low R&D-intensity. The subsectors are divided into categories based on their R&D-

intensity according to the OECD (2011). Table 1 (in Section 3.1) showed the characteristics of the individual subsectors. Like in the previous analysis, I ran an FD analysis for each of the four categories.

The results for the categories in Table 6 show that there is a significant effect for the categories of high-tech, medium-high-tech, and medium-low-tech on TFP. Investments in ICT have the largest impact for the high-tech subsectors (β = 0.049, $p < 0.001$), which indicates that a 1% increase in capital investments in ICT (index) results in a 0.049% increase in TFP (index), on average (c.p.). In the medium-high-tech (β = 0.033, $p < 0.001$) and medium-low-tech (β = 0.012, $p = 0.001$) categories the impact is lower compared to the high-tech category, but still positive. In the low-tech category ($p = 0.998$) no significant impact of investments in ICT on TFP can be identified.

In addition, the test for significant differences between subsector groups in Appendix Table 7 confirmed these results. It indicated that investments in ICT for the group with the highest R&D-intensity ([1]: β = 0.058, $p = 0.009$) have a significantly higher impact on TFP compared to the other subsectors. Overall, these results provide evidence to support my previously stated hypothesis (H6) for TFP.

Table 6:
H6 Analysis with the First Differences Estimator and Robust Standard Errors I: Influence of Capital Investments in ICT on TFP of Subsector Groups According to their R&D-Intensity

	Dependent Variable: log_tfp			
	High-tech	Medium-high-tech	Medium-low-tech	Low-tech
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.049*** (0.009)	0.033*** (0.007)	0.012*** (0.003)	-0.00005 (0.014)
Constant	0.008 (0.007)	0.001 (0.002)	0.002 (0.002)	0.002 (0.002)
Year	yes	yes	yes	yes
Observations	99	132	165	231
R^2	0.526	0.684	0.413	0.242
Adjusted R^2	0.286	0.578	0.265	0.115
F-Statistic	2.190***	6.431***	2.792***	1.905***

*Note: *p<0.1, **p<0.05, ***p<0.01*

The result for labor productivity in Table 7 showed a somewhat similar picture. There is a significant effect for the categories of high-tech (β = 0.069, $p < 0.001$), medium-high-tech (β = 0.031, $p = 0.022$), and medium-low-tech (β = 0.020, $p < 0.001$) on labor productivity. The effect is the largest for the high-tech sector, where a 1% increase in capital investments in ICT (index) results in a 0.069% increase in labor productivity (index), on average (c.p.). In the low-tech category ($p = 0.619$) there is no significant effect of ICT investments on labor productivity, like for TFP.

Beyond that, the test for significant differences between subsector groups in Appendix Table 8 confirmed these results and showed the same picture as for TFP. Investments in ICT for high technology R&D-intensive subsectors ([1]: β = 0.059, $p < 0.001$) have a significantly larger impact on labor productivity than investments in other subsectors.

In consequence, this provides additional evidence to confirm that the impact of investments in ICT is significantly higher for subsectors with high technology R&D-intensity (H6).

Table 7:

H6 Analysis with the First Differences Estimator and Robust Standard Errors II: Influence of Capital Investments in ICT on Labor Productivity of Subsector Groups According to their R&D-Intensity

	Dependent Variable: log_labor_prod			
	High-tech	Medium-high-tech	Medium-low-tech	Low-tech
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.069*** (0.009)	0.031** (0.014)	0.020*** (0.005)	0.008 (0.017)
Constant	0.018*** (0.004)	0.012*** (0.003)	0.014*** (0.002)	0.009*** (0.002)
Year	yes	yes	yes	yes
Observations	99	132	165	231
R^2	0.576	0.601	0.501	0.232
Adjusted R^2	0.361	0.466	0.375	0.104
F-Statistic	2.676***	4.467***	3.987***	1.806***

