AMERICAN UNIVERSITY OF BEIRUT

ARTIFICIAL INTELLIGENCE AND EMPLOYMENT IN THE OECD: A PANEL DATA ANALYSIS

by
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A thesis
submitted in partial fulfillment of the requirements
for the degree of Master of Arts
to the Department of Economics
of the Faculty of Arts and Sciences
at the American University of Beirut

Beirut, Lebanon
April 2024

AMERICAN UNIVERSITY OF BEIRUT

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Date of thesis defense: April 24, 2025

ACKNOWLEDGEMENTS

To my mother and father, who raised me with a love for knowledge, discipline, and humility, this achievement is yours.

To my siblings, thank you for your patience, your support through every step, and for always looking up to me.

To my friends, who showered me with care, motivation, and advice along the way, thank you.

To my advisor, Dr. Nadine Yamout—thank you for believing in my ideas, helping me grow and learn, and always being there for any concern. This work would not have been possible without your calm and reassuring supervision.

To my committee members, Dr. Nisreen Salti and Dr. Ali Abboud, thank you for your insightful and constructive feedback. I have learned so much from you both.

To my colleagues, who stood by me through every challenge, thank you for your constant support, your offers of help, and for making this journey so much more enjoyable.

To my university, AUB—thank you for this wonderful experience. I witnessed growth and joy every single day.

ABSTRACT
OF THE THESIS OF

Samira Nabil Ahmad for Master of Arts
Major: Economics

Title: Artificial Intelligence and Employment in the OECD: a Panel Data Analysis

This thesis examines the relationship between artificial intelligence (AI) and employment across 35 OECD countries from 2013 to 2022 using panel data analysis. By employing ordinary least squares (OLS) and fixed effects regression models, the study explores how AI, proxied through AI patent activity and private investment, affects total employment, with a focus on demographic (gender and age) and sectoral heterogeneity. The results illustrate a positive association between AI and employment, consistent with the labor augmentation theory. Employment growth was observed across all demographic groups and economic sectors. However, the employment gains were mostly concentrated among the middle-aged workers and in the service sector. While evidence indicates that AI can act as a complement to human labor and create new jobs, the analysis is constrained by data limitations and potential endogeneity concerns. The findings emphasize the importance of inclusive, forward-looking policies that promote skill development and equitable AI adoption across sectors and groups.

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CHAPTER 1

INTRODUCTION

In recent years, the Fourth Industrial Revolution has concerned people in all sectors. This industrial revolution includes a new generation of information technology that illustrates a new method of storing, transmitting, and understanding information, which includes artificial intelligence, 5G, and cloud computing. Artificial intelligence (AI) is the study and development of a computer or computer-controlled robot ("intelligent machine") that can perform cognitive and intellectual tasks, traditionally associated with humans.[1]. It started mainly as a tool that could analyze data; however, it has been significantly expanding, now creating information that could even surpass human intelligence in quality and accuracy, especially with the recent emergence of generative AI (GenAI). Generative AI is a new type of technology that is based on Large Language Models (LLMs), which allows the production of texts, images, videos, and other forms of data with just one click and with minimal time. One very well-known illustration of this mind-blowing technology is ChatGPT, which is a generative AI chatbot released by OpenAI in 2022. Just two months after its launch on November 30, 2022, ChatGPT witnessed exponential growth, with an estimated 100 million additional users monthly. Generative AI has captured significant attention from both industry and academia due to its transformative potential across sectors. In Figure 1, the global investment in generative AI dramatically surged from under $1 billion in 2019 to over $25 billion in 2023. This illustrates the large global appeal towards generative AI and highly predicts future growth in technology.

[1] See Russell & Norvig (2009), Neapolitan & Jiang (2018), and Agarwal et al. (2019).

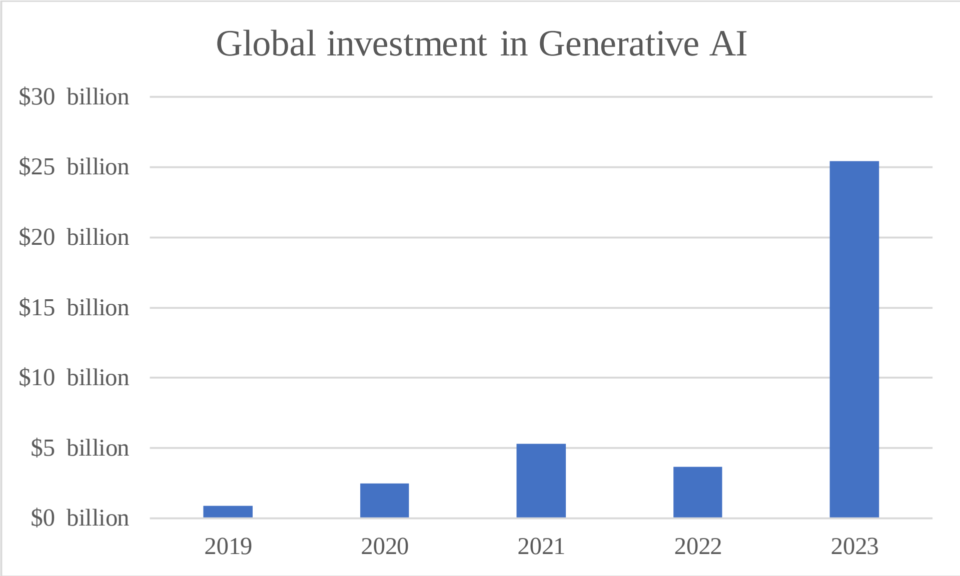

Figure 1 - Global investment in generative AI

Note. Data from Quid via AI Index Report (2025); U.S. Bureau of Labor Statistics (2025) – with major processing by Our World in Data

