The impact of artificial intelligence on labor productivity

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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON LABOR PRODUCTIVITY

Master thesis

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Zagreb, December, 2021.

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Marta Stojkovska

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“The heart and soul of the company is creativity and innovation”

Robert A. Iger

ABSTRACT

Since the early 18th century, our economies have witnessed several technological revolutions that altered how people worked, lived, and communicated. First came the steam engine innovation, then the combustion engine innovation, followed by the emergence of semiconductors and the Internet in the 1970s. The current technological revolution, characterized by the growing presence of automation, Artificial Intelligence and machine learning, goes one step further by involving all the industrial sectors. It is critical to investigate its causes and repercussions while keeping labor market dynamics in mind. This Thesis analyzes the impact of Artificial Intelligence and automation on labor productivity. It provides a basic explanation of the nature of AI in today's fast-developing society and indicates the possible challenges of tomorrow. The Thesis further explains the concept of AI in terms of employment. It looks at the factors of labour productivity by exploring information from a unique database of AI-related patenting firms within a 10-year period of time. The results from the theoretical framework are outlined in details in the discussion part of this Thesis and indicate a direct relationship between the number of AI-related patents and labour productivity within the firm.

Keywords: Artificial Intelligence, automation, employment, labor productivity, future of work, Cobb-Douglas function, factor of productivity

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ACCRONYMS AND ABBREVIATION

AI – Artificial Intelligence

CI – Confidence Interval

Df – Degrees of Freedom

DV – Dependent Variable

FEM – Fixed Effects Model

GPT – General Purpose Technology

IV – Independent Variable

PATSTAT – European Patent Office's Worldwide Patent Statistical database

REM – Random Effects Model

CHAPTER 1: INTRODUCTION

The introduction consists of a problem background (section 1.1) where the research topic, Artificial Intelligence and labor productivity, and its theoretical background is discussed; a problem statement (section 1.2) where the practical aspects and specific direction of this thesis are revealed; a research objective (section 1.3) that highlights the purpose of the research; a significance of the study (section 1.4) that further reveals the importance of the research and its contribution to the field; a research and methodology (section 1.5) that details the research setting; a limitations, assumptions, and design controls (section 1.6) that identifies the boundaries to the research; and a structure (section 1.7) of the thesis as a whole.

1.1. Background

The world is on the brink of yet another technological revolution. The global pandemic has made it clear that we are amidst a period of innovation that has the potential to disrupt past equilibria and affect social, cultural, and economic conditions. Since its outbreak in late 2019, the coronavirus COVID-19 pandemic has continuously reshaped science and technology and transformed businesses, leading to an accelerated adoption of digital tools and techniques. The availability of vast amounts of data is going to further alter economies and labor markets.

However, this is not the first revolution that humankind has faced. The First Industrial Revolution was a period from the late 18th century that witnessed the shift from an agrarian to a manufacturing society (Weightman, 2007). Water and steam power were utilized to mechanize production. New methods allowed for cheaper and higher quality materials that caused an expansion of iron and steel production. The emergence of the steam engine significantly decreased the required time to manufacture goods. Innovation led to more goods being produced due to machine manufacturing.

The Second Industrial Revolution was characterized by the use of gas, oil, and electricity to mass produce consumer goods (Schwab, 2016). It was during this period that humanity made significant advances in physics and chemistry. New modes of transportation that included railroads, steam boats, and automobiles, were introduced (Ward, 2019). This altered the manner in which people and goods traveled across the world. Ideas and words were exchanged through the radio, telegraph, and newspapers. In essence, it was the Second Revolution that ushered into the modern society.

The Third Revolution began around the 1970s through partial automation and digitization using electronics and computers (Schwab, 2016). This era witnessed the invention of the Internet and the discovery of nuclear energy. Manufacturing went digital, as information technology began to automate production (Ward, 2019). Think semiconductors, mainframe computing, and personal computing. The rise of telecommunications further paved the way for widespread globalization. The digital revolution altered almost every industry, once again transforming the manner in which people lived, worked, and communicated.

Now a Fourth Revolution is under way. But this time, the revolution is characterized by a fusion of technologies, such as cloud computing, genetic engineering, quantum computing, and more. The increasing computing power and data further lead to digitalization of manufacturing. This is a new chapter in human development, as the lines between the physical, digital and biological spheres are all being challenged.

The Industrial Revolution had far-reaching economic, social and cultural consequences, and changed the course of world history. It laid the foundations for modern society. The factory system, as well as the introduction of iron and steel, led to a division of labor and specialization (Weightman, 2007). Old ways of doing things were no longer efficient. Accordingly, the emergence of the spinning jenny removed the need to produce cloth by hand. With the introduction of electricity, manufacturing establishments were required not only to adapt, but instead to fully reorganize their plants. As McCloskey (1981) notes, “The Industrial Revolution was not the Age of Cotton or of Railways, or even of Steam entirely; it was an age of improvement.”

The rapid advent of technology had brought numerous changes and adjustments in the arrangement of society. These changes included advancements in production, growth in innovations, improved wages, and lower prices. Other adjustments resulted in the complete automation of tasks previously performed by labor (Weightman, 2007). The emergence of large factories transformed small towns into major cities in a short period. These unprecedented rates of urbanization had transformative impact, as overcrowded cities led to the emergence of new jobs, tasks, activities and industries. Exponential increases in computing power have further resulted in a great automation of tasks previously performed by labor. Over the past decades, bookkeepers, cashiers, and telephone operators have had their calculating, coordinating, and communicating activities replaced by computers. (Bresnahan, 1999).

Today, there are various technologies that have the potential for significant global impact. However, there is one particular technology that dominates the disruption of the current ecosystem – Artificial Intelligence. AI is typically referred to as the capability of machines to replicate human intelligence (IBM Cloud Education, 2020). These machines can distinguish complex patterns, process data, arrive at conclusions, and propose suggestions. AI systems have numerous applications, including speech recognition, automated stock trading, and recommendation engines. Indeed, AI is all around us, from virtual assistants that provide medical advice to self-driving cars and software that plays chess games (Yeung, 2020). The growing presence of AI is set to dramatically alter societies and economic systems.

As with previous technological advancements, AI will profoundly alter people's lives and reshape the future of work. The emergence of AI gives rise to much debate about whether automation could bear negative consequences for labor productivity and employment. Fears that AI would reduce the overall employment level and displace certain types of workers are beginning to emerge. However, whether robots and smart algorithms will take our jobs and put us out of the workforce is not a straightforward answer.

The relationship among technological change and productivity growth has been evolving over the past years suggesting its complex nature. While phases of intensive automation have often been associated with the risk of technological unemployment, economists have always been positive about the long-term impact of technological change on employment. However, economic theory does not provide a clear answer as to whether technological innovation is labor-friendly or labor-threatening. Therefore, the effect of artificial intelligence on labour productivity need to be explored at a greater level. Empirical study is crucial.

1.2. Statement of the Problem

In his work *The General Theory of Employment, Interest, and Money*, John Maynard Keynes (1936) defines the concept of "technological unemployment" as the "unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour". That is to say, technological efficiency leads firms to increase capital and decrease labor. In turn, unemployment increases in the short to medium term. According to Keynes (1936), "the increase of technical efficiency has been taking place faster than we can deal with the problem of labour absorption." The Economist (2014) further suggests that the increase in productivity leads to growth in income level, which then creates demand for products and services in new industries and occupations. In the past, however, this short-term dislocation has often caused negative reactions from workers.

Beginning in the early 19th century, the fear of technological progress replacing human labor began to increase. The Luddites (1811-16) emerged in Nottingham, England as a violent force against the increased use of machinery in the textile industry (Klein, 2019). The Luddites were mainly textile workers that objected to technological change and automation out of fear of job losses. They wanted things to go back as they were before the introduction of machinery and demanded reversal of wage reductions. The Luddite Movement was characterized by numerous protests that involved destroying machines and dispatching officious-sounding letters (Conniff, 2011). However, these claims were in large part subject to misinterpretation. Mokyr et al (2015) note that "workers were more concerned with low wages and work practices, in general, rather than mechanization." They limited their revolt against manufacturers that used technological innovation in a so-called "fraudulent and deceptive manner" to circumvent standard labor practices. Kevin Binfield, editor of the 2004 collection Writings of the Luddites, explains that the Luddites "just wanted machines that made high-quality goods and they wanted these machines to be run by workers who had gone through an apprenticeship and got paid decent wages. Those were their only concerns." (Conniff, 2011). Automation and mechanization, therefore, appear to have been the object of criticism for their dissatisfaction and not their genuine motive.

The concerns of the Luddites that automation would displace workers proved to be unfounded and failed to be realized. The emergence of machines created demand for labour in newly developed industries due to technological progress (Mokyr et al, 2015). In essence, technological change did not eliminate the need for human labour. Instead, it created new occupations and industries that enabled higher standards of living. Accordingly, in Britain, real wages tripled between 1570 – 1875, then more than tripled from 1875 to 1975 (The Economist, 2014). The impact of automation on the labour market at that stage of industrialization is captured in the writings of Knut Wicksell (1901 [1934]) who argues that technological innovation could both increase and decrease the marginal product of labour, and consequently wages. Wicksell (1901 [1934]) reasons, “The great inventions by which industry has from time-to-time been revolutionized at first reduced a number of workers to beggary… (but then) as accumulation continues, these evils must disappear… and wages will rise.” In like manner, John Bates Clark (1907) notes that, “The well-being of workers requires that progress should go on, and it cannot do so without causing temporary displacement of laborers.” The observations of Wicksell and Clark more or less encapsulate the conclusions of economists in the early 20th century.

It seems as though technological unemployment during the industrialization was a major issue. And while one can most certainly argue that the emergence of machinery could lead to short run unemployment, the evidence strongly disagrees that such technological unemployment actually had adverse effects on overall growth and productivity (Mokyr, 2002). Nonetheless, it is irrefutable that by distorting the demand for particular jobs, the Industrial Revolution created havoc and reshaped the economy. But things change and technologies advance beyond imagination. That said, only time will tell if the current period of technological change is truly different.

In today’s world, innovation is accompanied by the fundamental uncertainty in predicting technological change. Schwab (2016) suggests that, “In the future, technological innovation will also lead to a supply-side miracle, with long-term gains in efficiency and productivity. Transportation and communication costs will drop, logistics and global supply chains will become more effective, and the cost of trade will diminish, all of which will open new markets and drive economic growth.” However, Schwab (2016) also argues that technological innovation will lead to a segregation of the labour market into “low-skill/low-pay” and “high-skill/high-pay” roles. According to Schwab (2016), “The changes are so profound that, from the perspective of human history, there has never been a time of greater promise or potential peril.”

Even though Artificial Intelligence and other disruptors of the ecosystem might displace some workers, thus increasing technological unemployment, the displacement effect could easily be counterbalanced by a productivity effect. With growth in productivity, market demand for certain products and services would rise, thus increasing demand for labour. Depending on the productivity growth obtained by consumers and producers, consumers could benefit from reduced prices or producers could benefit from increased profits. Ford (2015) suggests that automation "might indeed drive down wages or cause unemployment but more efficient production would also make everything cheaper. So even if your income fell, you'd still be able to continue consuming since prices for the things you wanted would be lower." What is more, the overall level of employment as well as the price and profit effect of AI could differ from the corresponding firm-level impact due to certain firms automating their processes and thus displacing competitors.

Now, if we were to ask ourselves what the impact of AI on labor productivity and employment would be, at first glance the answer would be: AI is beneficial for labor productivity as it increases efficiency but detrimental for employment as it automates tasks performed by labor. Indeed, AI and machine learning can enhance the productivity of certain workers, while at the same time replace labor by machines and transform nearly every occupation at least to some extent.

Let us hence set aside the following generic question:

- *Is the future of technological innovation and Artificial Intelligence predictable?*

A more appropriate question would be,

- *How predictable are certain aspects of future technological innovation?*

But often, we will obtain greater efficiency out of asking,

- *How much more predictable can the employment effect of new technological innovations become if a certain amount of resources were devoted to researching it?*

Or better yet:

- *How does technological innovation, and thus AI affect the future of work?*

The main research question is therefore,

- *How does the introduction of AI related innovations within the company influence labor productivity?*

Answering the question of whether the introduction of AI within firms could lead to displacement of workers and decreased productivity growth implies exploring in great details previous knowledge, theoretical evidence and technological trends. Due to its high dependency on a multitude of economic forces, parameters and factors, the employment impact of technological progress among labourers, consumers, and producers requires an empirical study.

1.3. Research Objective

1.3.1. General Research Objectives

The aim of this Thesis is to provide an introduction to theoretical issues relating to the field of Artificial Intelligence. Main goals of this Thesis are to explore the concept of AI and discuss its impact on labor productivity. Accordingly, the Thesis provides a basic explanation of the nature of AI in today's fast-developing society and indicates the possible challenges of tomorrow. It further explains the concept of AI in terms of labor productivity and specifies the significance of technological innovation for the firm's success.

1.3.2. Specific Research Objectives

This Thesis attempts to estimate and critically analyze the potential effects of technological innovation on productivity growth. It examines the use of AI at the firm-level and its impact on labour productive capacity. Currently, there is no data on AI use at the enterprise level. In other words, there is a lack of understanding of how AI can complement or replace labour. It is essential that we understand how AI affects the company as a whole and, thus, shapes economies. Firm-level data on automation and AI can help researchers answer a variety of questions, including: how AI affects productivity at the enterprise or operational level; which type of company invest more in AI; how does the market structure affect the incentives of companies to devote capital to AI; how adoption impacts business strategy. It is important to collect such data in order to clarify these arguments and educate policy makers about the role of AI in society.