*Note: *p<0.1, **p<0.05, ***p<0.01*

4.6 Effect of ICT Investments on Other Productivity Related Variables

The last hypothesis (H7) forecasted that investments in ICT have a negative influence on other productivity related variables. In this analysis, I investigated the impact of ICT investments on the variables of employment, labor compensation, and hours worked in the United States manufacturing sector. Table 8 reveals that the variable log_cap_inv has a positive significant ($p < 0.01$) influence on the three selected dependent variables employment ($\beta = 0.036$, $p < 0.001$), labor compensation ($\beta = 0.054$, $p < 0.001$) and hours worked ($\beta = 0.039$, $p < 0.001$). Capital investments in ICT have the greatest impact on labor compensation, where a 1% increase in investments in ICT (index) results in a 0.054% increase in labor compensation (index), on average (c.p.). These results are against my expectations and showed that ICT investments have a significant positive influence on other productivity variables.

Moreover, the coefficients for the change in the relationship between capital investments in ICT and employment, labor compensation, or hours worked in the year 2020 are not significant at the 5% level. This showed that investments in the year 2020 have no significantly different impact than investments in other years.

Beyond that, the effect of the year 2020 on employment ($\beta = -0.272$, $p = 0.078$) and hours worked ($\beta = -0.232$, $p = 0.218$) is not significant. However, the effect on labor compensation is significant and negative ($\beta = -0.321$, $p = 0.030$). This shows that the COVID-19 pandemic negatively affected most of the productivity variables studied, but no reliable conclusion can be drawn for most variables due to non-significant coefficients. Therefore, H4 cannot be supported.

Furthermore, a robustness test was performed by adding log_tfp as a covariate. The coefficients for log_cap_inv did not change much, and the effect of the included variable for TFP had no significant effect on the dependent variables (Appendix Table 9). Therefore, the previously presented model appears to be robust to omitted variables.

The results are summarized, discussed and conclusions are drawn in the next section.

Table 8:

H7 Analysis with the First Differences Estimator and Robust Standard Errors: Influence of Capital Investments in ICT on Other Productivity Variables

	Dependent Variable		
	log_employment	log_labor_comp	log_hours_worked
	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.036***	0.054***	0.039***
	(0.008)	(0.011)	(0.008)
y2020	-0.272*	-0.321**	-0.232
	(0.154)	(0.148)	(0.188)
log_cap_inv*y2020	0.049	0.060	0.036
	(0.033)	(0.055)	(0.041)
Constant	-0.016***	0.012***	-0.016***
	(0.003)	(0.004)	(0.003)
Year	yes	yes	yes
Observations	627	627	627
R^2	0.574	0.526	0.595
Adjusted R^2	0.550	0.498	0.572
F-Statistic	23.496***	19.296***	25.596***

*Note: *p<0.1, **p<0.05, ***p<0.01*

5. Discussion

5.1 Discussion of Research Findings

In this dissertation, I aimed to answer the research question of how total capital investments in ICT equipment affected productivity statistics. Additionally, I aimed to understand how this effect differed in the various subsectors and how the COVID-19 pandemic influenced this relationship. The theoretical part of this thesis in Section 2 unveiled a research gap and led to six hypotheses that were tested with the use of regression analysis.

The results of this study have confirmed H1, which predicted that total capital investments in ICT equipment have a positive influence on productivity (measured in TFP and labor productivity) in the United States manufacturing sector. Existing research stating that there is a positive relationship between technology (ICT or robot intensity) and productivity (Cardona et al., 2013; Graetz & Michaels, 2018; Kromann et al., 2020; Vu et al., 2020) is supported by this result. The recent literature provides a large body of evidence suggesting that investments in ICT can lead to improvements in productivity. However, it is worth noting that the studies that were published several decades ago found no significant impact of ICT on productivity (Berndt & Morrison, 1995; Brynjolfsson, 1996). The field of technology and productivity has evolved significantly since then. It is possible that more recent research, using newer data and more sophisticated methods, may provide a more nuanced understanding of the relationship between ICT and productivity.