The evolution of AI came with a lot of promises, as people anticipate rapid and unprecedented productivity growth and new employment opportunities. Goldman Sachs (2023) has expected a 7% increase in global GDP, which is equal to $7 trillion, as well as a 1.5% yearly increase in productivity growth in the U.S. over 10 years. Similarly, McKinsey Global Institute (2023) predicts that generative AI will add productivity gains to the global economy as large as $17.1 to $25.6 trillion, in addition to the estimates of economic growth brought by work automation. They forecast that over the next 10 years, AI and other technologies could bring up to a 1.5- 3.4 percentage point rise in average annual GDP growth in advanced economies. However, a recent article by The Economist (2024) shows that AI has had almost no economic impact, as productivity growth remains slow. The reason for that is that only a small number of firms have adopted the usage of AI (or ChatGPT), apart from short queries. According to the U.S. Census Bureau's Business Trends and Outlook Survey (BTOS), as of

November 2023, only 3.8% of U.S. businesses reported using artificial intelligence (AI) to produce goods and services. This figure increased to 6.1% by November 2024, indicating a gradual rise in AI adoption among businesses. Those numbers are still too low, however, to have a significant impact.

One of the main concerns people have regarding the usage of AI is its effect on their jobs, with many people predicting that AI will replace them and leave a lot of them jobless. What differentiates AI indeed is its cognitive abilities, but there are different opinions regarding its impact on the labor market. On the one hand, some expect a positive overall impact of increased productivity, a fact that will increase the demand for labor and thus employment and wages. In addition, there will be numerous jobs created with the growth of the AI industry, especially tech-related jobs. On the other hand, a large portion of people see a negative impact. A recent Gallup poll illustrated that 75% of U.S. adults believe AI will decrease job opportunities (Marken 2023). While some believe that AI will have a job displacement effect, others believe that AI will have a job reinstatement effect, and others still believe that AI will have a combined effect, including both the positive and negative. The interest of this thesis is to examine the overall effect of AI on the job market, and specifically in the OECD[2].

Thus, our research questions are: Does the integration of AI impact employment in the OECD? If so, what is the direction and magnitude of this impact? Does this impact vary by gender or age? Does the impact on employment differ across sectors?

Using simple OLS regression and fixed effects models, this paper aims to analyze the effect of AI adoption on employment in the OECD. This thesis starts with a

[2] The Organization for Economic Co-operation and Development is an intergovernmental organization with 38 member countries, founded in 1961 to stimulate economic progress and world trade.

literature review, moving to illustrate the specifics of its model and the results. After discussing the results, the thesis provides policy recommendations.

CHAPTER 2

LITERATURE REVIEW

With every technological advancement, there come questions related to the future of the labor market. Looking back at the technological evolutions in the twentieth century, Keynes (1930) saw that the new technology would lead to an increase in per capita income, but it would contribute to widespread technological unemployment. Also pessimistic, the economic historian Robert Heilbroner (1965) believed that “as machines continue to invade society, duplicating greater and greater numbers of social tasks, it is human labor itself—at least, as we now think of ‘labor’—that is gradually rendered redundant”. Similarly, Wassily Leontief believed that “Labor will become less and less important.... More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job” (quoted in Curtis 1983, 8)

The development of artificial intelligence as a new way of dealing with information has raised questions about its implications on humans, as it could act as a competitor and even a threat to human intelligence. Specifically, there have been fears of AI taking over jobs, as the accelerated automation of tasks would make labor redundant (e.g., Brynjolfsson and McAfee 2014; Akst 2013; Autor 2015). Having said that, those fears are novel because this technology is recent; therefore, research is still preliminary, and it will take time to answer the broader question: Will AI replace us?

The literature on AI and employment reveals a complex and multifaceted relationship between the two. The first theory is the labor displacement theory: it argues that AI will take over humans' jobs and hence replace humans in the workplace. The basis of this theory says that AI and robotics will be responsible for tasks that were previously assigned to humans and therefore cause a powerful displacement effect (Acemoglu & Restrepo, 2018). This effect will not only cause a decrease in wages and labor demand, but also the share of labor in the national income (Acemoglu & Restrepo, 2018).

From a different angle, the labor augmentation theory believes that AI will act as a complement to human efforts and make them more productive, known as the productivity effect, which eventually will increase labor demand. The basis they argue from is that automation will cut the cost of output, increase capital accumulation, and deepen automation, all of which breed a rise in labor demand (Acemoglu & Restrepo, 2018).

2.1 Labor Displacement Theory

One of the early studies on automation is that of Frey and Osborne (2017), who created a methodology to estimate the computerization for 702 detailed occupations in the U.S. Their study estimates that 47% of the total employment in the U.S. faces a high risk of automation as close as the next decade or two. Low-skill workers would have to be reallocated to tasks that require creative and social skills, which won't be computerized. In response, Arnz et al. (2017) argue that automation risk assessments should focus on individual tasks rather than entire occupations. With that, they estimate that only about 9% of jobs are highly automatable.

Building on those concerns, Acemoglu and Restrepo (2018-2020) argue, using a theoretical task-based framework, that artificial intelligence could create new tasks and increase labor demand by increasing productivity and increasing the demand for products (reinstatement effect), counterbalancing the labor displacement effect;

however, the reinstatement effect is minimal compared to the displacement effect. Furthermore, using empirical evidence in the U.S., Acegemoglu and Restrepo (2019a) show that the slowdown in employment growth over the last three decades has been rooted in the increasing displacement effect, weaker reinstatement effect (mostly in manufacturing), in addition to the slower productivity effect over the last decades.

Looking at the types of jobs most affected by automation, Acemoglu and Restrepo (2020) find that the introduction of industrial robots in U.S. manufacturing led to reduced employment and wages, especially in blue-collar occupations. Webb (2019) demonstrates that artificial intelligence is likely to affect different types of occupations, with the highly skilled, highly educated, and older workers being exposed the most.

With empirical evidence, Acemoglu et al. (2022) use online job vacancy data and firm-level surveys to reveal that AI adoption often leads to a significant reduction in both employment and wages. Specifically, they estimate that each additional robot per 1,000 workers led to a decrease in the employment-to-population ratio by 0.2 to 0.3 percentage points. The negative impact of automation was mostly witnessed among workers in routine manual occupations, especially in manufacturing, as well as among young and less educated workers. The literature thus suggests that AI has displacement effects that reach workers of different occupations and skill levels.