1.4. Significance of the Research Study

This Thesis outlines the development of technology, the growing popularity of AI, and the role of automation within the company. It addresses the gradual transformation of business operations over the years due to the emergence of new practices and innovations. It further provides insight into the field of Artificial Intelligence and critically evaluates the significance of automation for labor productivity. The Thesis provides a comprehensive theoretical setting that critically evaluates, reveals, and discusses assumptions, theories, and possible research gaps. It goes on to deliver an overview of previous empirical studies that provide further insight into the complexity of the research question and set the basis for the analysis. Eventually, the Thesis empirically tests and analyzes the potential impact of new technologies and AI on labor productivity.

1.5. Research Methodology and Methods

This Thesis uses literature as well as statistical methods to analyze and discuss the research findings. Part of the literature was obtained via the Internet. Specific books, articles, as well as academic and commercial publications were used to enrich the research process. With the aim to gather a better insight into the effects of AI on labor productivity, a combination of several different methods to collect data was used. In that manner, quantitative approach was employed to gather data. The required data was collected from the PATSTAT database from the European Patent Office as well as Bureau van Dijk's private entity ORBIS database. The sample data covers firms active in AI patenting. The gathered data was prepared before analysis and the dataset was reviewed for any missing data and potential outliers. The data was then analyzed using statistical methods. Descriptive statistics, graphs and tables are used to illustrate the findings of the research study and highlight the association among variables.

1.6. Structure of the Thesis

- Chapter 1: Introduction

The introduction consists of a problem background that discusses the research topic and its theoretical background. A problem statement is introduced where the practical aspects and specific direction of the thesis are revealed, followed by a research objective section that highlights the purpose of the research. A significance of the study further reveals the importance of the research and its contribution to the field, while the limitations, assumptions, and design controls section identifies the boundaries to the research. Ultimately, a structure of the thesis as a whole is delivered.

- Chapter 2: Research Design and Methodology

This chapter designs the methodology of the research approach using a combination of techniques and provides an appropriate framework for the study. The general design of the research and the techniques used for data collection are explained in greater detail. This chapter justifies the chosen methods, describes the research setting, and provides a detailed explanation of how those methods are implemented in the study.

- Chapter 3: Literature Review

The literature review identifies and summarizes all the existing research relating to this specific topic. It provides an overview of key literature indicating what research has already been done in the field and what is contested in relation to the research topic. The focus of the literature review is use existing literature to create research context so as to identify knowledge gaps and recognize ways in which the study can further advance knowledge on the topic.

- Chapter 4: Theoretical Framework

The theoretical framework consists of further information about the relevant theories of this thesis. It details the theories, propositions, hypotheses and concepts used to address the research problem. The theories that explain the existence of this research study are introduced and described in greater detail. The aim is to compare and critically evaluate the approaches that different researchers have proposed. Assumptions will be derived from the theory and presented throughout this chapter, which will be then used to construct hypotheses.

- Chapter 5: Practical Model

The aim of this chapter is to present the hypothesis as well as describe the population and sample. The variables to be used and statistical tests to be conducted are then introduced. Lastly, it addresses the data collection process.

- Chapter 6: Data Analysis

Descriptive statistics, graphs and tables will be used to present the findings of the research study. The analysis will then discuss the results and present the interpretations of the findings.

- Chapter 7: Conclusion

The conclusion encapsulates a summary of the thesis, and the thesis' contribution to new knowledge, answers the research question and suggests possible avenues for further research.

CHAPTER 2: RESEARCH DESIGN AND METHODOLOGY

This chapter will state which scientific approach (section 2.1) the author will take, including the ontological (section 2.1.1), epistemological (section 2.1.2) perspectives, and research paradigm (section 2.1.3); the research approach (section 2.2) and design (section 2.3), literature search (section 2.4), and overview of research methodology (section 2.5). Some ethical considerations (section 2.6) will then be explored in greater detail.

2.1. Scientific Approach

During research, the author needs to know what to find, what the goals are, and what issues the research will solve. It is all about problematizing, i.e. identifying a problem that can be solved by research. Research objectives should be formulated into answerable research questions. Subsequently, the appropriate methodology should be elected so as to provide answers to the said questions. In that manner, this Thesis will adopt a Functionalist scientific approach that bears an objective ontological stance and a positivist epistemological stance. Saunders et al. (2012) indicate that this is a typical stance in economic research, as organizations are believed to be rational entities capable of producing rational explanations to potential issues. Understanding the chosen research philosophy is critical to deliver a well-structured dissertation and effectively conduct research consistent with scientific applications within economic research methods. Although they can be assigned to the same research philosophy, terms can be perplexing in studies in different disciplines. Therefore, it is essential to explicate the scientific approach so that the reader can assess the thesis and the author can justify the work.

2.1.1. Ontology

Ontology is the philosophical field that studies the nature of reality as a whole (Lawson, 2004). As the ‘study of being’, it is concerned with anything or everything that ultimately exits (Flew, 1984). Grix (2002) refers to ontology as the study of “what is out there to know about”. Ontology then revolves around the different entities and categories within reality that are “apart from the nature of any existent object” (Flew, 1984). Lawson (2004) further emphasizes the significance of the ontological standpoint as it delivers “clarity and directionality” to the research. In essence, ontology reflects an interpretation by the author about the existence of the object that is being researched. It provides factual knowledge about things that already exist in nature.

Grix (2002) identifies objectivism and constructivism as ontological positions. Namely, objectivism states that social entities are independent of human actors, while constructivism refers to social phenomena being produced by social interaction and, therefore, being subject to constant altercations. In other words, objectivism "is an ontological position that asserts that social phenomena and their meanings have an existence that is independent of social actors" (Saunders et al. 2012). Alternatively, constructivism can best be explained as an "ontological position which asserts that social phenomena and their meanings are continually being accomplished by social actors" (Bryman, 2012). Ontology, therefore, revolves around the dilemma whether social entities ought to be considered objective or subjective.

Burrell and Morgan (1979) explain that "the social world exists separate from the individuals' perception of it". They argue that "relationships are concrete" and can be identified and examined through hypothesis testing. That is to say, the evidence already exists within reality and is independent of the author's method of collecting data. Therefore, regardless of whether the research was conducted or not, if the data used to analyze the issue still exists, the data is author-independent and the information revealed by the data can be classified as objective. However, the information disclosed may be considered subjective if the data exists solely due to the author's data collection methods or other interactions.

Every research begins with the author's perception of the world (Grix, 2002). This is in large influenced by the experience the author brings to the research process. Research approaches rely on ontological assumptions. Grix (2002) asserts that "ontology is the starting point of all research, after which one's epistemological and methodological positions logically follow". Authors, therefore, must take an ontological stance before adopting an epistemological one (Spencer, 2000). Furlong and Marsh (Marsh and Stoker, 2010) further suggest that the author's ontological and epistemological positions "shape the approach to theory and the methods" that they use. Blaikie (2007) concurs that ontological assumptions are important during research as "they can also influence the choice of research methods". These views are then encouraged by Hay (2007) who states that "ontological assumptions inform epistemological assumptions" and "both inform methodological choices". Understanding the author's ontological and epistemological positions is then fundamental to the successful realization of the Thesis.

The purpose of this Thesis is to examine and deliver empirical evidence about the impact of AI on labour productivity. The data required for the purpose of completing this Thesis will be collected from various reputable financial sources. The data is independent from the author and will, therefore, not be created by the author. That is to say, there will be no subjective interpretation or manipulation of the data and concepts used in the Thesis will be considered as if they were without the study. An independent stance will be taken when conducting the analysis of the productivity variables, and the data will not be altered whatsoever throughout the gathering and calculating processes. Accordingly, an objective ontological position will be taken for the purpose of completing this Thesis.

2.1.2. Epistemology

Crotty (1998) defines epistemology as "a way of understanding and explaining how we know what we know". Bryman (2012) suggests that epistemology is "an issue concerns the question of what is (or should be) regarded as acceptable knowledge in a discipline". Maynard (1994) argues that epistemology is further "concerned with providing a philosophical grounding for deciding what kinds of knowledge are possible and how we can ensure that they are both adequate and legitimate". Epistemology then is all about the very bases of knowledge, the manner in which that knowledge should be obtained and delivered to other social entities (Maynard, 1994).

Furlong and Marsh (Marsh and Stoker, 2010), explain that "if an ontological position reflects the researcher's view about the nature of the world, his or her epistemological position reflects his/her view of what we can know about the world…". The main epistemological question, therefore, concerns "the nature of the relationship between the knower and what can be known…" (Marsh and Stoker, 2010).

The two assumptions of epistemology most typically discussed include positivism and interpretivism. Grix (2002) defines positivism as the "application of methods of natural science to the study of reality", while interpretivism differentiates among subjects and objects of natural sciences and those applicable to the social sciences, which are commonly regarded as being subjective in nature.

Positivism often focuses scientifically on the relationships and common features among the variables selected for analysis (Burrell and Morgan, 1979). The underlying principle of positivism is to look at knowledge and the world scientifically. It examines the relative knowledge of phenomena related to other phenomena rather than the absolute essence of the phenomenon (Mackenzie, 2011). In that manner, the identification of the exposed components and the method of measuring the concepts are critical for positivist research approaches. Data is collected based on statistics and a grand amount of participants. Adopting a positivist approach indicates advancing research through hypotheses and deductions and trying to observe the data objectively. Positive studies are then quantitative and generalizing in nature.

Alternatively, the Interpretivist approach concentrates on methodologies that produce and manipulate information with the aim to discover something specific to the context (Burrell and Morgan, 1979). Phenomena outside our own observations are fundamental (Mackenzie, 2011). The basic idea is that authors are integral to the study and interpret the data. Thus, they cannot be completely and objectively excluded from the study. The authors recognize that knowledge is not objective but influenced by the social entities in the surroundings. This philosophical view is more subjective and prejudiced and, therefore, cannot be as generalized as in positivist studies.

This Thesis will study the impact of AI on labour productivity. This will be conducted through the collection of firms' AI patent portfolios. It will then be studied by statistics and hypothesis. The Thesis will attempt to explain the reality found in the empirical evidence. In that manner, the Thesis will examine what already exists in reality and not what the author desires to portray. Accordingly, the Thesis will be accomplished with a positivist epistemological approach.

2.1.3. Research Paradigm

Burrell and Morgan (1979) explain the philosophy of research method and form a quadrant of four paradigms. The quadrant implies that authors of sociological studies can take different stances from an objective or subjective point of view due to regulatory or radical changes (see Figure 1 below). In essence, the quadrant contains "fundamentally different perspectives for the analysis of social phenomena" (Burrell and Morgan, 1979). Burrell and Morgan (1979) further suggest that the paradigm is a guideline that allows to comprehend individual perspectives, explicate assumptions, and shape the overall study.

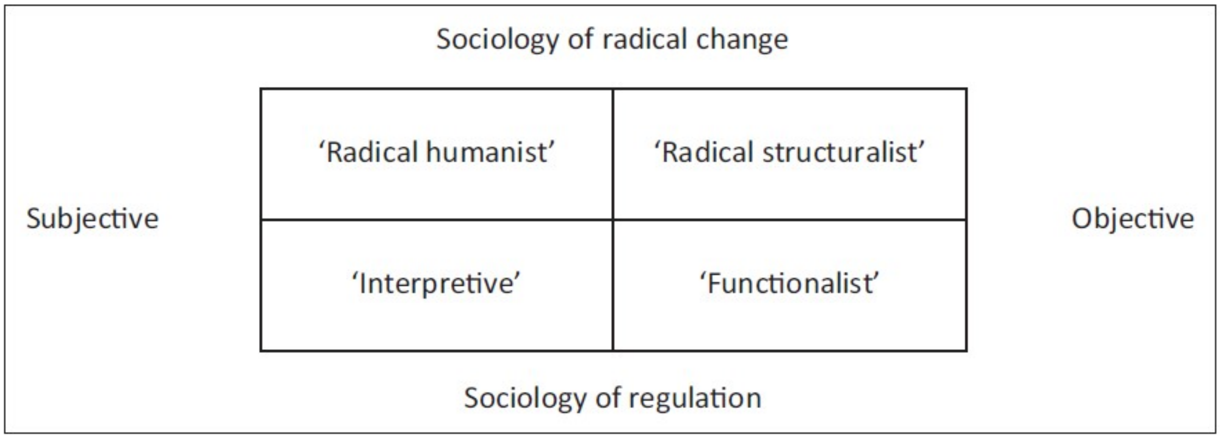

Figure 1 Burrell and Morgan's (1979, pg.22) paradigmatic differentiation schema.

The functionalist paradigm is considered to be on the objective axis and to relate to the 'sociology of regulation'. It attempts to find an explanation of social phenomena from a realist view. This can also be called a positivist perspective. It holds a logical and rational standpoint, and is often "problem-oriented in approach". This paradigm is utilized in sciences that can quantify, evaluate and monitor issues.

The radical structuralist paradigm is closely related to the functionalist view as it also takes an objective standpoint. This paradigm is all about structure, structural relationships, and the belief that everything can be explained in a logical manner.

The interpretative paradigm revolves around understanding and portraying the world and all situations, conditional on the material and in-material variables that existed at the time. It asks for a view "within the frame of reference of the participant as opposed to the observer of action". This frame of reference is critical for research primarily related to humans, knowledge, and cultural contexts.