However, productivity was assessed considering TFP and labor productivity, following previous research that considers one or the other (Cardona et al., 2013) and, while not highlighting the differences, implicitly treat them as equivalent. H2 directly tested whether these two proxies for productivity were similarly affected by ICT. It was predicted that investments in ICT would have a similar impact on TFP and labor productivity. Results suggest that the impact of investments in ICT is slightly higher for labor productivity, even though both relationships are significant, and go in the same direction. This allows for the hypothesis to be confirmed when considering the entire manufacturing sector and subsector groups, as in H6. However, a differentiated picture emerges when considering the individual subsectors (see H5). The elasticity of productivity (TFP and labor productivity) in ICT differed in some individual subsectors, which indicates that the productivity-enhancing effect of ICT is dependent on the measurement of productivity. Therefore, the hypothesis is not supported for individual subsectors. The analysed literature has not pointed out these differences in TFP and labor productivity for the individual subsectors, and thus these findings represent a novelty.

However, some events might disrupt this relationship, leading to exceptional outcomes, and suggesting such relationship to be contextually bounded. As such, I tested if the relationship between productivity and capital investments in ICT changed in the year 2020 due to the COVID-19 pandemic. The regression analysis showed that the relationship did not change significantly, and as a result, H3 cannot be supported. Investments in ICT in the year 2020 had on average almost the same impact on TFP and labor productivity compared to investments in other years. Moreover, the pandemic had a not significant influence on the productivity variables TFP, labor productivity, employment and hours worked, contrarily to what has been suggested by the literature (Bloom et al., 2020; Furceri et al., 2021). According to this, H4 is not supported.

Furthermore, there are significant differences among individual subsectors within the manufacturing sector. Therfore, H5 forecasted strong differences regarding the impact of ICT investments in the individual subsectors. In some subsectors, the influence is positive and significant, but there are subsectors with no significant effects or even significant negative effects. This result supports H5 and indicates that not in every industry ICT equipment leads immediately to increased productivity. This finding is in line with the results of Gordon (2000) and Waldman (2016). ICT investments have the greatest impact on the IT-producing subsector of computer and electronic products (naics_id = 14). The previous literature found that IT-intensive industries achieved higher productivity gains than sectors with less IT intensity (Acemoglu et al., 2014; Stiroh, 2002). Therefore, H6 predicted that the impact of investments in ICT is higher for subsectors with high technology R&D-intensity. The results in Tables 6 and 7 confirmed the outcome of the previous literature and showed that for TFP and labor productivity, the subsectors with higher technology R&D-intensity showed higher productivity gains. This means that subsectors with higher technology R&D-intensity account for the majority of productivity gains made from ICT investments, supporting the idea that productivity gains are fundamentally linked to technology intensity and information technology (Stiroh, 2002).

Finally, H7 forecasted that ICT investments have a negative effect on employment, labor compensation, and hours worked. This was predicted since tasks previously performed by humans will be executed by machines or AI in the future (Acemoglu & Restrepo, 2020; Atack et al., 2019). The literature yielded a variety of results. Some argued that increased automation will lead to reduced labor demand (Acemoglu & Restrepo, 2020) and technological unemployment (Keynes, 1931), while others argued that increased automation leads to an expansion of the scale and thus an increase in aggregate demand for labor (Kromann et al., 2020; Shuai et al., 2022). The results of my thesis supported the latter. Total capital investments in ICT showed a significant positive effect on the number of jobs in the manufacturing sector (employment), the number of labor hours worked by all workers to produce goods and services (hours worked), and the payments made as compensation for labor (labor compensation).

5.2 Academic and Managerial Implications

This work offers valuable implications for managers, academics, and policymakers. While productivity has been studied extensively and from a variety of perspectives, only a small number of studies have examined the impact of ICT on productivity in manufacturing at the industry-level in the United States. Moreover, no study has explicitly addressed the concrete differences between the individual subsectors and considered the impact of the COVID-19 pandemic on the relationship between investments in ICT and productivity.