2.2 Labor Augmentation Theory

In contrast to labor displacement theory, a growing body of research highlights that the implementation of artificial intelligence can augment human labor by stimulating productivity and creating new types of tasks. Brynjolfsson and McAfee (2014) believe that technological advances, including AI, often boost worker productivity instead of replacing it. Their concept of "second age machine" differs from the first (industrial machine), as it involves cognitive abilities rather than physical abilities. This makes it an adequate tool to complement humans' efforts and not replace them. They thus suggest that AI can create new tasks and opportunities, reshaping the labor market in ways that benefit both firms and employees.

According to Autor (2015), technology has displaced tasks, not entire jobs; the same is true of artificial intelligence. He argues that automation complements human labor by taking over routine tasks and creating non-routine creative tasks that require human intelligence (creativity, social skills, and leadership); this means that automation transforms the nature of work rather than eliminating it.

Coming with a novel concept, Agrawal, Gans, and Goldfarb (2019) see artificial intelligence as a prediction technology that focuses on reducing the cost of forecasting future events or behaviors. They argue that AI does not replace human labor entirely but shifts the skill focus on judgment, decision-making, and creativity, skills that complement the enhanced prediction. In the following study, however, Agrawal et al. (2024) highlights that the overall impact of AI adoption on the labor market heavily relies on supporting investments, such as reskilling workers and reorganizing workflows. Without those systemic changes, the full productivity gains of AI may not be realized, and the displacement risks could even increase. Together, these studies suggest that without the presence of strategic adaptation by firms and workers, the augmenting potential of AI cannot be materialized.

Furendal and Jebari (2023) argue that artificial intelligence can be labor augmenting or labor-stunting. Both scenarios increase productivity, but the former is more desirable as it saves labor from mass unemployment, promoting human-machine cooperation. They expand their argument by emphasizing that the implementation of AI carries two outcomes: it either enhances decision making and creativity, or it could replace human judgment, limiting future labor market opportunities. They thus stress that the outcome depends on effective organizational behavior, updated educational systems, and efficient policy choices.

While the existing literature provides valuable insights into the potential impacts of AI on the labor market, most studies focus on specific tasks or specific sectors without looking at employment on an aggregate level. Also, studies are done on a unique country only, and mostly the U.S. Hence, there comes the need for a study that includes cross-country analysis.

In this thesis, those gaps will be addressed by looking into the effect of AI on employment in OECD countries. Beyond that, the thesis will dig deeper by addressing the demographic (age and gender) and sector-related differences.

CHAPTER 3

DATA

The thesis uses a panel dataset for 35 OECD member countries[3] from the year 2013 to 2022, with the aim of analyzing the relationship between artificial Intelligence (AI) and employment.

3.1 Variables and Data Sources

The dataset is compiled from the Center for Security and Emerging Technology, the U.S. Bureau of Labor Statistics, and the OECD data explorer.

AI is a newly emerging participant in the economy, therefore, there is no single standardized variable used for AI across the literature. In our model, we use two separate variables:

1. Annual patent applications related to artificial intelligence (patents submitted in each country's patent office)
2. Annual private investment in artificial intelligence

Indicators for employment are grouped based on gender, age, and sector.

General control variables used are: Annual inflation rate (CPI), GDP Growth, and GDP per Capita.

The control variable for education is Population with tertiary education

The control variable for productivity is GDP per person employed.

[3] The 35 OECD countries are: The 35 countries are: Australia, Austria, Belgium, Canada, Switzerland, Colombia, Czechia, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Hungary, Iceland, Israel, Italy, Japan,Korea,Lithuania,Luxembourg,Latvia,Mexico,Netherlands,Norway, New Zealand, Poland, Portugal, Slovak Republic, Slovenia, Sweden, Turkiye, United States

The variables and data sources are grouped as follows:

Table 1 - Variables and data sources

Variable	Description	Source
AIPATENT	Annual patent applications related to artificial intelligence	Center for Security and Emerging Technology – processed by Our World in Data
INVAI	Annual private investment in artificial intelligence	Center for Security and Emerging Technology (2024), U.S. Bureau of Labor Statistics (2025) – processed by Our World in Data
EMPTOT	Number of the employed population	OECD Data Explorer
EMPMEN	Number of men employed	OECD Data Explorer
EMPWOM	Number of women employed	OECD Data Explorer
EMPIND	Employment in industry (without construction)	OECD Data Explorer
EMPMFG	Employment in manufacturing	OECD Data Explorer
EMPSRV	Employment in services	OECD Data Explorer
EMPAGR	Employment in agriculture, forestry, and fishing	OECD Data Explorer
INFL	Consumer Price Index	OECD Data Explorer
GDPGROWTH	Real GDP growth rate	OECD Data Explorer
GDPCAP	GDP per capita (current prices)	OECD Data Explorer

Variable	Description	Source
EDUTRY	Population with tertiary education	OECD Data Explorer
GDPEMP	GDP per person employed (labor productivity proxy)	OECD Data Explorer

All variables are harmonized across countries and years and transformed where necessary.

Missing data was handled via listwise deletion.