The radical humanist paradigm is closely related to the interpretative standpoint as it also enables and bolsters subjectivity. This paradigm sees the world as a place in which everyone has the capability to "do better" and "be better". Such perspective of "endless possibilities" gives rise to the view of the "critical social researcher".

These four paradigms are fundamental to any researcher since once selected, the research paradigm acts as the author's "set of lenses". Knowledge of the chosen paradigm allows the author to recognize the limits of what they can do on their topic. Each of the four paradigms represents a different type of social theorization. To ensure that the study is conducted fairly and rigorously, it is of critical importance that the author sets the research methodology within an appropriate research paradigm and clearly articulates the assumptions associated with that research paradigm.

This Thesis aims to explain how AI relates to labour productivity and whether this effect can be predicted by a set of rules created by prior authors. It will utilize data that already exists in reality and conduct hypothesis testing to obtain and interpret results. Accordingly this Thesis will adopt an approach of a functionalist so as to explicate the research process. At its most basic level the functionalist approach allows for clearly defined facts and evaluation of findings. It enables for total independence from the observer to the observed and provides the author the ability to observe the subject without affecting it anyhow. It presupposes that there are universal scientific standards that condition what comprises a proper description of what is observed. In essence, the functionalist paradigm aims to deliver a rational clarification for social issues and to deliver regulative sociology.

2.2. Research Approach

This Thesis employs multiple components to test and reveal empirical evidence on the causal relationship among AI and labour productivity. It utilizes a deductive approach in an attempt to derive hypothesis from theory. Wilson (2010) explains that deductive reasoning is concerned with "developing a hypothesis (or hypotheses) based on existing theory, and then designing a research strategy to test the hypothesis". The Thesis then studies literature conducted by others and tests the hypothesis that emerges from those observations in order to measure the concepts quantitatively as well as generalize the research findings to a particular extent.

Relevant research methods are then selected and exerted to test the newly formulated hypothesis to prove or deny its validity. The Thesis follows reductionism in order to simplify the problem into its individual form. In essence, reductionist thinking revolves around the idea that complex explanations should be broken down into less complex parts, however, the sample should be of considerable size so as to delineate the general idea as a whole (Barendregt and van Rappard, 2004).

2.3. Research Design

The quantitative research design ought to maximize the reliability and minimize the bias in terms of the data collected and examined. The testing will be achieved by an analysis of different labour productivity variables that are already quantitative. The sample size will be taken from historical time series data taken from various countries that represent a sufficiently large population. The Thesis will analyze the productivity growth of time series data between the year 2010 and 2020. The sample data will cover firms active in AI patenting.

The Thesis will utilize secondary quantitative data to collect actionable insights and answer the research question from an objective ontological and positive epistemological standpoint. Secondary data will be collected using the internet. Such research is cost effective and time efficient as data required is readily available. However, since secondary data is based on data already collected by other authors, the successful completion of this Thesis will largely depend on the quality of the research conducted by prior authors.

The Thesis will further adopt a quasi-experimental research to estimate the causal effect of the independent variable on target population with no random assignment. Causal-comparative or quasi-experimental research studies the cause-effect relationship among two or more variables, where one or more variables are dependent on the other independent variable. The independent variable is identified but not altered by the author, and its effect on the dependent variables is quantified. The data is then analyzed and conclusions are achieved. Ultimately, the hypothesis is proven false or not false.

2.4. Literature Search

The literature search was conducted via various sources including commercial information sources, educational institutions, and the Google Scholar search engine. The articles cited in this Thesis include recently published peer reviewed scientific articles as well as articles cited in these recently published articles that provide relevant information about the research objective of this paper. Key words used to find the articles include Artificial Intelligence, labour productivity, automation, employment and future of work.

2.5. Overview of Research Methodology

A model has been created to outline the methodological choices used throughout this Thesis (see below).

Figure 2 Methodology Model

2.6. Some Ethical Considerations

Simons (1995) defines ethics as "the search for rules of conduct that enable us to operate defensibly in the political contexts in which we have to conduct educational research" (Pring, 2004). Saunders et al. (2009) denote research ethics as the manner in which "we formulate and clarify our research topic, design our research and gain access, collect data, process and store our data, analyze data and write up our research findings in a moral and responsible way." Chilisa (2005) further argues that "ethical issues in research include codes of conduct that are concerned with protection of the researched from physical, mental, and/or psychological harm. The codes of conduct to protect the researched include ensuring anonymity of the researched and confidentiality of the responses."

This Thesis will build on methods utilized by other appreciated authors, so that the chosen methodology does not violate any law, rule, or regulation regarding the use of data in research. Accordingly, the Thesis will take an objective research approach. The data will not be tampered with in a manner that misleads the reader, and the testing and modeling will be explicitly documented so that the reader can understand the adopted method and the achieved results.

Saunders et al. suggest that such data utilization methods will allow to “answer your research question and meet your objectives in an unbiased way and to produce reliable and valid data” (2009).

Ethical issues can further arise as a result of behavioral appropriateness, for instance, an interaction between a student and a supervisor or a student and the organization of the dissertation. Saunders et al. (2009) explain that coercion, confidentiality, as well as usefulness of research are some issues that can take place during a research. However, when developing and clarifying the research topic, the thesis supervisor did not force the author to write about a topic not chosen by him. In addition, the supervisor concurred that the gaps observed in the study are worthy of communicating and favored the methodology chosen with the purpose of answering the research question.

CHAPTER 3: LITERATURE REVIEW

This chapter will briefly reiterate the purpose of the study and research question (section 3.1). It will provide an overview of literature review (section 3.2) where information presented throughout the chapter will be summarized. The theoretical rationale (section 3.3) will provide reasons for doing the study. The review of related research (section 3.4) will deliver a carefully organized account of all existing research relating to this specific topic and establish a context for the study. The conclusion (section 3.5) will then emphasize the most significant ideas.

3.1. Introduction

Prior to the 18th century, people generally adopted a pessimistic attitude about the prospects for rapid technological advancements. Concerns over the impact of automation on productivity augmented with the growth of mass unemployment. Yet some scholars and economists began to oppose these pessimistic views and argued that innovation could actually have positive effects on jobs. They claimed that machinery could have negative short-term impact on employment. However, in the long run wages would increase and unemployment would decrease with the emergence of novel occupations and lines of business. In the early 19th century, classical economists formalized these claims, implying that technological advancements were beneficial to society at large, including the labour community. Fears over the adverse effects of automation decreased dramatically.

Today too we are experiencing a period of expeditious innovation. With the introduction of Artificial Intelligence, concerns about technological unemployment began to grow once again. Advancements in AI have already proven to be superior to humans in numerous activities. Intelligent machines have excelled in performing tasks at the human-level including speech recognition, translation, visual image recognition and similar. In 2016, a Google program defeated Lee Se-dol, the world's best Go master, and in late 2017, an AI powered program called AlphaZero beated the best chess engine in the world (Somers, 2018). These achievements in computing vision have brought both enthusiasm about AI capabilities to improve the future of work and fear for the stability of workers' jobs as algorithms and robots now have the power to perform many of the tasks that humans can.

What is more, the likes of Tesla and Google are using AI to disrupt the auto business through self-driving cars (Breunig et al., 2017). Nicolas Yan (2016) reports that “Google’s fleet of self-driving cars, for example, has collectively logged more than 1.5 million autonomous miles on the road”. This trend toward automating self-driving cars further testifies of the grandiosity of the probable disruption to the labour force. Accordingly, the truck driving industry, which at the moment employs nearly 8.7 million people in the US and is characterized as “ being the most common job in 29 of the 50 US states“, could face serious rise in unemployment in the short to medium term (Yan, 2016).

With AI altering the manner in which firms work, many assume that those who do that work will alter as well – and companies will begin employing intelligent systems rather than human workers. Indeed, machines are already displacing some workers in manufacturing, construction, driving, hospitality, and financial services, thus taking away jobs or moving humans towards lower-paid jobs (Vega, 2021). Nonetheless, the role that AI will ultimately play in the labour market is not to be perceived as a zero-sum game in which there is one single victor (De Cremer and Kasparov, 2021). The idea that AI and robots will completely replace workers assumes that intelligent algorithms and humans possess identical features and capabilities. But it is not that simple. AI systems are speedy, accurate and logical. They are not, however, instinctual, emotional, or tactful. It is precisely these qualities that humans possess that make us productive and efficient.

It is crucial that we understand the impact novel technology can have on workers and the labour market. As history suggests, in the long-run, societies have benefited from integrated technological innovation through increased productivity and economic growth. This economic model simply combines technology with capital and labour to obtain increased output. However, in actuality, things do not work that way and technological change does not impact all labourers equally (The Economist, 2014). While some labourers will benefit from novel technology, others will not. Those who do not possess skills that complement these new technologies will find themselves in a rather subordinate situation. In the case of the Industrial Revolution, as suggested by Mokyr et al (2015), "”by many estimates it took longer than an average working lifetime to do so, and in the long run, we are all dead"’.

Answering the question of how AI affects labour productivity requires in-depth knowledge that connects AI with the worplace skills of today. Different skill requirements for different job titles can obscure the impact of technology, as the demand for a particular type of workforce changes for each particular technology. Depending on the nature of the work, novel technology can benefit or detriment workers. Accordingly, advances in AI can reduce wages and employment possibilities for manufacturing workers. At the same time, AI seems to increase the productivity of software developers as well as create new investment. To make matters worse, vocational eligibility requirements do not remain static, but alter as technology alters.

3.2. Overview of Literature Review

The potential relationship among AI and the ensuing impact upon labour productivity has been widely analyzed by scholars in both qualitative and quantitative terms (Piva and Vivarelli, 2014; Calvino and Virgillito, 2018; Ugur et al. 2018). Altogether, previous empirical studies differ greatly in the interpretation of their findings in large due to the level of analysis (firm, sector, or macro), data sample selection (choice of countries, firms, etc.), and time of analysis. The overall picture is somewhat miscellaneous. The great majority of the existing literature explores the technological effects on growth at the micro-level, thus suggesting the existence of a job-creating impact when highly innovative companies adopt technological change through R&D expenditures (Dosi et al., 2021). The findings are less definite when the effect of innovation is analyzed at the sectoral level (Bogliacino and Pianta 2010; Aldieri and Vinci 2018; Piva and Vivarelli 2018; Falk and Hagsten 2018; Dosi and Monhen 2019).

Innovation is linked across sectors, so macro-level analysis best depicts the general impact of innovation on labor productivity. In this regard, the employment reduction impacts of increased productivity (related to process innovation) can lead to sectoral unemployment if they are followed by product innovation. Therefore, it is necessary to balance the labor-saving effect in some sectors with the job-creation effect in other sectors (Dosi et al. 2019).

Prior literature shows the complementarity among novel technologies and skilled laborers, in terms of both education level and professional occupation. It is precisely skilled laborers that are able to effectively and efficiently implement these novel technologies. Therefore, a positive relationship is expected (and commonly established) among novel technologies and skilled laborers. However, a substitution effect among novel technologies and unskilled laborers is generally recognized (Machin and Van Reenen 1998; Los et al. 2014).

3.3. Theoretical Rationale

Technological change can impact employment either by creating demand for products and services in novel industries and jobs or by directly displacing workers from their previous jobs. The effects of technological innovation on labor productivity and employment have been a growing concern among prominent scholars and economists of the time. In 1772, the economic writer Thomas Mortimer wrote that he opposed the emergence of sawmills and other machines as they would "exclude the labour of thousands of the human race, who are usefully employed". He argued that machines would directly displace workers from their previous tasks by what is known as the displacement effect. David Ricardo, in the third edition of his *Principles of Political Economy* (1821 [1971]), revisited his earlier conviction that "an application of machinery to any branch of production was a general good" and subsequently concluded "that the substitution of machinery for human labour, is often very injurious to the interests of the class of labourers. . . [It] may render the population redundant and deteriorate the condition of the labourer." He did not, however, discourage the extensive employment of machinery in the society nor suggest that technological unemployment was the end result of technological advancements. It was due to his "wage-fund" theory wherein capital invested in machinery with funds intended for workers' pay that Ricardo argued employment would be decreased. As a result, long run productivity and savings would rise thus leading to an increased labour demand (Berg, 1980).

While Mortimer, Ricardo, and others acknowledged the possible negative impact of automation on the labour market in the short run, they usually distinguished between short run dislocations and long run effects. Economist Sir James Steuart (1767) conceded that machinery "might force a man to be idle" temporarily, but the advantages of higher productivity would be permanent. Steuart (1767) addressed the displacement effect, however, argued that technological unemployment could only take place when the change is introduced abruptly. He recognized that machinery could in fact yield positive productivity growth, otherwise known as the productivity effect. Indeed, both of these effects took place in the Industrial Revolution. A study by the Economist (2014) reports that "in the 19th century the amount of coarse cloth a single weaver could produce in an hour increased by a factor of 50, and the amount of labor required per yard of cloth fell by 98%." This caused the price of cloth to go down, which in turn increased the demand for the good, creating more jobs for weavers in the long run. Instead of displacing the weaver, innovation gradually altered the nature of the job and the necessary skills to complete it. That is to say, the displacement effect was more notable in the short run, while the productivity effect prevailed in the long run.

Post-Ricardians including John Stuart Mill argued that technological innovations could momentarily be injurious to human labourers. However, Mill (1848 [1929]) quickly revisited his initial belief: "I do not believe that . . . improvements in production are often, if ever, injurious, even temporarily, to the labouring classes in the aggregate." The German philosopher and economist Karl Marx, asserted that technological unemployment was a critical issue in the short run, but also argued that technological improvement was a vital force of production that would ultimately lead to widespread prosperity.