This study, in contrast to the previous literature, explicitly addressed this issue and helped to close this knowledge gap. According to the results of this thesis, the productivity growth of the manufacturing sector in the United States can be explained, among other factors, by increasing investments in ICT. This demonstrates that if managers want to boost productivity, they should not overlook the impact that increased ICT investments can have in the long run. However, managers must keep in mind that this effect is highly dependent on the manufacturing subsector in which they operate.

Capital investments in ICT have the greatest positive effect on technology R&D-intensive subsectors. In these subsectors, investments are most important, and managers should invest a substantial part of their budget in ICT to reach productivity growth.

The wide variation in the productivity effect across subsectors could be explained by the varying complexity of the tasks, the length, and intensity with which ICT technologies have been used in the respective subsector or internal concerns against the use of ICT. Therefore, the productivity gains from ICT investments have been far more visible in some subsectors than in others. Nonetheless, even if technological investments did not result in increased productivity in some subsectors, they may have resulted in improved quality or other aspects of the manufacturing process.

Interestingly, investments in ICT during the COVID-19 pandemic had the same impact on productivity as investments in other years. Many other factors, such as lockdown, quarantine, and production workers illness, have influenced productivity in that year. Nevertheless, the relationship between ICT and productivity has remained constant, implying that investments make sense even during this crisis and should not be overlooked to maintain high productivity.

Aside from the managerial implications, one implication for academics is that the impact of the pandemic on productivity was not significant. This showed that the productivity standard deviation between the subsectors was very high and that the pandemic did not lead to an immediate decline in productivity in all subsectors, as might have been expected by academics. It is an empirical matter, that time will allow to test, whether the pandemic did have an effect on these measures, visible only on a longer time scale (Furceri et al., 2021). Another academic implication is that the productivity-enhancing effect of ICT is dependent on productivity measurement in individual subsectors. In order to draw conclusions about productivity in specific industries, both productivity measures should be used and compared to see if the factors excluded when using labor productivity compared to TFP play a significant role and alter the results.

Beyond that, a positive relationship between ICT investments and employment or labor compensation was detected. These results could be helpful for policymakers to make macroeconomic decisions. Policymakers could possibly influence the employment ratio or the mean salary of production workers by incentivizing investments in ICT (for example with tax reductions) in the manufacturing sector. Favorable treatment for investment could lead to increased employment and higher wages, potentially influencing a country's economic power and wealth in the long run.

5.3 Limitations and Future Research

The results of the present thesis are subject to certain limitations, which are outlined below. Recommendations for future research are then derived from the limitations.

Firstly, the results of this study are regionally limited to the United States. In addition, this study only looks at the manufacturing sector. This means that the effects of ICT cannot be transferred unchanged to other sectors or countries, particularly as previous research suggests this relationship to be one that is subject to differences depending on the country used (Cardona et al., 2013). Moreover, the results in absolute values are not easily comparable with most of the previous literature, as most of the previous literature used different time frames, looked at different regions or used a different unit of analysis (firm-level, industry-level, country-level).

The second point is that while the macro perspective used here has some advantages in that it provides the most comprehensive picture of the manufacturing sector and its subsectors, it also has some limitations. These are that the effect may not apply to individual, low-performing companies, or in specific regions of the manufacturing sector. It would thus be very interesting to investigate the results of this thesis at the micro-level. Hereby, it could be interesting to observe the effect for individual companies or in different geographical regions.

Another important point is the problem of endogeneity that was mentioned by Cardona et al. (2013). This problem can be due to omitted variables. Despite the attempt to keep the probability as low as possible through robustness checks, other factors such as market conditions, environmental regulations or organizational structures could have led to increased productivity. Moreover, according to Cardona et al. (2013), ICT can be a driver and outcome of productivity and productivity growth, so reverse causality could be a possible bias. The reverse causality test showed that for TFP this bias could exist. However, for labor productivity reverse causality does not present a problem. As a necessary consequence, there is the possibility of unobserved shocks, and causality statements should be treated with great caution.