3.2 Descriptive Statistics

3.2.1: AI Patents

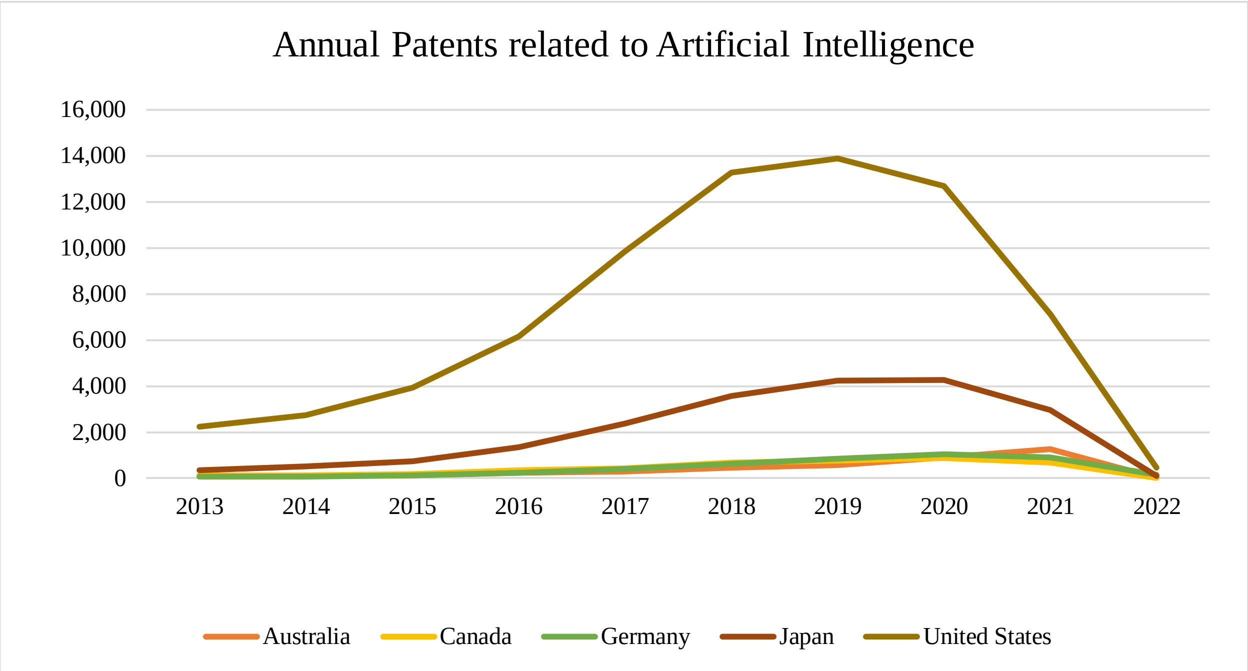

Figure 2 - Annual AI Patents Submitted in some OECD Countries

Note. Data from Center for Security and Emerging Technology (2025)

Figure 2 depicts the number of artificial intelligence-related patents in the five AI- innovation leading OECD countries. The United States is illustrated as a remarkably leading country in AI innovation. Between 2013 and 2019 the number of AI patents rose in all countries, with 2019 representing a peak. Nevertheless, data illustrated a steep fall in the number of patents after 2020, which could be caused by changes in research and development funding priorities or disruptions post-COVID-19. However, another possible explanation is that the drop in AI patents could be due to reporting lags in patent data, as there frequently exists a time lag between filing, reviewing, and publication. This suggests that the data does not necessarily represent a decline in AI innovation, but rather a lack of accurate and comprehensive data at the current time.

3.2.2: Average AI Patents

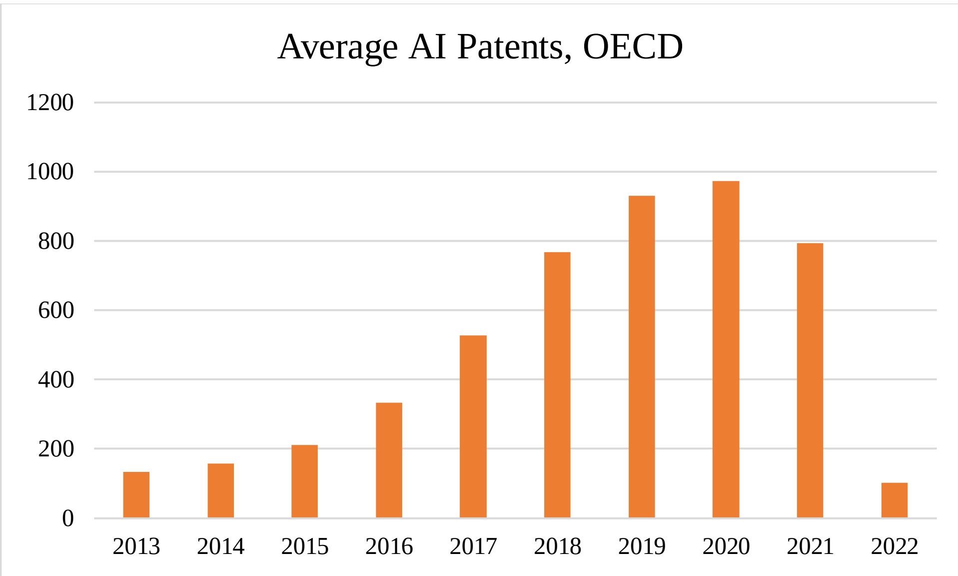

Figure 3 - Average submitted patents related to artificial intelligence in the OECD

Note. Data from Center for Security and Emerging Technology (2025)