Mokyr (2004) implies that numerous sources report solid evidence that there was rather insignificant growth in total factor productivity during the Industrial Revolution. It was not until the middle of the 19th century that real wages began to increase, long after the beginning of the Industrial Revolution (Feinstein, 1998). It should come as no surprise that such an evident disengagement between the advancement of a certain technological innovation and the stagnation of the economy as a whole exists. Indeed, a defining characteristic of general purpose technology (GPT) is that it is a lengthy process. GPT's contribution to growth can be modest for decades after its first invention. For instance, Crafts (2004) indicates that steam had little contribution to macroeconomic growth in the pre-1830 Industrial Revolution. This is in large due to complementary investment often being required to maximize the gains. Accordingly, even a groundbreaking invention such as steam required further innovation including high-pressure steam, before it could permanently and extensively improve living standards. Another reason for the slow rise in living standards was that many of the productivity gains initially failed due to population growth during the "post-Malthusian" period (Galor and Weil, 2000). At that time, population growth was still positively correlated with technological progress, but not strong enough to cancel the rise in living standards per capita. Even if wages rose in the first half of the Industrial Revolution, these rises were modest and probably did not represent a real improvement in living standards. In fact, the higher wages came with longer work hours, often worked under horrific circumstances (Voth, 2001).

While technology generally leads to a growth in productivity, AI can significantly reduce some of today's employment possibilities. As a result, researchers around the world are concerned about the future of work in developed and developing countries. In 1952, Wassily Leontief, winner of the 1973 Nobel Prize in Economics, observed that "labour will become less and less important. . . More workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job" (Dorfman, 1973). In like manner, in 1964, US Attorney General Robert F. Kennedy noted, "automation provides us with wondrous increases of production and information, but does it tell us what to do with the men the machines displace? Modern industry gives us the capacity for unparalleled wealth—but where is our capacity to make that wealth meaningful to the poor of every nation?" (Culey, 2018)

Economists have always been inconclusive. Classical economic theories imply that all growth relies on technological change (Solow 1957; Romer 1990). However, recent theories assume that technological innovation is likely to result in wage polarization due to the relative increase in the demand for unskilled workers compared to skilled workers (Autor et al. 2003; Barbieri et al. 2020), and the possibility of job loss due to automation (Vivarelli 1995, 2013; Autor and Dorn 2013; Piva and Vivarelli 2018). However, if automation increases production efficiency and thus expands labor demand, the productivity effect may outweigh the displacement effect (Acemoglu and Restrepo 2018, 2019a, b, 2020). The real question then becomes whether the displacement or productivity effect will take over in the times of AI.

3.4. Review of Related Research

Current research on automation and employment indicates that automation can both displace and complement labour. Frey and Osborne (2017) suggest that nearly half of all labour in the United States is at risk of being replaced by a machine over the next 20 years. Brynjolfsson and McAfee (2014) suggest that automation of cognitive tasks may allow new technology to act as an alternative rather than a complement. Meanwhile, another study shows that past positive technology shocks have increased employment opportunities and overall employment (Alexopoulos and Cohen, 2016).

Whichever the impact of automation on employment in directly affected industries, the adoption of new technology can lead to a positive upstream and downstream impact on work. Autor and Salomons (2017) indicate that employment within one industry appears to decline as industry-specific productivity increases, however, positive spillover impacts to other sectors have unfavorable impacts on employment in their own industry. In addition, Bessen (2017) states that novel technologies ought to have a favorable impact on employment if they manage to increase productivity in markets in which there exists great amount of unmet demand. Bessen (2017) further suggests that advances in technology lead to employment reduction in manufacturing, but also to employment growth in less saturated, non-manufacturing sectors. In like manner, Mandel (2017) examining the impact of e-commerce, observes that job losses in conventional department stores are more than offset by new possibilities in commercial activities. Dauth et al. (2017) combining German labor market data with IFR robot dispatch data, realize that with the introduction of each new robot two jobs in manufacturing are being lost, however, sufficient amount of new jobs in the service industry are created that offset the negative employment effects in the manufacturing industry.

Using a Gaussian process classifier, Frey and Osborne (2017) identify jobs that are most susceptible to automation and show the extent to which automation impacts the US workforce. Their object of particular interest is machine learning and its application to mobile robotics. In essence, Frey and Osborne (2017) attempt to estimate the magnitude of the impact of computerization on extraordinary tasks. After classifying the tasks based on their susceptibility to automation, the authors map those tasks to the O * NET Occupation Survey. This survey provides a free description of occupational skills and responsibilities over time. By integrating this dataset with the Labor Statistics Bureau's (BLS) employment and wage data, Frey and Osborne (2017) propose what specific subset of the labor market could be at a potential high, moderate, or low risk of automation. In that manner, cashiers, retail salespersons, and secretaries and administrative agents are occupations at greatest risk of automation. The authors further find that Black and Hispanic workers are more inclined to take positions at high risk of being automated. The survey implies that 47 per cent of US workers are at high risk of computerization. However, this survey is a holistic survey and does not look at how enterprises respond to potential labor-saving innovations or potential productivity or economic growth.

Frey and Osborne's work has served as basis for additional research by authors in different countries. In that manner, Brzeski and Burk (2015) analyze German labour market data and conclude that 59 per cent of German jobs are at risk to automation. Pajarinen and Rouvinen (2014) further indicate that 35.7 per cent of Finnish workplaces are exposed to high automation risk.

Autor et al. (2003) find that technological advancements can substitute human work in everyday activities, however they cannot substitute human work in non-routine activities. Goos and Manning (2007) imply that that the effect of technology generally leads to an increase in the relative demand for high-paying skilled jobs that require non-standard cognitive skills, and an increase in the relative demand for low-wage and less-skilled jobs that normally require non-standard manual skills. The authors also argue that demand for “intermediate” jobs that require routine physical exertion and cognitive skills will decrease through a process known as job polarization. Acemoglu and Autor (2011) report analogous findings in the US, while Darvas and Wolff (2016) disclose such developments in numerous European countries including France, Spain, Germany, and the UK. All these countries reveal growth in the amount of high-education occupations including managers, doctors, and engineers, as well as a decline in the amount of secondary-education occupations including machine operators, administrators, and office workers. On the other hand, low-education service jobs in particular clerks who are non-regular workers and cannot be substituted by automation are on the rise. The bottom line is that the inclusion of technology in a subset of core job activities formerly executed by mid-skilled workers has led to significant altercations in the business environment. The quality of human capital is also important as the capability of people to utilize technological innovations in their work requires the development of certain digital skills through prudent policies. This underscores the significance of utilizing the right tools to ensure that employees are ready to exploit the disruptive power of digital technology.

Recent researches study the growth of AI technology development by examining the evolution of AI patent applications (De Prato et al. 2018; Fujii and Managi 2018; Cockburn et al. 2019; Van Roy et al. 2020; WIPO 2019). The innovative AI landscape that emerged from these studies shows a similar pattern. The biggest surge in AI has occurred in the last five years and is dominated by China, Japan, South Korea, and the United States. AI development is primarily focused on the telecommunications, software services, and electronics manufacturing sectors, but almost every other industry is increasingly taking advantage of the opportunities offered by a new level of automation with AI technology.

Mann and Püttmann (2017) go a step further and adopt a different approach to estimate the impact of technology on employment and identify all automation-related patents issued in the US from 1976 to 2014. The authors associate the automation patent with the corresponding industry and determine which US region the industry belongs to. Comparing the economic performance and the number of automation patents used in a given sector, they estimate that while automation reduces manufacturing employment, it increases service sector employment and has a favorable effect on employment.

This Thesis aims to critically assess the extent to which AI impacts the productivity of firms active in patenting of such innovation. So far, there is little empirical evidence focused primarily on AI use at the aggregate level. Raj and Seamans (2019) point out that acquiring greater insight and examining empirical evidence on AI is of critical value. Using country-level data on global industrial robot shipments, Graetz and Michaels (2018) find that industrial robots are associated with increased average cumulative productivity in 17 countries by more than 15% between 1993 and 2007. In a study based on a sample of 3000 manufacturers in seven European countries, the European Commission (2016) observes that the use of industrial robots leads to increased labor productivity. Alderrucci et al. (2020) combine US Census Bureau firm-level microdata with AI-related patents from 1997 to 2016 to evaluate the effect of AI on a variety of outcomes. Comparing AI patenting companies to similar control companies, the authors observe that AI patenting companies are associated with increase in sales, employment, and income inequality within the company as opposed to the control group.

3.5. Conclusions

The sectors of the labor market that are most vulnerable to automation tend to be very repeating in character, for instance, driving vehicles in the modern age or being a factory worker in the Industrial Era. Not surprisingly, since 1950, manufacturing employment in the United States has declined from 30% to 10%, while total employment in the services sector has increased from 50% to 70% (The Economist, 2014). Therefore, it is clear that the transition from low-skilled, low-wage jobs to high-skilled, high-wage jobs is accelerating. Some studies further show that every job created in the high-tech industry is equivalent to generating five additional jobs (OECD, 2016). As Mokyr et al. (2015) argue on this matter, “the future will surely bring new products that are currently barely imagined, but will be viewed as necessary goods by the citizens of 2050 or 2080. These product innovations will combine with new occupations and services that are currently not even imagined”.

Some researchers argue that the disruptive feature of AI that is amplified by automating tasks, reducing uncertainty, and creating novelty (Agrawal et al. 2019a, b) will eventually generate an increase in productivity (Brynjolfsson et al. 2019). More pessimistic models suggest that the current decline in productivity is to carry on due to increases in inequality (Gries and Naudié, 2018), the cost of knowledge (Jones 2009), as well as the lower rate of disruptiveness of AI as opposed to other GMTs (Gordon, 2018). Such conflicting projections posit the need for quantitative analytics that measures the effect of AI on growth, productivity, and employment (Raj and Seamans 2019; Furman and Seamans 2019). Empirical studies have only recently gained a better understanding of the effect of AI on a company's labor productivity, and are, nonetheless, limited to just a small amount of researches (Graetz and Michaels 2018; Alderucci et al. 2020). To the author’s comprehension, there is no empirical work that quantifies the effect of AI on corporate productivity, taking causality into account. This study aims to fill the voids identified in previous studies and provide new empirical evidence.

This Thesis builds on Alderucci et al. (2020). It utilizes an exclusive database of firms active in AI patenting to estimate the impact of AI on labour productivity. It tests for this possible effect using a global sample of firms from numerous countries that filed patents related with AI between 2010 and 2020. The patent data is obtained from the European Patent Office's Worldwide Patent Statistical database (PATSTAT). Financial data about the corresponding firms is then obtained from Bureau Van Dijk's ORBIS database that contains information on private entities. The study employs a panel data model generated from a knowledge-stock augmented production function.

CHAPTER 4: THEORETICAL FRAMEWORK

The theoretical framework consists of further information about the relevant theories of this thesis. Assumptions will be derived from the theory and presented throughout this chapter, which will be used to construct the hypothesis in chapter 5.

4.1. Definition of Key Terms

4.1.1. Labour Productivity

Economists generally agree that productivity is critical to economic success and the primary driver of long-run per capita growth (Krugman, 1994; Hall and Jones, 1999). The neo-classical growth model implies that labour productivity is affected by total factor productivity (TFP) and capital deepening (Solow, 1957). Improvements in TFP growth or technical advancement are the major determinants of long-run growth in this class of models. Modern growth theories that aim to explain TFP within the model, emphasize the significance of innovation, such as R&D expenditure, in generating productivity growth (Romer, 2000; Barro and Sala-iMartin, 2004).

Productivity is the key driver of economic growth (OECD, 2001). Productivity implies efficiency in production. That is, how much output is generated from a specific set of inputs. A greater understanding of the factors impacting labor productivity can help managers utilize limited resources more effectively, give better support to workers, and boost worker motivation (Marešová et al., 2011).

Few information are required to properly comprehend the situation at hand.

There is no globally acknowledged definition of labor productivity; instead, different nations and writers have proposed different criteria for defining the idea. To develop new measures of labor productivity, each area or industrial sector employs its own adjustments, specifications, or degree of detail tailored to their individual demands (Bureš and Stropková, 2014). Mohanty (1992) has proposed 12 distinct definitions of productivity, categorizing them as macro-level and micro-level. Bernolak (1997) and Hannula (2002) go into great detail about the usage and applicability of different approaches. Productivity is divided into various sub-concepts, such as total productivity, total factor productivity (TFP), and partial productivity. The table below shows a collection of definitions as well as their authors:

Definition	*Author*
GDP per worker	Key indicators of the labour market (KILM)
GDP per engaged worker and GDP per hour worked	Key indicators of the labour market (KILM)
Total cost to sales	Hannula (2002)
Value added per worker	Bala Subrahmanya (2006)
The ratio of output to input	Enshassi et al. (2007)
The amount of work generated per man-hour, equipment-hour or crew-hour worked	Durdyev et al. (2012)
Total sales volume to number of employees	Abad et al. (2013)
Real output per hour worked	Calcagnini and Travaglini (2014)

Table 1 Productivity definitions specified by different authors

The European Cooperation refers to productivity as “the quotient obtained by dividing output by one of the factors of production.” Today, there is a wealth of empirical research on the factors that influence labour productivity. The dependent variable in most research is labour productivity, while the independent variables include physical capital, labour, and technological change. Even though there are many input resources in a transformation process, labor productivity is particularly important. A better knowledge of the labor productivity can assist managers in allocating limited resources more effectively.

4.1.2. Factors of Influence

Labour productivity is measured as the total volume of output generated per unit of labour during a specific time period (OECD, 2001). In other words, labour productivity is represented as the output that each employee produces per unit of his or her time.