In the future, researchers could examine how productivity evolved throughout the pandemic period (2020–2021) or post-pandemic. Beyond that, the results could be replicated in a different country or economic sector. Another possibility for future research is to distinguish between various ICT technologies and observe the individual effects of these technologies. This would allow for a more nuanced understanding of which specific technologies are most effective at increasing productivity in different situations. This information could be useful for companies as they consider which technologies to invest in to improve productivity. It is likely that some technologies will have a larger role in increasing productivity than others. There is already some research on the individual effects of different ICT technologies on productivity. For example, some studies have found that the increased use of robots can lead to significant productivity gains (Acemoglu & Restrepo, 2020; Kromann et al., 2020).

Moreover, other variables beyond productivity might be impacted by ICT technologies. Thus, it would be interesting to research what other consequences - positive and negative - ICT investments may bring (Yadav et al., 2020). For instance, ICT investments might lead to automated and digitized manufacturing processes, which can reduce the occurrence of human error. Another way that ICT investments can improve quality is by using sensors and data analytics to monitor and optimize production processes in real time. This can help to identify and address issues before they result in defective products and can enable manufacturers to continuously improve their processes based on data-driven insights (Li et al., 2022).

Likewise, beyond the *what*, the *when* is also of theoretical and practical interest. How long ICT investments take to pay off is a highly consequential open question.

However, while ICT investments, employment, and wages are key factors, one could also consider employee well-being and happiness, as these factors influence employee engagement and motivation, and thus employee productivity. Indeed, 40% of workers in Norway fear being replaced by a machine, which negatively influences job satisfaction (Schwabe & Castellacci, 2020). Therefore, future research could investigate the impact of production workers' fear of being replaced and job satisfaction on productivity.

6. Conclusion

The relationship between technology and productivity is a particularly important area of research, as there are constant innovations and improvements in technologies. This thesis contributes to this important field of research by examining in detail the relationship between ICT and productivity, addressing the impact of different subsectors, as well as the COVID-19 pandemic, and thus filling this relevant research gap. The results provide a clear message to decision-makers and managers: ICT investments pay off! They lead to significant productivity increases, but managers must be mindful of the sector their company is part of. Consequently, I hope that my findings will in their own way contribute as decision support for managers and policymakers and encourage other researchers to investigate further factors influencing the relationship between ICT and productivity.

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Appendix

Table 1

Multicollinearity Check with the Variance Inflation Factor (VIF):

Independent Variable	Variance Inflation Factor (VIF)										
cap_inv_index	1.22	1.19	1.24	1.34	1.53	1.24	1.46	1.28	1.38	1.29	1.46
year	1.61	1.05	1.65	7.94	8.28	1.25	8.22	1.92	1.93	1.93	8.22
naics_id	1.19	1.20	1.19	1.21	1.23	1.33	1.33	1.33	1.33	1.33	1.33
employment_index	1.63	1.09	1.67	17.79	172.36			1.66	189.99		
labor_compensation_index				11.87	12.05	1.13	12.58				12.58
hours_worked_index					172.24		18.80		192.24	1.68	18.80
tfp_index						1.36	1.43	1.34	1.51	1.33	1.43

Table 2

Shapiro-Wilk Normality Test:

Variable	Shapiro-Wilk Normality Test *p*-value
cap_inv_index	< 2.2e-16
tfp_index	0.002
labor_prod_index	4.248e-10
employment_index	< 2.2e-16
labor_compensation_index	< 2.2e-16
hours_worked_index	< 2.2e-16

Table 3

Studentized Breusch-Pagan Test for Heteroskedasticity:

Dependent Variable:	Independent Variable:	
	log_cap_inv	diff_log_cap_inv
	p-value	
log_tfp	< 2.2e-16	
diff_log_tfp		0.247
log_labor_prod	0.025	
diff_log_labor_prod		0.218
log_employment	0.004	
diff_log_employment		0.310
log_labor_comp	0.005	
diff_log_labor_comp		0.770
log_hours_worked	0.001	
diff_log_hours_worked		0.237

Table 4

Granger Causality Test:

	Dependent Variable:		
	log_tfp	log_labor_prod	log_cap_inv
		p-value	
log_cap_inv			
lag order = 1	0.006	0.009	
lag order = 2	0.247	0.078	
lag order = 3	0.107	0.054	
lag order = 4	0.316	0.125	
log_tfp			
lag order = 1			0.045
log_labor_prod			
lag order = 1			0.103

Table 5

Robustness Check H1 for Dependent Variable TFP:

	Dependent Variable: log_tfp			
	(1) Estimate (SE)	(2) Estimate (SE)	(3) Estimate (SE)	(4) Estimate (SE)
log_cap_inv	0.020** (0.008)	0.022*** (0.008)	0.014** (0.008)	0.021*** (0.008)
log_employment		-0.050 (0.059)		
log_labor_comp			0.104 (0.065)	
log_hours_worked				-0.033 (0.048)
Constant	0.003** (0.001)	0.002 (0.001)	0.002 (0.002)	0.002** (0.001)
Year	yes	yes	yes	yes
Observations	627	627	627	627
R^2	0.296	0.298	0.311	0.297
Adjusted R^2	0.257	0.258	0.271	0.257
F-Statistic	7.562***	7.400***	7.859***	7.366***

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 6

Robustness Check H1 for Dependent Variable Labor Productivity:

	Dependent Variable: log_labor_prod			
	(1) Estimate (SE)	(2) Estimate (SE)	(3) Estimate (SE)	(4) Estimate (SE)
log_cap_inv	0.026*** (0.008)	0.029*** (0.008)	0.019** (0.010)	0.033*** (0.008)
log_employment		-0.058 (0.083)		
log_labor_comp			0.215* (0.115)	
log_hours_worked				-0.173* (0.099)
Constant	0.013*** (0.001)	0.012*** (0.002)	0.009*** (0.002)	0.002** (0.001)
Year	yes	yes	yes	yes
Observations	627	627	627	627
R^2	0.327	0.329	0.403	0.345
Adjusted R^2	0.290	0.291	0.369	0.307
F-Statistic	8.751***	8.540***	11.744***	7.366***

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 7

Robustness Check for Significant Difference Between Subsector Groups I:

	Dependent Variable: log_tfp			
	(1)	(2)	(3)	(4)
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.010** (0.004)	0.018*** (0.007)	0.020*** (0.008)	0.027** (0.012)
high_tech*log_cap_inv	0.058*** (0.019)			
medium_high_tech*log_cap_inv		0.008* (0.005)		
medium_low_tech*log_cap_inv			-0.002 (0.017)	
low_tech*log_cap_inv				-0.024* (0.013)
Constant	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Year	yes	yes	yes	yes
Observations	627	627	627	627
R^2	0.314	0.297	0.300	0.301
Adjusted R^2	0.274	0.256	0.259	0.261
F-Statistic	7.964***	7.341***	2.792***	7.488***

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 8

Robustness Check for Significant Difference Between Subsector Groups II:

	Dependent Variable: log_labor_prod			
	(1)	(2)	(3)	(4)
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.017**	0.025**	0.020***	0.027**
	(0.007)	(0.010)	(0.008)	(0.012)
high_tech*log_cap_inv	0.059***			
	(0.014)			
medium_high_tech*log_cap_inv		0.005*		
		(0.003)		
medium_low_tech*log_cap_inv			-0.005	
			(0.016)	
low_tech*log_cap_inv				-0.032*
				(0.018)
Constant	0.012***	0.013***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Year	yes	yes	yes	yes
Observations	627	627	627	627
R^2	0.338	0.328	0.328	0.332
Adjusted R^2	0.300	0.289	0.289	0.294
F-Statistic	8.882***	8.482***	8.499***	8.657***