3.2.3 AI Patents by Industry

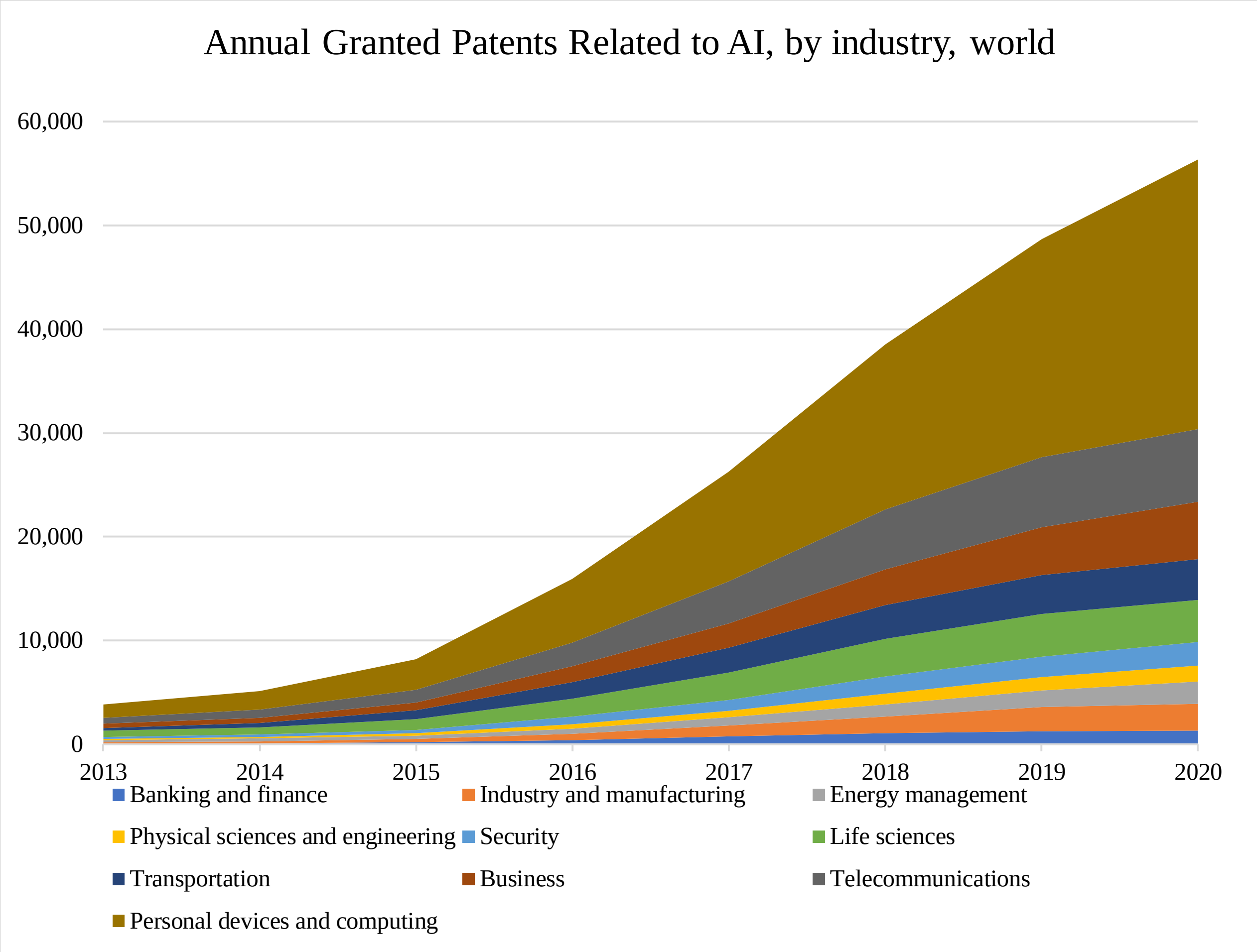

Figure 4 - Annual granted patents related to artificial intelligence, by industry, world

Note. Data from Center for Security and Emerging Technology (2025)

Figure 4 shows the growth of annual patents related to AI globally and across multiple industries in the period from 2013 to 2020. This number has increased dramatically, starting from just over 5,000 patents to nearly 60,000 patents in 2020, suggesting a worldwide concentration on innovation in AI. The highest number of AI patents was granted to personal devices and computing, followed by the telecommunications sector. This reflects that AI has been deeply integrated into communication technologies, such as 5G networks, natural language processing, virtual assistants, and intelligent communication systems.

Growth in AI patents is also witnessed in other sectors, such as Business, Security, Life Sciences and Manufacturing, a fact that reveals the versatility and benefit of AI usage across the sectors.