But what exactly determines how productive employees are? The answer can be pretty subjective. However, there are three key determinants of labor productivity. These include physical capital, human capital, and technological knowledge (OECD, 2001).

Physical capital involves the plant, machinery, equipment, and structure that the firm utilizes in order to produce output. The greater the physical capital the firm possesses the greater the output it generates. Physical capital can impact productivity through:

1) an increase in the amount of physical capital (more machines of the same quality)
2) an increase in the quality of physical capital (same number of machines but with greater efficiency, and so on)

Access to information and communication technology is one of the most essential physical capitals of a firm that has been studied empirically. Increasing a company's physical capital in the field of information and communication technology generates higher labour productivity (Papadogonas and Voulgaris, 2005). IT equipment enables the expansion of corporate processes and information transactions between managers and staff, resulting in a rise in labor productivity (Papadogonas and Voulgaris, 2005). Using data from 500 enterprises in the United States, Lichtenberg (1993) and Brynjolfsson and Hitt (1995), find that increasing physical capital in the field of ICT leads to an increase in labor productivity. What is more, in their research of industrial enterprises in Greece, Papadogonas and Voulgaris (2005), find that increasing capital equipment intensity leads to an increase in labor productivity.

Human capital includes the skills, knowledge, and experience that the employees accumulate throughout the process of creating economic value for the firm. Technological knowledge further influences the labour productivity within the firm. Technological change can be seen as a fusion of invention and innovation. It refers to the firm's knowledge of how to generate the maximum output utilizing the minimum input.

Knowledge capital refers to increases in productivity caused by novel technological applications. Many studies define knowledge capital as accumulated and still useful research capital generated from prior R&D investments (Griliches, 1989; Hall and Mairesse, 1995; Del Monte and Papagani, 2003). Other studies consider "knowledge" to encompass previous investments in innovation, organizational practices, and human capital, in addition to R&D spending (Rogers and Tseng, 2000). Despite these indices, most research utilize R&D spending as a proxy for firm knowledge capital. In general, when technology improves, the amount of per worker production rises, hence any factor, such as R&D spending, that produces technological advancement would raise labor productivity (Papadogonas and Voulgaris, 2005). In fact, numerous empirical studies have been conducted to investigate the impact of R&D spending on company functioning. According to a study by Papadogonas and Voulgaris (2005), R&D investment has a favorable and substantial influence on labor productivity among 3035 enterprises in Greece's manufacturing sector.

In essence, all these classify as internal drivers of productivity. For instance, some researchers find that higher quality labour and capital lead to higher productivity (Fox and Smeets, 2011; Ilmakunnas et al., 2004). Some external determinants include productivity spillovers, market demand, as well as competition and regulation. This Thesis, however, will focus more attention on quantifying the internal drivers of productivity.

4.2. Cobb-Douglas Production Function

The abovementioned principles can be formalized by establishing the concept of the production function. (Griliches, 1979) refers to the production function as the process of converting economic inputs such as labour, machinery, and raw materials into consumer goods and services. A microeconomic production function defines the relationship between a firm's inputs and outputs. The econometric model this Thesis utilizes includes a Cobb-Douglas Production function. The general form of the Cobb-Douglas Production function is (Cobb and Douglas, 1928):

$$Y = f\,(X_1, X_2, X_3 \ldots\ldots\ldots\ldots X_n) \qquad (1)$$

Where, Y is the physical quantity of output and $X_1, X_2, X_3 \ldots\ldots\ldots\ldots X_n$ represent the physical quantities of inputs employed. When X_1 and X_2 are replaced by labour and capital, respectively, the following equation is obtained:

$$Y = f(L, K) \tag{2}$$

Or,

$$Y = AL^{\beta} K^{\alpha} \tag{3}$$

Where, Y is output and represents the dependent variable. Capital (K) and labour (L) are independent variables (Cobb and Douglas, 1928). The parameter A represents the total factor productivity which estimates the change in output that is not due to the inputs. Usually, total

factor productivity is the outcome of an improvement in technology. The Greek letters α and β

indicate the output elasticity of the inputs. Equation 3 is defined as the Cobb-Douglas production function.

Griliches (1979) established the notion of a knowledge production function to quantify the contribution of R&D and knowledge spillovers to productivity development. The fundamental premise is that the outcome of the innovation process is basically the outcome of R&D capital or investment, i.e.

$$\text{R\&D output} = f\,(\text{R\&D input}) \tag{4}$$

Thus, the Knowledge Production Function is,

$$\text{R\&D output} = \alpha \text{R\&D input}^{\beta} \tag{5}$$

The knowledge production function is critical to growth models based on R&D. The knowledge production function indicates how investments in various knowledge based activities lead to an increase in knowledge. That is, new knowledge within the firm is generated in the R&D sector. Therefore, an increase in knowledge leads to an increase in the innovation output which in turn raises the productivity rate (Griliches, 1979).

This equations denotes the dependence of total output on the firm size, i.e. number of employees. Accordingly, it is very probable that the greater the number of employees exploring for novel ideas, the more likely it is that work might be duplicated or overlapped. In such situation, doubling the number of employees may result in less original ideas or discoveries. This concept of duplication in research may best be represented as a decline in total number of employees with the purpose of generating higher output.

4.3. Panel Data

Panel data is sometimes referred to as *longitudinal data* or *cross-sectional time-series data* (Hsiao, 2003). That is to say, panel data takes both the characteristics of time-series and cross-sectional data. Time-series data observes the same object at multiple points in time. Cross-sectional data observes multiple cross-sections at a certain point in time. Panel data is, therefore, a multi-dimensional concept in which the same cross-sections are observed repeatedly in several different time periods (Gujarati, 2006).

Panel data observes the same cross-sections across time. Examples of cross-sections include individual people, countries, and firms. It includes two types of information: the cross-sectional information reflected in the differences among the cross-sections, as well as the time-series information reflected in the changes within cross-sections over time (Greene, 2008).

In panel data, groups are often referred to with the subscript i and time periods with the subscript t. In that manner, a panel data observation Y_{it} is observed for all entities $i = 1 \ldots N$ across all time periods $t = 1 \ldots T$. That is to say, the dataset consists of N entities observed at T time periods.

To illustrate these properties the following is a hypothetical dataset containing four columns and six rows.

Individual	**Year**	**Y**	**X**
A	1980	50	75
A	1985	20	82
B	1980	35	69
B	1985	18	80
C	1980	46	53
C	1985	23	74

Table 2 Panel Dataset Example

The dataset contains six observations of three different individuals. For each individual, two variables are measured. These measurements take place in two different time points – 1980 and 1985.

Panel data can further be characterized as balanced or unbalanced (Hsiao, 2003). Balanced panel datasets suggest that the entities have no missing values at specific time observations. When there are no missing values, the dataset contains NT observations. In contrast, unbalanced panel datasets include missing values at some periods in time for some cross-sections. Unbalanced data consists of less than NT observations.

Panel data can be short and contain observations of multiple entities and few time periods. It can be long and include multiple time periods and few entities. And finally, panel data can consist of both multiple entities and multiple time periods.

Panel data enables empirical tests for a wide variety of hypothesis (Gujarati, 2006). The use of panel data allows for more efficient estimates as observations that include both time periods and entities provide more information. In other words, panel allows for "more informative data, more variability, less collinearity among variables, more degrees of freedom and more efficiency." Panel data minimizes the estimation bias that arises from aggregating the entities into a single time-series. It further estimates statistical effects that pure cross-sectional and time-series data cannot. In addition, panel data controls for unobserved sources of individual heterogeneity. The model allows for heterogeneity across cross-sections and introduces individual-specific effects.

4.3.1.1. Types of Panel Data

a) Pooled OLS

Pooled OLS model assumes that the model parameters are common across entities (Greene, 2008). It neglects the time and individual dimensions of the data and only focuses on the dependencies among the entities. The pooled OLS model does not distinguish between the entities and through pooling these entities, the heterogeneity or uniqueness that might exist between the entities is denied. Therefore, the assumptions are comparable to those of ordinary linear regression (Hsiao, 2003). The model takes the following form:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + u_{it,} \tag{6}$$

Where,

1) Y_{it} – the dependent variable

2) X_{it} – the explanatory variable

3) u_{it} – the error term

4) β_0 – the intercept

5) $\beta_1, \ldots, \beta_n$ – the structural parameters

Pooled OLS is used when the all the cross-sections in the panel are more or less identical in terms of intercept and coefficient. That is to say, the pooled OLS assumes that all entities within the model contain the same β_0 and β_n (Park, 2011).

Pooled OLS consists of five assumptions (Greene, 2008; Kennedy, 2008).

1) Linearity implies that there is a linear relationship among the independent and dependent variable. Linearity can be tested with a simple scatter plot. The residuals should be spread equally around the horizontal line.

2) Exogeneity implies that the expected value of the disturbances is zero and the disturbances are not correlated with any regressors.

3) The variance of the error terms is constant with respect to the independent variable (homoscedasticity) and the disturbances are not related among each other (no autocorrelation).

4) The independent variables are not stochastic.

5) No multicollinearity among the independent variables, i.e., the independent variables do not depend on each other.

If these assumptions are violated then the OLS estimators are biased and/or inefficient. In the case that assumption (2) or (3) or both are violated, then the pooled OLS is not the most suitable model for data analysis. Accordingly, the fixed effects model or random effects model could be more appropriate (Hsiao, 2003).

b) Fixed Effects

The fixed effect model assumes that all units are homogenous and controls for differences among individual entities (Baltagi, 2008). The FE model explores the relationship among the independent and dependent variable within the cross-section. Each cross-section possesses unique characteristics that might or might not influence the outcome variable. In essence, the model assumes that a certain entity feature might bias the outcome variable and, therefore, needs to be controlled for. The FE model further assumes that the slopes of the regression lines are the same across cross-sections (Kennedy, 2008).

The general equation of the FE model is:

$$Y_{it} = \beta_{1i} + \beta_2 X_{2it} + \beta_3 X_{3it} + \ldots + \beta_k X_{kit} + \varepsilon_i \qquad (7)$$

Where,

$$\varepsilon_{it} = \varepsilon_i + v_{it} \tag{8}$$

Here, ε_i is the individual unit specific time-invariant effect. The subscript i implies that the intercept of the entities might be unassociated due to certain characteristics of each of the entities.

The FE model assumes that α (i.e. the unobserved heterogeneity) is constant and subtracts the mean values from each equation term so as to obtain α value of zero and, subsequently, neglect the α (Baltagi, 2008). As a result, the idiosyncratic error is perceived to be exogenous and noncollinear. The model, therefore, allows for heterogeneity within the model. However, since the individual effects are fixed, the dependencies can only be observed within the entities.

The FE model assumes that the intercept of all entities is different due to different factors affecting those entities. There are three methods to consider a different intercept (Baltagi, 2008):

- Within group Fixed Effect

The *within* model uses deviations from entity and points in time means. In essence, the *within* estimation uses variation within each entity (Greene, 2008). It does not use a large number of dummy variables as the LSDV model does. There is no dummy variable used, which causes the model to contain larger degrees of freedom for errors. Therefore, the incorrect standard errors need to be adjusted. The number of observations in the *within* estimator equals NT. This model resolves the issue of incidental parameter. However, it also removes all time-invariant variables that do not vary within the cross-section (Kennedy, 2008).

- First Difference FE

The first difference estimator uses first differences of all variables in the model. It takes the following form (Hsiao, 2003):

$$Y_{it} - Y_{i(t-1)} = \beta_0 + \beta_1(X_{it} - X_{i(t-1)}) + (u_{it} - u_{i(t-1)}) \quad (9)$$

This model uses the one period changes for each entity. It ignores the time-invariant variables and does not estimate their coefficients (Park, 2011). Here, the number of observations equals N(T-1) as the first period is missing due to differencing. This model is typically used when there are multiple time periods with strong serial correlation in the errors.

- Least square dummy variable (LSDV)

The LSDV model uses dummy variables (Hsiao, 2003). The model takes the following form:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \alpha_1 d_1 + \alpha_2 d_2 + \ldots + \alpha_k d_k + u_{it} \qquad (10)$$

Where, d_k represents a dummy variable. For instance, $d_1 = 1$ for the first entity and zero for every other entity. There are N dummy variables, one for each entity. However, if too many dummy variables are introduced in the model, then the degrees of freedom problem might arise. Additionally, the presence of too many variables in the model can lead to multicollinearity, which in turn can make accurate estimation of certain parameters complicated.

c) Random Effects

The random effects model is the alternative to the fixed effects model. The random effects model determines the individual effects of the independent variables as random variables across time (Baltagi, 2008). That is to say, the RE model assumes that the difference in the intercept is due to sample randomness and not some specific factor of influence. The model incorporates a composite error term, $w_{it} = u_i + v_{it}$ (Hsiao, 2003). The error term is serially correlated within the cross-section over time. The u_i is independent of the combined time series and cross-section

error component v_{it} and the regressor X_{it}.

Therefore, the RE model is (Hsiao, 2003),

$$Y_{it} = \alpha + \beta_1 X_{it} + u_{it,} + v_{it} \tag{11}$$

Here, the individual specific effect u_i is assumed to be random and not correlated with the

independent variable.

This model allows for time-invariant variables to be included in the model. The REM is, therefore, a weighted average of the pooled OLS and the FE *within* estimator (Kennedy, 2008).

4.3.1.2. Model Selection Process

Selecting an appropriate technique for the considered data is of critical importance for the successful interpretation of the analysis. The following is an illustration of panel data model selection process.