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 9

Robustness check H7:

	Dependent Variable		
	log_employment	log_labor_comp	log_hours_worked
	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.038***	0.050***	0.040***
	(0.009)	(0.012)	(0.009)
y2020	-0.273*	-0.316**	-0.233
	(0.152)	(0.142)	(0.188)
log_cap_inv*y2020	0.049	0.059*	0.036
	(0.032)	(0.031)	(0.041)
log_tfp	-0.059	0.202	-0.048
	(0.062)	(0.154)	(0.066)
Constant	-0.016***	0.011***	-0.015***
	(0.001)	(0.004)	(0.003)
Year	yes	yes	yes
Observations	627	627	627
R^2	0.576	0.536	0.596
Adjusted R^2	0.550	0.508	0.572
F-Statistic	23.962***	19.482***	24.889***

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 10

H5 Analysis with the First Differences Estimator and Robust Standard Errors:

Influence of Capital Investments in ICT on TFP in Different Subsectors (1-10)

	Dependent Variable: log_tfp									
	Subsector 1	Subsector 2	Subsector 3	Subsector 4	Subsector 5	Subsector 6	Subsector 7	Subsector 8	Subsector 9	Subsector 10
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	-0.069***	-0.016**	-0.003*	-0.030***	0.006***	0.071***	-0.026***	-0.014***	0.029***	0.037***
	(0.008)	(0.008)	(0.002)	(0.002)	(0.000)	(0.008)	(0.006)	(0.005)	(0.001)	(0.006)
Constant	0.001***	0.002***	-0.005***	0.009***	0.003***	0.002***	0.001	-0.002***	0.003***	0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)
Observations	33	33	33	33	33	33	33	33	33	33
R^2	0.209	0.009	0.0004	0.021	0.005	0.263	0.022	0.008	0.048	0.060
Adjusted R^2	0.183	-0.023	-0.032	-0.011	-0.027	0.239	-0.009	-0.025	0.017	0.030
F-Statistic	8.183***	0.267	0.012	0.661	0.158	11.073***	0.707	0.235	1.554	1.976

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 11

H5 Analysis with the First Differences Estimator and Robust Standard Errors: Influence of Capital Investments in ICT on TFP in Different Subsectors (11-19)

	Dependent Variable: log_tfp								
	Subsector 11	Subsector 12	Subsector 13	Subsector 14	Subsector 15	Subsector 16	Subsector 17	Subsector 18	Subsector 19
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	-0.012**	0.111*	0.051***	0.121***	0.045***	0.021***	0.073***	0.119***	0.008***
	(0.005)	(0.056)	(0.015)	(0.027)	(0.006)	(0.002)	(0.002)	(0.026)	(0.001)
Constant	0.009***	-0.002	0.001	0.019***	0.003***	0.003***	0.001	-0.008**	0.002***
	(0.000)	(0.004)	(0.001)	(0.003)	(0.000)	(0.001)	(0.001)	(0.004)	(0.001)
Observations	33	33	33	33	33	33	33	33	33
R^2	0.006	0.236	0.092	0.406	0.077	0.043	0.189	0.337	0.003
Adjusted R^2	-0.026	0.211	0.063	0.387	0.047	0.012	0.163	0.316	-0.029
F-Statistic	0.183	9.570***	3.154*	21.207***	2.573	1.390	7.209**	15.773***	0.086

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 12

H5 Analysis with the First Differences Estimator and Robust Standard Errors:

Influence of Capital Investments in ICT on Labor Productivity in Different Subsectors (1-10)