3.2.4 Private Investment in AI

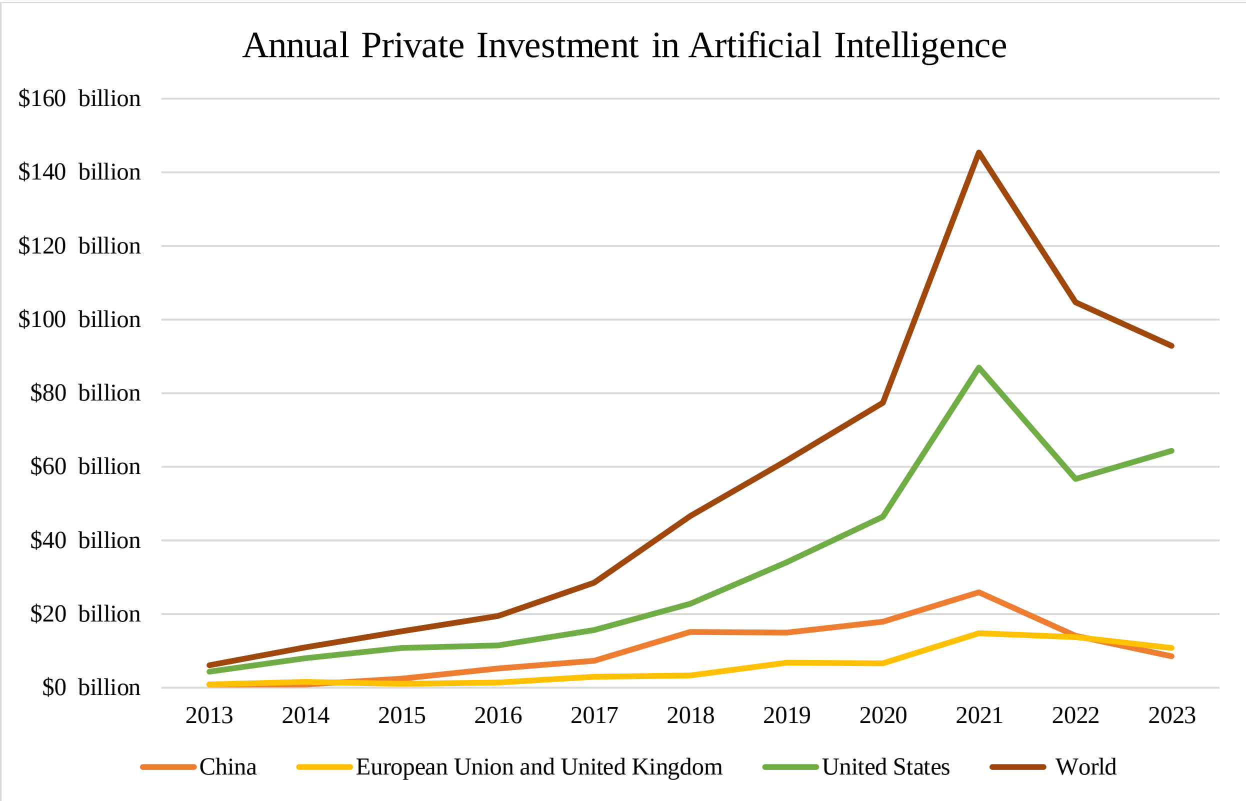

Figure 5 - Annual Private Investment in Artificial Intelligence

Note: Data from Center for Security and Emerging Technology (2025); U.S. Bureau of Labor Statistics (2025) – processed by Our World in Data

Figure 5 illustrates the trends in annual private investment in AI across multiple regions between 2013 and 2023. Investment in AI shows a significant increase starting from

2013, with the United States being the leading player. In almost all the regions, funding related to artificial intelligence reached a peak in 2021, with the United States reaching approximately $90 billion. Post-2021, the value of investment starts to drop, which suggests, similar to Figure 1, either a change in funding priorities or disruptions caused by the COVID-19 pandemic, or simply the lack of accurate data that shows that investment in AI is still high, if not increasing.

It can thus be inferred that at the current time, most of the global investment in AI is being performed by the United States, paving the way for the other countries.

3.2.5 Average Private Investment in AI

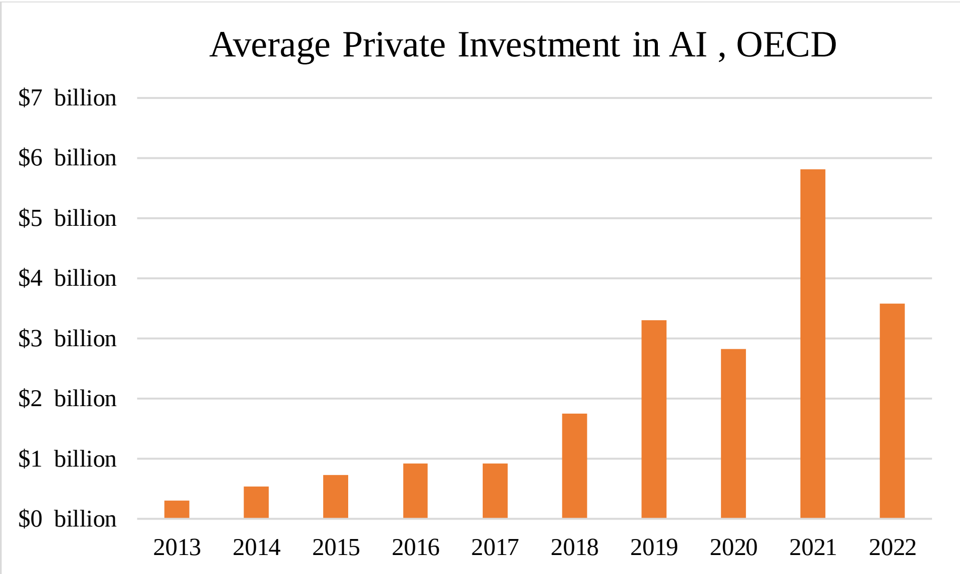

Figure 6 - Average private investment in artificial intelligence in the OECD

Note. Data from Center for Security and Emerging Technology (2025); U.S. Bureau of Labor Statistics (2025) – processed by Our World in Data

3.3 Summary Statistics

Table 2 - Summary Statistics

	Mean	SD	Units
EMPTOT	15032.92	24845.36	Thousand persons
EMPMEN	8422.25	13623.47	Thousand persons
EMPWOM	6796.89	11590.51	Thousand persons
EMPYTH	1736.36	3282.61	Thousand persons
EMPSNR	2457.39	4428.84	Thousand persons
EMPSRV	11965.82	21197.45	Thousand persons
EMPMFG	2146.69	3252.57	Thousand persons
EMPIND	3582.76	5304.33	Thousand persons
EMPAGR	813.004	1449.76	Thousand persons
AIPATENT	514.75	1845.75	Applications per year
INVAI	2.05e+09	1.16e+10	U.S. Dollars
INFL	2.67	4.35	Percent
GDPGROWTH	2.26	3.17	Percent
GDPCAP	43616.47	20073.02	U.S. Dollars
EDUTRY	42.41	10.91	Percent of 25–34-year-olds
GDPEMP	1.18	2.65	Percent per annum
Observations	494		

CHAPTER 4

METHODOLOGY

To analyze the relationship between artificial intelligence (AI) and labor market outcomes, we apply multiple linear regressions. To count for AI, two proxies are used: (1) Annual patent applications related to artificial intelligence (AIPATENT) and Annual private investment in artificial intelligence (INVAI).

The model tries to answer several questions:

1. Is there a visible relationship between the integration of AI and employment?
2. If there exists a relationship, what is the direction?
3. Where is this relationship most evident?

4.1 Empirical Model

We use an empirical model based on the data presented in the previous chapter.

The baseline specification is given by:

$$Y_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \delta_t + \epsilon_{it}$$

Where:

- Y_{it}: Employment indicator in country i at time t
- AI_{it}: Number of AI patents or Value of investment in AI
- X_{it} : Vector of control variables
- δ_t : Year fixed effects
- ϵ_{it}: Error term

Year fixed effects are included to remove any time-invariant characteristics.