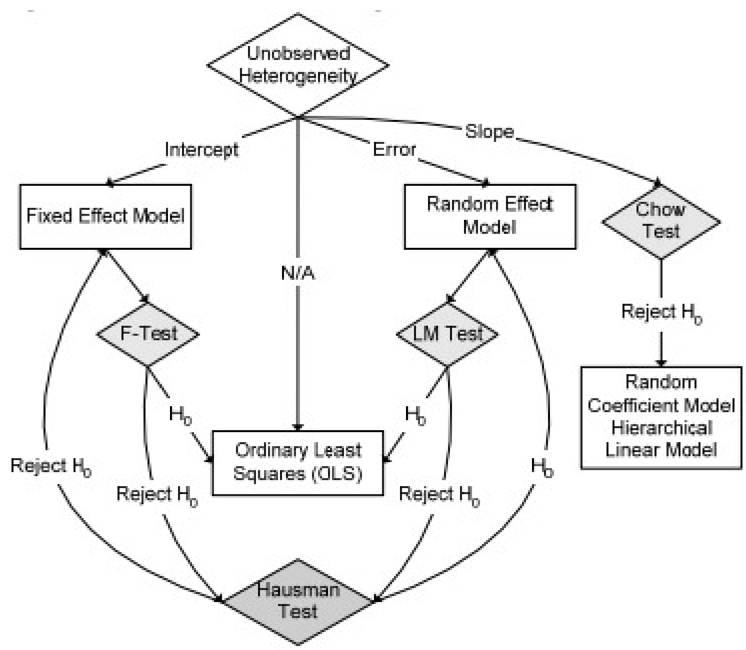

Figure 3 Panel Data Model Selection Process (Park, 2011)

The figure above implies that whenever the individual heterogeneity is prevalent in the disturbance term and the individual effect is not correlated with any explanatory variables, the random effect model is favored. However, in the case that heterogeneity can be controlled with individual specific intercepts and the individual effect is potentially correlated with any explanatory variables, the fixed effect model is more suitable. If each entity has the same disturbance variance with other entities within the model, then the fixed effect model is selected. If each entity has its own unique disturbance, the random effect model is more appropriate for estimating the heteroscedastic disturbances.

The individual group and time effects are then examined with the use of suitable tests. If the null hypothesis of the LM test is rejected, the random effect model is preferred. If the null hypothesis of the F-test is rejected, the fixed effect model is selected. If both hypotheses fail to be rejected, the pooled OLS is favored. If both hypotheses of the F-test and LM test are rejected, the Hausman test for endogeneity is performed. If the null hypothesis of non-correlation among an individual effect and explanatory variables is rejected, the fixed effect model is more appropriate.

Similarly, Kennedy (2008) implies that the individual specific intercepts need to be examined first. In the case they are equal, the data is poolable and OLS can be used. When the individual specific intercepts are not equal, the Hausman test needs to be performed to check whether the FE or RE model is more appropriate. If the group effect is not correlated with the error term then the random effect model is favored.

CHAPTER 5: PRACTICAL MODEL

This Chapter will present the hypothesis (section 5.1) as well as describe the population and sample (section 5.2) and time horizon (section 5.3). The variables (section 5.4) and statistical tests (section 5.5) to be conducted will then be introduced. It will then address the data collection process (section 5.6) and critique (section 5.7) the data sources and result quality.

5.1. Hypothesis

This Thesis will atempt to test the following hypothesis,

- *H_0: There is a direct relationship between labour productivity (on one side) and firms active in AI patenting (on the other side).*
- *H_a: There is not a direct relationship dependence between labour productivity (on one side) and firms active in AI patenting (on the other side).*

The hypothesis will be tested using statistical inference with the aim to answer the research question,

- *How does the introduction of AI related innovations within the company influence labor productivity?*

5.2. Population and Sample

The studied population is composed of AI patenting firms in various countries worldwide. Different countries have been analyzed to allow a regional comparison. The sampling method used is stratified random sampling as it divides the population into regional groups to assure greater accuracy of the analysis (Saunders et al. 2009). Systematic sampling focuses on identifying defining characteristics for stratification (Saunders et al. 2009). Through this process, multiple subgroups are obtained from the larger population. This Thesis divides the targeted population across regions. In that manner, firms active in AI patenting are categorized based on the region in which they operate.

5.3. Time Horizon

The time horizon of this analysis will be from January 1st 2010 until December 31st 2020, which is 10 years of data. Even though shorter time horizons might provide varying data than longer time horizons, the Beta (β) is believed to perform better under shorter time horizons (Bali and Engle, 2010; Adrian and Franzoni, 2009).

The Thesis utilizes panel data set that consists of a time series for each cross-sectional entity in the data set. It follows the same set of cross-sectional units over a given period of time. The Thesis is framed within a 10-year period which enables for the use of a time series data estimation approach. The annual data used in the analysis is in accordance with the AI industry practice for economic analysis. What is more, the variables used in the model all take the natural logarithmic form.

5.4. Variables

This Thesis provides an econometric framework with the aim to examine the impact of AI on labour productivity at the firm-level. The model has identified annual AI patenting firm data over 10-year period from 2010 to 2020. Data obtained from the PATSTAT and ORBIS database has been used.

All the variables are analyzed in natural logarithms so as to obtain the respective elasticities. Variables in levels will be transformed into natural logarithms. The table below consists of data collected over a period of 10 years that is used to identify the variables used in the regression model. The table below represents a summary of the variables used in the econometric model.

Variable	*Variable Description*
Labor productivity	Natural logarithm of labor productivity
Asset	Natural logarithm of total fixed assets
AI patent applications	Natural logarithm of the number of AI patent applications
Non AI patent applications	Natural logarithm of the number of non AI patent applications
Turnover	Natural logarithm of total asset turnover
Invest	Natural logarithm of R&D investments
Labour	Natural logarithm of number of employees

Table 3 Variable Description

5.5. Statistical Tests

The Software for Statistics and Data Science will be used to test and model the data. STATA is a general-purpose statistical software package that enables data manipulation, graphical visualization, and automated reporting.

5.5.1. Jarque-Bera Test

The Jarque-Bera test tests for normality (Gujarati, 2006). It measures the direction and degree of asymmetry. When the p-value is less than or equal to 0.05 at a 95% confidence level then the assumption of normality is rejected (Pallant, 2007). Accordingly, the hypotheses take the following appearance,

- H_0: $\chi \sim N$
- H_1: $\chi \neq N$

Where,

- X = data sample
- N = normal distribution

The test checks whether skewness is zero and kurtosis is three to conclude a normal distribution (Spider Financial, 2014). Skewness equal to zero indicates perfect symmetry around the mean. A positive skewness implies skewness to the right and a negative skewness implies skewness to the left. Kurtosis then indicates how "peaked" the distribution is. Value greater than three suggests the distribution has thicker tails than the normal. When skewness and kurtosis both equal zero then the distribution is perfectly normal (Pallant, 2007).

The figure below indicates what (a) positive skew, symmetrical distribution, and negative skew look like, as well as (b) kurtosis greater than (leptokurtic), smaller than (platykurtic) or equal to three (mesokurtic) (Gujarati, 2004).

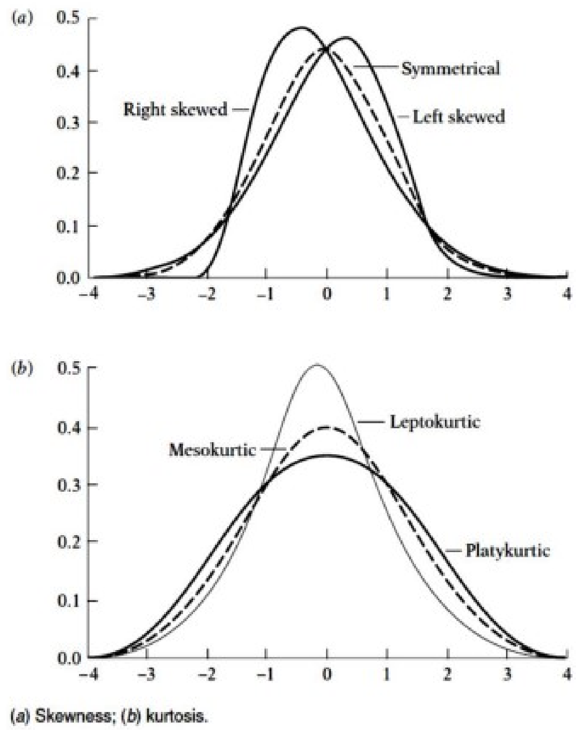

Figure 4 Skewness and Kurtosis (Gujarati, 2004, p.887)

A symmetrical skew which is mesokurtic suggests a normal distribution. Gujarati (2006) implies that in the event heteroscedasticity is present in the data the data ought to be transformed.

5.5.2. Wald Test

The Wald test checks whether the explanatory variables are significant (Agresti, 1990). The Wald test tells which explanatory variables in the model are significant. When the null hypothesis is rejected, the explanatory variables can be excluded from the model. When the parameters are different than zero, the variables can be included in the model.

5.5.3. Breusch-Pagan Test

The Breusch-Pagan test checks for heteroscedasticity in the model (Gujarati and Porter, 2009). Heteroscedasticity suggests that the error variance has non-constant variance. The null hypothesis implies that the residuals are homoscedastic. That is to say, when the errors have constant variance, they are labeled as homoscedastic. The Breusch-Pagan / Cook-Weisberg test for heteroscedasticity tests for,

- H_0: Constant variance, against
- H_1: Heteroscedasticity

If the p-value is greater than 0.05 (5%) then the null hypothesis fails to be rejected.

5.5.4. White Test

The White Test is actually a special case of the Breusch-Pagan Test as it enables for the X variables to have a nonlinear and interactive effect on the error (Gujarati and Porter, 2009). It identifies heteroscedastic errors in the analysis. The test checks for:

- H_0: Homoscedasticity, against
- H_1: Unrestricted Heteroscedasticity

The null hypothesis fails to be rejected when the p-value is greater than 0.05 (5%).

5.5.5. Variance Inflation Factor

VIF is a metric that tests for multicollinearity among the explanatory variables (Gujarati, 2006). It estimates the variance inflation factors for the independent variables. Multicollinearity suggests that two or more explanatory variables are highly correlated to each other, and, therefore, do not generate independent information in the model. In general, VIF is interpreted as follows:

- A value of 1 suggests no correlation among a certain control variable and any other control variables in the model.
- A value between 1 and 5 suggest moderate correlation among a certain control variable and other control variables in the model.
- A value greater than 5 suggests potentially severe correlation among a certain control variable and other control variables in the model.

In essence, VIF values greater than 10 suggests multicollinearity in the model.

5.5.6. Hausman Test

The Hausman Test detects endogeneity in the regression model (Gujarati and Porter, 2009). It is used to decide whether the FE or RE estimator is more appropriate. The null hypothesis implies that the covariance between the independent variable and *alpha* is zero. That is to say, there is no correlation between the unique errors and the regressors in the regression model. The preferred model in this case is random effects. When the null hypothesis is rejected, the preferred model is fixed effects.

H_0: FE and RE coefficients are not significantly different from each other

H_1: FE and RE coefficients are significantly different from each other

If p-value < 0.05, H_0 is rejected, implying that the fixed effect model is the appropriate model.

5.6. Data Construction

Labour productivity is the variable of interest in this analysis. Productivity growth measures how efficiently production inputs are used in the economy to generate a particular level of production. That is to say, labour productivity is related to the amount of ouptut produced by each worker in the firm. Therefore, the labour productivity in this Thesis is considered as the ratio of total firm output to labour.

Patent applications are a significant resource for quantifying innovation and have been widely utilized as metrics of technical progress in the patent literature (Hausman et al., 1984; Kortum and Lerner, 1998). Furthermore, Griliches (1989) and Joutz and Gardner (1996) contend that patent applications are an adequate indicator of technological output. Firms have devoted resources in creating a novel technology that they believe has economic worth, and they are willing to file an application in order to reap significant benefits on their early investments. Alderucci et al. (2020) note that "Firms that succeed in using artificial intelligence to create new goods and services have a strong incentive to patent at least some of their inventions. If they fail to do so, other firms can copy their innovations without penalty or use patents to block the original innovator from applying their inventions in the marketplace." As a result, this Thesis adheres to the patent literature and employs patent applications to generate knowledge flows.

Patents have long been utilized in studies as a result of intellectual activity and technical advancement. Kortum and Lerner (1998) explain that, "firms are restructuring, redirecting and resizing their research organizations as part of a corporate-wide emphasis on the timely and profitable commercialization of inventions combined with the rapid and continuing improvement of technologies in use." Venkata Naveen, senior disruptive tech analyst at Global Data, explains that, "the huge number of patent filings in AI indicate a paradigm shift from theoretical research". The dramatic increase in patenting might be attributed to a spike in discovery and invention.

This Thesis has been restricted to the number of AI innovations registered for patenting, which indicates the output of R&D operations. Alternative metrics of R&D input include R&D expenditures over the previous ten years as well as the number of employees at the start of each year. However, R&D spending is a more complete statistic than the number of employees since it involves inputs to the R&D process acquired from other organizations.

The data used in this Thesis are: the labour productivity (*produc*), R&D investments (*invest*), the number of AI-related patents (*AIpat*), the number of non AI-related patents (*nonAIpat*), the number of employees (*labour*), and the total fixed assets (*asset*).The source of the data is the PATSAT database combined with the ORBIS database. The labour productivity is considered here as the ratio of total firm output to labour. The data is expressed in dollars. The time period ranges from 2010 to 2020. The data includes 33 firms operating in 3 different regions. These regions are USA, Europe, and Asia.