	Dependent Variable: log_labor_prod									
	Subsector 1	Subsector 2	Subsector 3	Subsector 4	Subsector 5	Subsector 6	Subsector 7	Subsector 8	Subsector 9	Subsector 10
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	-0.066***	-0.055***	-0.011	-0.015***	-0.005***	0.085***	-0.015***	0.002	0.005***	0.041***
	(0.008)	(0.009)	(0.008)	(0.001)	(0.001)	(0.014)	(0.001)	(0.002)	(0.002)	(0.006)
Constant	0.011***	0.009***	-0.003**	0.010***	0.013***	0.013***	0.020***	0.007***	0.014***	0.009***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Observations	33	33	33	33	33	33	33	33	33	33
R^2	0.093	0.035	0.001	0.010	0.002	0.246	0.013	0.0001	0.001	0.050
Adjusted R^2	0.063	0.004	-0.031	-0.022	-0.030	0.222	-0.019	-0.032	-0.031	0.019
F-Statistic	3.168*	1.127	0.026	0.318	0.065	10.118***	0.399	0.003	0.031	1.618

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 13

H5 Analysis with the First Differences Estimator and Robust Standard Errors:

Influence of Capital Investments in ICT on Labor Productivity in Different Subsectors (11-19)

	Dependent Variable: log_labor_prod								
	Subsector 11	Subsector 12	Subsector 13	Subsector 14	Subsector 15	Subsector 16	Subsector 17	Subsector 18	Subsector 19
	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
log_cap_inv	0.024**	0.058	0.030	0.117***	0.036***	0.025***	0.073***	0.153***	0.062***
	(0.009)	(0.042)	(0.024)	(0.060)	(0.005)	(0.006)	(0.008)	(0.023)	(0.003)
Constant	0.016***	0.010***	0.012***	0.024***	0.015***	0.018***	0.016***	-0.001	0.013***
	(0.000)	(0.003)	(0.002)	(0.007)	(0.000)	(0.000)	(0.002)	(0.003)	(0.001)
Observations	33	33	33	33	33	33	33	33	33
R^2	0.009	0.106	0.022	0.141	0.031	0.015	0.081	0.330	0.097
Adjusted R^2	-0.023	0.077	-0.010	0.113	-0.001	-0.017	0.051	0.309	0.068
F-Statistic	0.288	3.682***	0.699	5.094**	0.978	0.473	2.723	15.289***	3.332*

*Note: *p<0.1, **p<0.05, ***p<0.01*

Table 14

Breusch-Godfrey/Wooldridge Test for Serial Correlation:

	Dependent Variable:				
	log_ tfp	log_ labor_prod	log_ employment	log_ labor_comp	log_ hours_worked
	p-value				
H1 & H2:					
Model 1	0.044	0.003			
H3 & H4:					
Model 3	0.044	0.003			
H5:					
Subsector 1	1.461e-06	7.208e-08			
Subsector 2	1.617e-06	8.884e-07			
Subsector 3	1.285e-06	4.908e-06			
Subsector 4	0.0002	2.578e-08			
Subsector 5	8.541e-07	1.142e-06			
Subsector 6	5.119e-05	3.155e-08			
Subsector 7	9.067e-06	5.685e-08			
Subsector 8	1.281e-05	1.462e-07			
Subsector 9	3.242e-07	5.824e-08			
Subsector 10	2.002e-06	5.968e-08			
Subsector 11	4.227e-07	6.405e-08			
Subsector 12	0.0008	4.907e-07			
Subsector 13	7.332e-06	2.335e-07			
Subsector 14	2.76e-05	0.0005			
Subsector 15	4.974e-05	5.724e-06			
Subsector 16	5.333e-07	2.206e-07			
Subsector 17	3.577e-06	2.65e-07			
Subsector 18	0.0246	3.678e-06			
Subsector 19	6.391e-05	1.291e-05			
H6:					
High-tech	0.049	0.060			
Medium-high-tech	0.006	0.019			
Medium-low-tech	0.035	0.059			
Low-tech	0.015	0.003			
H7:					
Model 7.1			2.2e-16		
Model 7.2				2.2e-16	
Model 7.3					9.873e-13