4.2 Estimation Strategy:

Each employment variable is estimated using six different regressions – three for each AI proxy:

- Regression (1) is a simple OLS regression with the AI proxy (number of AI patents) being the only independent variable.
- Regression (2) is a simple OLS regression with the AI proxy being an independent variable, in addition to five control variables:
  - Inflation (INFL) influences real wages and firm behavior.
  - GDP Growth (GDPGROWTH) influences business cycles and hiring rates.
  - GDP per capita (GDPCAP): proxy for development stage.
  - Population with tertiary education (EDUTRY) affects labor adaptability to tech.
  - GDP per employee (GDPEMP) determines labor demand efficiency

- Regression (3) is a year-fixed effects regression, estimated using OLS. This accounts for time-specific global trends that could have an impact on employment in any country. It includes the same dependent and independent variables as regression (2).
- For the same employment indicator, regressions (1), (2) and (3) are repeated, but with the substitution of AIPATENTS for INVAI

To account for heteroskedasticity, robust standard errors are used in all regressions

CHAPTER 5

RESULTS

In this chapter, we present and analyze empirical findings on the relationship between artificial intelligence (AI) and employment across OECD countries in the period between 2013 and 2022. As discussed in the previous chapter, the methodology used is multiple regression models, with two proxies for AI innovation: AI patent applications and private investment in AI.

5.1 General Employment Effects

Table 3 - AI and Total Employment

VARIABLES	(1) EMPTOT	(2) EMPTOT	(3) EMPTOT	(4) EMPTOT	(5) EMPTOT	(6) EMPTOT
AIPATENT	10.43***	11.26***	11.54***			
	(1.288)	(1.239)	(0.671)			
INFL		345.3*	359.6		238.1**	495.7*
		(181.7)	(279.3)		(111.7)	(268.4)
GDPGROWTH		594.9	-460.3		-231.8	-1,022
		(458.6)	(912.0)		(374.4)	(776.1)
GDPCAP		-0.0250	-0.00590		-0.172***	-0.135**
		(0.0636)	(0.0749)		(0.0433)	(0.0679)
EDUTRY		-426.3***	-409.2***		68.76	107.1
		(129.7)	(128.3)		(114.3)	(119.6)
GDPEMP		-984.0	-624.2		-596.6	-347.7
		(620.1)	(856.8)		(498.3)	(729.1)
INVAI				1.46e-06***	1.50e-06***	1.51e-06***
				(3.04e-07)	(3.13e-07)	(9.13e-08)
Constant	13,563***	31,863***	32,038***	13,046***	18,393***	15,830***
	(999.9)	(4,863)	(5,955)	(974.3)	(4,321)	(5,352)
Observations	283	275	275	352	336	336
R-squared	0.480	0.519	0.539	0.430	0.457	0.471

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Columns (1) to (3) in Table 3 show the relationship between AI patent activity and total employment. Column (1) illustrates a simple OLS regression with AIPATENT being the only independent variable. Column (2) counts for the addition of macroeconomic control variables, and column (3) counts for controls as well, with the addition of year fixed effects.

In the three regressions, AIPATENT is highly significant, with a coefficient of 11.54, when accounting for year-fixed effects. This suggests that, on average, an increase of one unit in AI patent activity is associated with an increase of approximately 11,540 employed individuals across OECD countries.

Columns (4) to (6) in Table 3 show the relationship between private investment in AI and total employment. Column (4) illustrates a simple OLS regression with INVAI being the only independent variable. Column (5) counts for the addition of macroeconomic control variables, and column (6) counts for controls, with the addition of year fixed effects.

Similarly, the results illustrate that INVAI is highly significant. Nevertheless, a smaller impact on employment, suggesting that on average, a one-billion-dollar AI-related investment is associated with an increase of employment by 1.51 units.

Comparing the estimates before and after the year-fixed effects shows a relatively stable and consistent relationship.

Overall, Table 3 supports the labor-augmenting argument of AI, as it reflects that AI could complement the skills of workers and possibly lead to a productivity-induced expansion in labor demand.

5.2 Gender-Specific Employment Effects

Table 4 - AI and Employment for Men

VARIABLES	(1) EMPMEN	(2) EMPMEN	(3) EMPMEN	(4) EMPMEN	(5) EMPMEN	(6) EMPMEN
AIPATENT	5.526***	6.038***	6.176***			
	(0.675)	(0.652)	(0.364)			
INFL		258.2**	288.3*		194.5***	358.5**
		(112.8)	(151.4)		(68.33)	(147.4)
GDPGROWTH		364.7	-136.5		-84.34	-460.7
		(259.8)	(494.3)		(214.7)	(426.2)
GDPCAP		-0.0296	-0.0157		-0.105***	-0.0822**
		(0.0337)	(0.0406)		(0.0243)	(0.0373)
EDUTRY		-248.4***	-237.6***		18.53	39.70
		(72.19)	(69.51)		(66.07)	(65.71)
GDPEMP		-570.6	-416.1		-367.0	-260.8
		(350.5)	(464.3)		(287.3)	(400.4)
INVAI				7.65e-07***	7.93e-07***	8.01e-07***
				(1.60e-07)	(1.66e-07)	(5.01e-08)
Constant	7,588***	18,765***	18,445***	7,274***	11,311***	9,620***
	(563.7)	(2,776)	(3,227)	(543.4)	(2,559)	(2,940)
Observations	283	275	275	352	336	336
R-squared	0.462	0.517	0.535	0.405	0.440	0.454

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 - AI and Employment for Women

VARIABLES	(1) EMPWOM	(2) EMPWOM	(3) EMPWOM	(4) EMPWOM	(5) EMPWOM	(6) EMPWOM
AIPATENT	4.905***	5.226***	5.363***			
	(0.614)	(0.588)	(0.310)			
INFL		87.16	71.29		43.55	137.2
		(70.83)	(129.0)		(46.04)	(121.8)
GDPGROWTH		230.3	-323.8		-147.5	-561.7
		(202.0)	(421.1)		(161.9)	(352.1)
GDPCAP		0.00467	0.00983		-0.0667***	-0.0523*
		(0.0303)	(0.0346)		(0.0194)	(0.0308)
EDUTRY		-177.9***	-171.6***		50.21	67.43
		(58.29)	(59.22)		(48.69)	(54.29)
GDPEMP		-413.4	-208.0		-229.6	-86.82
		(273.4)	(395.6)		(213.6)	(330.8)
INVAI				6.92e-07***	7.06e-07***	7.14e-07***
				(1.44e-07)	(1.47e-07)	(4.14e-08)
Constant	5,975***	13,098***	13,593***	5,772***	7,082***	6,210**
	(443.7)	(2,132)	(2,749)	(435.8)	(1,786)	(2,429)
Observations	283	275	275	352	336	336
R-squared	0.494	0.521	0.543	0.454	0.477	0.490