5.7. Empirical Model

The model used for the purpose of this analysis is a log-log model or double-log model. The model implies that both sides of the equation have been logged. That is to say, both the independent and the explanatory variables take the log-log specification. The model implies that if X changes by one per cent, then Y is expected to change by β_1 per cent (Baddeley and Barrowclough, 2009). The coefficients indicate the elasticity of the Y variable in terms of the X variable (Baddeley and Barrowclough, 2009). Regression is then used to estimate the unknown effect of altering one variable over another (Stock and Watson, 2003). That is to say, the regression model estimates the extent of change in Y when Xn, changes one percentage unit.

In this model, the natural logarithm of labour productivity within a specific firm serves as the dependent variable. The dependent variable was chosen as part of a knowledge-augmented production function. AI patent applications are the major explanatory variable of interest, since they quantify the change in a firm's knowledge stock in the field of AI.

The primary focus in this Thesis is the influence of AI on labour productivity. Therefore, the econometric model used in the estimation of the data takes the following form,

$$Y_{it} = \alpha_i L^{\beta}{}_{it} C^{\gamma}{}_{it} K^{\delta}{}_{it}\, e^{\sigma_{it}} \tag{1}$$

Here, Y_{it}, L_{it}, C_{it}, and K_{it} represent the output, labour input, physical capital stock, and

knowledge stock, respectively. The parameters β, γ and δ denote the elasticity of labour,

physical capital and the knowledge stock, respectively. The constant term α_i is a firm-specific and time-invariant efficiency parameter. The parameter σ_{it} represents a time-variant entity-related efficiency parameter.

Applying log on both sides of the equation we get:

$$\text{Log}\, Y_{it} = \text{Log}\,(\alpha L^{\beta}_{it} C^{\gamma}_{it} K^{\delta}_{it}\, e^{\sigma_{it}}) \qquad (2)$$

Or,

$$\text{Log}\, Y_{it} = \text{Log}\alpha + \beta\ \ \text{Log}L_{it} + \gamma \text{Log}C_{it} + \delta \text{Log}K_{it} \qquad (3)$$

Dividing both sides of the equation by labor and differentiating the resulting equation in two consecutive periods so as to drop out the paraemter α, leads to the following estimating equation:

$$p_{it} = (1 + \boldsymbol{\theta})p_{it-1} + (\beta - 1)\Delta l_{it} + \gamma\Delta c_{it} + \delta\Delta k_{it} + \mu_i + \varepsilon_{it} \qquad (4)$$

Where p_{it} represents labor productivity, Δl_{it} is the growth in labor input, Δc_{it} is growth in fixed capital and Δk_{it} is the change in knowledge stock. The parameter μ_i denotes the idiosyncratic individual and time-invariant firm's fixed effect, while ε_{it} is the usual error term.

CHAPTER 6: DATA ANALYSIS

The goal of this chapter is to present the findings of the empirical study (section 6.1). The analysis will then discuss the results and present the interpretations of the findings.

6.1. Empirical Results

The model consists of a balanced panel on data on firms from three different regions, by year for 2010-2020. The dataset is termed "balanced" as there are no missing values within the dataset.

For terms of simplicity, only the following columns provided by the dataset will be used in the further analysis:

- *Region*: This column represents the three different regions in which the firms operate.
- *Firm*: The column Firm suggests the name of the observed firm.
- *Year*: This column documents the collected data between 2010 and 2020.
- *Produc*: Produc is the dependent variable and is represented as the labour productivity.
- *Labour*: Labour is IV and represents the number of employees.
- *AIPat*: Pat is IV and includes the number of AI-related patents.
- *nonAIpat*: nonAIpat is IV and represents the number of non AI-related patents
- *Invest*: Invest is IV and includes total investments in R&D.
- *Asset*: Asset is IV and represents total fixed assets within the firm.

The research question is then: *How does the introduction of AI related innovations within the company influence labor productivity?*

The empirical model is tested in STATA with the aim to obtain significant results that explain the relationship among the independent variables and the dependent variable.

In STATA, the *.describe* command portrays general information of variables listed after the command. With the ambition to create numeric values for the *firm* and *region* variables, the following function has been used:

.egen firmcode = group (firm)

.egen regionID = group (region)

.egen yearID = group (year)

Description of variables

name	Varlab
region	Region
Firm	Firm name
Year	Year
Produc	Labour productivity
Labour	Number of employees
AIpat	AI-related patents
nonAIpat	Non AI-related patents
Invest	R&D investment
Turnover	Physical Capital Stock
Firmcode	group(firm)
regionID	group(region)

The *.summary* command provides descriptive statistics. It portrays the mean, standard deviation, minimum, and maximum of the variables listed. Accordingly, the output suggests that the thirty three firms are coded from 1 to 33 and the time periods are set from 1 through 11. The three regions covered in the analysis are set from 1 to 3.

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
regionID	363	2.091	.831	1	3
firmcode	363	17	9.535	1	33
yearID	363	6	3.167	1	11
Lproduc	363	-.806	1.159	-6.063	1.552
Llabour	363	4.592	1.204	.704	7.169
lAIpat	363	4.721	.428	3.434	5.969
lnonAIpat	363	-.324	.425	-1.839	.789
Linvest	363	2.316	1.823	-2.056	6.588
Lturnover	363	1.495	1.297	-2.244	5.052

The analysis begins by performing pooled OLS. As stated in Chapter 4, certain conditions for pooled OLS need to be fulfilled. If assumption (2) exogeneity or (3a) homoscedasticity and (3b) non-autocorrelation (or both) are violated, then the FE or RE models are likely more appropriate. Exogeneity can be tested with the use of the Hausman Test, which is why the analysis will first attempt to prove assumption (3). Homoscedasticity and non-autocorrelation can be tested with a variety of statistical tests. The analysis will perform the *White test* and *Breusch-Pagan test* to identify heteroscedasticity. Non-autocorrelation will be tested with the *Durbin-Watson test*.

Linear regression

lproduc	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Llabour	-.448	.046	-9.71	0	-.538	-.357	***
lAIpat	.692	.118	5.85	0	.46	.924	***
lnonAIpat	.438	.119	3.67	0	.203	.673	***
Linvest	.388	.033	11.83	0	.324	.453	***
Lturnover	.272	.049	5.54	0	-.368	-.175	***
Constant	-2.37	.587	-4.04	0	-3.524	-1.215	***

Mean dependent var	-0.806	SD dependent var	1.159
R-squared	0.408	Number of obs	363
F-test	49.300	Prob > F	0.000
Akaike crit. (AIC)	957.576	Bayesian crit. (BIC)	980.942

*** *p<.01,* ** *p<.05,* * *p<.1*

The output consists of several important pieces of information. The R^2 value ("R-squared") indicates the proportion of the variance in the dependent variable that can be explained by the independent variable (Gujarati, 2006). In this model, the independent variables explain 40.8% of the variance in labour productivity. This model estimates a total of 363 observations. In addition, the F-statistic value of 49.3 indicates that the predictors are significantly related to the response variable.

The analysis of the results implies that the model is significant. The statistical significance of the regression model (" Prob > F") is the p-value of the model. It tests whether R^2 differs from 0 (Greene, 2008). The p-value lower than 0.05 shows a statistically significant relationship between X and Y. Two-tail p-values test the hypothesis that each coefficient diverges from 0. A p-value less than 0.05 rejects the null hypothesis. For the purpose of the model estimation, a significance level of 95% has been chosen. The model experiences a statistically significant relationship between the independent variables and the labour productivity.

The t-values are obtained through the division of the coefficients by the corresponding standard errors. The t-values indicate the importance of a particular variable in the observed model. Here, all variables besides labour indicate importance for the dependent variable. A t-value greater than

1.96 (at the 0.05 level of confidence) rejects the null hypothesis that the coefficient differs from zero. The coefficient column indicates the relationship between the independent variables and (Y).

The model suggests a negative relationship between the number of employees and labour productivity. When the number of employees experiences a 1% fall (ceteris paribus), the labour productivity increases by 0.448%. Conversely, the number of AI-related patents, total asset turnover, and R&D investments indicate a positive relationship with total labour productivity.

In STATA, the function: rvfplot, yline(0) draws a scatterplot between residuals and predicted values. The variance in the residuals should be homoscedastic, which is why there should not exist any pattern when plotting residuals and predicted values in a chart. Stock and Watson argue that, "The error term [e] is homoscedastic if the variance of the conditional distribution of $[e_i]$ given $X_i[\mathrm{var}(e_i|X_i)]$, is constant for $i=1\ldots n$, and in particular does not depend on x; otherwise, the error term is heteroskedastic" (2003). This implies that there should not be any traces of pattern-like behavior of the residuals in a well-fitted model. The figure below plots the relationship between the residuals and the fitted values in the model.

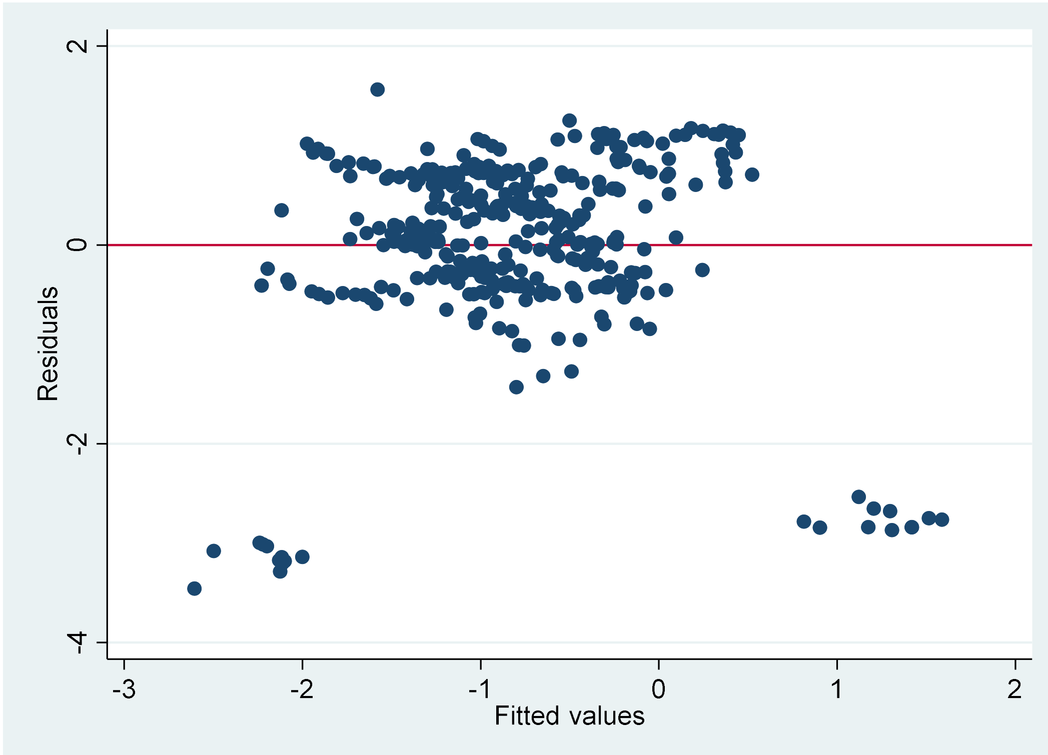

Figure 5 Residuals plot for Heteroskedasticity

The plotted data points spread out, which is an indicator for growing variance and therefore, for heteroskedasticity. This might be an indicator of an assumption violation. However, the analysis will provide formal statistical estimations with the White- and the Breusch-Pagan-Test.

The analysis goes on to conduct the Breusch-Pagan test in order to identify heteroscedasticity in the model. Heteroscedasticity implies that the error variance has non-constant variance. The null hypothesis suggests that the residuals are homoscedastic. In other words, when the errors have constant variance, they are labeled as homoscedastic. In essence, the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity tests for,

- H_0: Constant variance, against
- H_1: Heteroscedasticity

The results from the Breusch-Pagan test are summarized as follows:

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of lproduc

H0: Constant variance

chi2(1) = 4.72

Prob > chi2 = 0.0298

The Prob > chi2 is 0.0298 and does not exceed 0.05. This suggests heteroscedasticity, i.e. the data observed is not at liberty to provide a sufficiently accurate estimate of the effect of X on Y. This could be due to a sample size issue or presence of noise in the data. Additionally, it might indicate that the effect of X on Y is small. The Breusch-Pagan tests for each variable separately.

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of llabour

H0: Constant variance

chi2(1) = 0.07

Prob > chi2 = 0.7955

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of lAIpat

H0: Constant variance

chi2(1) = 18.65

Prob > chi2 = 0.000

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of lnonAIpat

H0: Constant variance

chi2(1) = 6.64

Prob > chi2 = 0.0100

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of lturnover

H0: Constant variance

chi2(1) = 21.57

Prob > chi2 = 0.0000

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of linvest

H0: Constant variance

chi2(1) = 10.31

Prob > chi2 = 0.0013

The findings indicate that all variables besides the number of employees are the source of heteroscedasticity. A p-Value < 0.05 indicates that the null hypothesis can be rejected and therefore heteroscedasticity exists.

The White Test for heteroscedasticity is then performed. In fact, the White Test is a special case of the Breusch-Pagan Test as it enables for the X variables to have a nonlinear and interactive effect on the error. The results are as follows:

White's test
H_0: Homoscedasticity
Ha: Unrestricted heteroskedasticity
chi2(14) = 212.73
Prob > chi2 = 0.0000

Here, Prob > chi2 = 0.000. At the significance level of 0.05, it rejects the null hypothesis of constant variance. Once again, the findings indicate that there is heteroscedasticity in the residuals.

Furthermore, The Cameron-Trivedi decomposition displays tests for heteroscedasticity, skewness and kurtosis. The obtained estimations are summarized below. They conform to the Breusch-Pagan test and the White test and imply heteroscedasticity. Similar to the previous results, here too Prob > chi2 = 0.000. The null hypothesis of constant variance can thus be rejected at the 5% level of significance.

Cameron & Trivedi's decomposition of IM-test

Source	chi2	Df	p
Heteroskedasticity	236.660	14	0.000
Skewness	41.420	4	0.000
Kurtosis	29.300	1	0.000
Total	307.390	19	0.000

Therefore, the first assumption (homoscedasticity) has been violated.

The presence of multicollinearity is then examined using the STATA command *vif* and the results are presented below.

Variance inflation factor

	VIF	1/VIF
lturnover	1.821	.549
linvest	1.61	.621
llabour	1.382	.723
lnonAIpat	1.155	.866
lAIpat	1.151	.869
Mean VIF	1.424	.

The following values indicate high correlation and cause for concern:

- Vif > 10, or
- 1/Vif < 0.10

In the model, however, the mean *vif* is 1.424 and suggests no multicollinearity among the observed variables.

Next, the Durbin-Watson statistics is performed to check for autocorrelation. The Durbin-Watson statistics ranges from one to four, with a value equal to 2 suggesting no autocorrelation present in the sample (Hsiao, 2003). Values from 0 to less than 2 indicate positive autocorrelation. In fact, the nearer to zero the value the higher the correlation. Values from 2 to 4 point to negative autocorrelation. The outcome of the DW statistic is:

Durbin-Watson d-statistic (6, 363) = 0.2406842

This indicates negative autocorrelation. Such outcome suggests that assumption (3b) is also violated. Therefore, a FE or RE model will be more suitable.

In order to use panel data commands in Stata, the cross-sectional (*firm*) and time-series (*year*) variables need to be declared. The *.xtset* command is followed by cross-sectional and time-series variables in order.

Panel variable: firmcode (strongly balanced)
Time variable: yearID, 1 to 11
Delta: 1 unit

In this case *firmcode* represents the entities and *yearID* represents the time variable. The note *strongly balanced* implies that all firms have data for all periods of time. If, for instance, a certain firm does not have data for a particular year then the data is unbalanced.

The *.xtsum* command provides summary statistics of the data. The total number of observations is 363 since there are 33 entities and 11 time periods. The overall mean (-0.806) and standard deviation (1.159) of labour productivity below are identical to the ones in the *.sum* output above.

Variable	Mean	Std.	dev.	Min	Max		Observations
regionID overall	2.091	0.831	1	3	N	=	363
between	0.843	1	3	n	=	33	
within	0	2.091	2.091	T	=	11	
firmcode overall	17	9.535	1	33	N	=	363
between	9.670	1	33	n	=	33	
within	0	17	17	T	=	11	
yearID overall	6	3.167	1	11	N	=	363
between	0	6	6	n	=	33	
within	3.167	1	11	T	=	11	
lproduc overall	-0.806	1.159	-6.063	1.552	N	=	363
between	1.146	-5.367	1.311	n	=	33	
within	0.256	-2.253	-0.083	T	=	11	
llabour overall	4.592	1.204	0.704	7.169	N	=	363
between	1.160	1.343	6.357	n	=	33	
within	0.374	2.676	6.327	T	=	11	

lAIpat overall	4.721	0.428	3.434	5.969	N	=	363
between	0.326	4.144	5.403	n	=	33	
within	0.283	3.542	5.465	T	=	11	
lnonAIpat overall	-0.324	0.425	-1.839	0.789	N	=	363
between	0.387	-1.074	0.583	n	=	33	
within	0.188	-1.265	0.695	T	=	11	
lturnover overall	1.495	1.297	-2.244	5.052	N	=	363
between	1.194	-0.499	4.484	n	=	33	
within	0.544	-0.687	3.294	T	=	11	
linvest overall	2.316	1.823	-2.056	6.588	N	=	363
between	1.773	-1.434	6.281	n	=	33	
within	0.516	0.195	4.483	T	=	11	

Stata lists three different types of statistics: overall, between, and within. *Overall* statistics are ordinary statistics based on 363 observations. It estimates the variation over time and entities. The *between* statistics are estimated on the basis of summary statistics of 33 firms (cross-sections) regardless of time period. In essence, the *between* variation measures the variation among the entities. The *within* statistics are calculated as a summary statistics of the 11 time periods regardless of the firm. This is the variation within the entities over time.

In the panel data set up, *firm* has only between (9.670) and not within (0) variation. In contrast, *year* has only within (3.167) and no between variation (0). The standard deviation estimations indicate that there is more variation for the labour productivity rate between firms (1.146) than within firms (0.256).

Next, the STATA command *.xtreg, fe* is used to obtain fixed effects model estimations:

Regression results

lproduc	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
llabour	-.678	.045	-15.22	0	-.765	-.59	***
lAIpat	.447	.037	9.25	0	.273	.421	***
lnonAIpat	.343	.051	6.68	0	.242	.444	***
lturnover	.148	.031	4.82	0	.088	.209	***
linvest	.358	.04	8.94	0	.279	.437	***
Constant	-.272	.234	-1.16	.246	-.732	.189	

Mean dependent var	-0.806	SD dependent var	1.159
R-squared	0.586	Number of obs	363
F-test	92.155	Prob > F	0.000
Akaike crit. (AIC)	-268.832	Bayesian crit. (BIC)	-245.466

**** p<.01, ** p<.05, * p<.1*

The analysis of the results implies that the multiple regression model is significant. The Prob>F is 0.000, which is less than 0.05 (for a 95% confidence). The coefficients of the regressors indicate how much Y changes when X increases one percentage unit. Here, all variables indicate statistical significance. What is more, the t-statistics has to be higher than 1.96 (for a 95% confidence) in order to reject the null hypothesis that each coefficient is different than zero. In fact, the higher the t-value the greater the significance of the variable. In the model, all variables except from labour exhibit high t-values.

In STATA, the command *.xtreg, re* generates the random effects model estimations:

Regression results

lproduc	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
llabour	-.66	.043	-15.48	0	-.744	-.576	***
lAIpat	.453	.037	9.44	0	.28	.426	***
lnonAIpat	.341	.051	6.66	0	.241	.441	***
lturnover	.138	.03	4.55	0	.078	.197	***
linvest	.352	.038	9.31	0	.278	.426	***
Constant	-.353	.283	-1.25	.212	-.907	.201	

Mean dependent var	-0.806	SD dependent var	1.159
Overall r-squared	0.298	Number of obs	363
Chi-square	467.728	Prob > chi2	0.000
R-squared within	0.586	R-squared between	0.285

**** p<.01, ** p<.05, * p<.1*

Again, the model is significant as stated by Prob>chi2, which is less than 0.05 (for a 95% confidence). All variables indicate statistical significance and have p-values less than 0.05. Additionally, they indicate high t-values.

Both the FE and RE exhibit similar results. Therefore, the Hausman test is performed to decide the preferred model:

Hausman (1978) specification test

	Coef.
Chi-square test value	2.235
P-value	.693

The p-value > 0.05 fails to reject the H_0 that FE and RE coefficients are not significantly different from each other, implying that the random effect model is the appropriate model. To recall, the random effects estimator is used whenever the differences across the entities possess some influence on the dependent variable. That is to say, the differences across the firms have potential influence on the labour productivity.

Since, the Hausman Test fails to reject H_0 and the chosen method is random effect, the analysis proceeds with the Lagrange Multiplier Test to determine whether the Random effect is still preferred over the simple OLS regression. In STATA, this is tested using the *.xttest0* command.

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

        lproduc[firmcode,t] = Xb + u[firmcode] + e[firmcode,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                 lproduc |   1.342841       1.15881
                       e |   .0322298      .1795267
                       u |   .9702115      .9849931

        Test: Var(u) = 0
                             chibar2(01) =  1663.82
                          Prob > chibar2 =   0.0000
```

Figure 6 LM Test

In essence, the LM test suggests whether a random effects regression or a simple OLS regression is more appropriate. The null hypothesis implies that the variances across entities are zero and there is no significant difference across entities (i.e. no panel effect). However, Prob>chibar2 is less than 0.05 and, therefore, the null hypothesis is rejected, concluding that the random effects model is more suitable. That is, there is evidence of significant differences among the cross-sections (firms).

6.2. Summary

The scope of this Thesis is to observe the AI patent strategy at the firm-level. The estimations provide an econometric analysis that examines the interrelation between the firm labour productivity and the relevant independent variables. Throughout the analysis, greater focus has been allocated to the number of AI-related patents and their effect on the productivity rate. The empirical results suggest a direct relationship between the labour productivity and the number of AI-related patents.

The investigated dependencies and the results generated that are according expectations are as follows:

1) The number of AI-related patents has a significant positive effect on labor productivity. This implies that the introduction of AI innovations within the firm leads to an increased labour productivity. That is, the more resources the firm devotes to AI, the greater the labour productivity and potentially the higher the economic value of the firm.

2) The number of non AI-related patents also has a significant positive impact on labour productivity. However, its effect is lower when compared to that of AI-related patents. That is, AI-related innovations have greater impact on labour productivity growth.

3) Given the positive relationship among physical capital stock and productivity, it appears that investment in manufacturing facilities, particularly in information and communication technologies, can boost labour productivity within the firm and consequently overall industry productivity.

4) Based on the results, there is positive effect of R&D expenditure on labour productivity. Therefore, encouraging firms to increase R&D investments can increase labor productivity. The relationship emphasizes the need of firms to focus more on building and improving R&D units.

5) There is a negative relationship among the number of employees and labour productivity. That is, the number of employees decreases as productivity increases. This effect could be explained with both the productivity and displacement effects discussed in the previous chapters.

CHAPTER 7: CONCLUSION

The conclusion will encapsulate a summary of the thesis, and the thesis' contribution to new knowledge, answer the research question and suggest possible avenues for further research.

7.1. Conclusions of the Research Study

The relationship between innovation and labour productivity is rather complicated: technological development has both direct and indirect consequences. As the continuous discussion over the influence of technological advancements in AI on labour productivity yields conflicting forecasts, empirical research might provide valuable insights (Agrawal et al. 2019a, b; Brynjolfsson et al. 2019; Cockburn et al. 2019). Despite this, only a few articles have looked into the effectiveness of AI and robots on labour productivity (Graetz and Micheals 2018; Alderucci et al. 2020). However, not for a moment did these works attempt to quantify the impact of AI on labour productivity within the firm while accounting for a causal-effect relationship.

This Thesis provides a careful analysis of the impact of AI on labour productivity. It aims to contribute to addressing this gap in the literature by evaluating the impact of AI on labour productivity within the firm. Therefore, this Thesis attempts to answer the research question,

- *How does the introduction of AI related innovations within the company influence labor productivity?*

To do so, the Thesis employs a database of AI patenting firms over a 10-year period. It tests for this possible direct relationship using a sample of global firms that filed a minimum of one AI-related patent between 2010 and 2020.

Consistent with results generated by antecedent literature, this Thesis finds a significant labour-friendly effect of investments in R&D, which are in large associated with the introduction of innovative AI-related products. The Thesis concludes that the number of AI-related patents leads to a higher labour productivity within the firm. Both models in the analysis exhibit similar results and both indicate that there is a positive significant relationship between the total number of patents (AI- and non AI-related) and the labour productivity. However, the coefficient of AI-related patents is higher, thus, indicating higher impact on productivity. That is, the introduction of AI-related innovations within the firm has a higher effect on labour productivity than other non AI-related innovations.

The results further indicate a positive relationship among physical capital stock and R&D expenditures and labour productivity. That is to say, the more capital the firm has the greater the labour productivity. Having more physical stock implies greater quality of materials and labour. In turn, the effort required to produce output efficiently declines. What is more, higher R&D expenditures signify higher labour productivity within the firm.

7.2. Contribution to Research

This Thesis contributes to research by investigating various study gaps and analyzing research findings concerning the introduction of AI-related innovations within the firm. Accordingly, this Thesis develops an econometric model to study the impact of AI on labor productivity. Statistically significant evidence provides further information regarding the impact of AI on labour productivity. Significant results provide solid statistical inference that answers the hypotheses based on assumptions affected by past research and ideas. As a result, the research question has been answered.

7.3. Further Research Suggestions

This Thesis contains a variety of limitations that point to future research directions. The model includes solely firms that have filed a minimum of one AI-related patent from 2010 to 2020. Since patents in the field of AI serve as an indication of technological competence, such sample might be selected as the most desirable and, thus, the findings may be biased by sample selection. Evaluating the facts on a larger sample that includes firms that never patent along with firms that solely patent in non-AI related disciplines is an obvious potential for additional study.

Another constraint shared by most AI-related scientific investigations is the deficiency of a specific and globally agreed definition of AI. As this research is limited only to current AI definitions, there is reasonable need to extend this study to a more comprehensive definition of AI to generalize the findings to the context of automation and robotics. The author further proposes conducting a qualitative study so as to deepen the research process to a greater extent and provide a better understanding of the matter.

What is more, AI patents offer the significant benefit of being available on a global scale across nations and time, however, they do not enable for the entire depth of new breakthroughs in AI to be captured. As this model is based on AI patent applications, it excludes ideas covered by other formal and informal intellectual property rights.

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