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

When comparing employment across the genders, we find that the positive relationship between AI and employment is present for both men (EMPMEN) and women (EMPWOM). The coefficients for both men and women are highly significant and have similar magnitudes with an increase of around 5-6 thousand jobs per unit increase in AI patents, as well as an increase of 7-8 jobs per one dollar increase in AI investment.

The results suggest that AI could be playing a role in reshaping jobs across a wide spectrum of roles, regardless of gender, meaning that the increase in employment is not concentrated in traditionally male- or female-dominant occupations.

5.3 Age-Specific Employment Effects

Table 6 - AI and Employment for Youth (Population aged 15-24)

VARIABLES	(1) EMPYTH	(2) EMPYTH	(3) EMPYTH	(4) EMPYTH	(5) EMPYTH	(6) EMPYTH
AIPATENT	1.299***	1.450***	1.482***			
	(0.185)	(0.171)	(0.0924)			
INFL		60.16*	73.89*		46.26***	89.85**
		(30.60)	(38.46)		(17.24)	(35.50)
GDPGROWTH		147.3**	76.35		24.21	-32.16
		(73.92)	(125.6)		(55.51)	(102.7)
GDPCAP		0.000839	0.00611		-0.0196***	-0.0132
		(0.00829)	(0.0103)		(0.00503)	(0.00899)
EDUTRY		-75.09***	-72.31***		-12.76	-7.852
		(18.56)	(17.66)		(14.28)	(15.83)
GDPEMP		-193.2*	-172.7		-127.4*	-107.3
		(99.85)	(118.0)		(74.75)	(96.44)
INVAI				1.92e-07***	2.00e-07***	2.02e-07***
				(3.98e-08)	(4.19e-08)	(1.21e-08)
Constant	1,491***	4,396***	4,109***	1,445***	2,835***	2,307***
	(137.6)	(811.7)	(820.0)	(128.1)	(686.0)	(708.0)
Observations	283	275	275	352	336	336
R-squared	0.425	0.490	0.506	0.429	0.460	0.474

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7 - AI and Employment for Seniors (Population aged 55-64)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	EMPSNR	EMPSNR	EMPSNR	EMPSNR	EMPSNR	EMPSNR
AIPATENT	1.980***	2.066***	2.119***			
	(0.227)	(0.221)	(0.118)			
INFL		24.40	6.573		6.715	32.40
		(25.50)	(49.19)		(17.52)	(47.70)
GDPGROWTH		50.21	-201.6		-90.94	-270.6*
		(73.57)	(160.6)		(61.95)	(137.9)
GDPCAP		0.00568	0.00493		-0.0221**	-0.0183
		(0.0124)	(0.0132)		(0.00860)	(0.0121)
EDUTRY		-53.45**	-52.09**		36.99*	42.85**
		(23.41)	(22.59)		(21.52)	(21.26)
GDPEMP		-125.4	-26.78		-54.18	6.838
		(99.18)	(150.9)		(81.29)	(129.6)
INVAI				2.68e-07***	2.71e-07***	2.74e-07***
				(5.61e-08)	(5.63e-08)	(1.62e-08)
Constant	2,194***	4,171***	4,637***	2,148***	1,788**	1,636*
	(171.4)	(797.6)	(1,049)	(172.7)	(694.8)	(951.2)
Observations	283	275	275	352	336	336
R-squared	0.524	0.542	0.564	0.447	0.473	0.484

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Upon isolating employment for youth (population aged 15-24) and seniors (population aged 55-64), results show a positive relationship between AI and employment, similar to the above results. However, the magnitude of the increase in population is small relative to the general population. So, for example, a one-unit increase in AI patents is associated with an increase of about 1,500 in the youth employed (13% of the total increase in employment) and 2,100 in the seniors employed (18% of the total increase in employment).

This suggests that the increase in employment associated with AI innovation could be concentrated in middle-aged employees (25-54) years.

5.4 Sector-Specific Employment Effects

Upon looking at the variation in employment sectors, we notice a difference in the magnitude of impact of AI.

5.4.1 Services

Table 8 - AI and Employment in the Services Sector

VARIABLES	(1) EMPSRV	(2) EMPSRV	(3) EMPSRV	(4) EMPSRV	(5) EMPSRV	(6) EMPSRV
AIPATENT	9.055***	9.564***	9.824***			
	(1.126)	(1.080)	(0.565)			
INFL		182.9	175.4		114.5	291.1
		(131.1)	(234.8)		(83.15)	(223.1)
GDPGROWTH		301.2	-703.6		-393.0	-1,227*
		(366.9)	(773.3)		(296.3)	(656.6)
GDPCAP		0.0260	0.0267		-0.137***	-0.112*
		(0.0657)	(0.0708)		(0.0397)	(0.0639)
EDUTRY		-293.8***	-277.6**		143.6	177.2*
		(106.9)	(108.3)		(87.07)	(99.56)
GDPEMP		-675.3	-260.4		-266.5	59.85
		(491.0)	(720.1)		(391.0)	(621.9)
INVAI				1.27e-06***	1.30e-06***	1.31e-06***
				(2.64e-07)	(2.68e-07)	(7.57e-08)
Constant	10,296***	21,231***	22,220***	10,205***	11,007***	9,496**
	(800.2)	(3,866)	(5,118)	(813.9)	(3,120)	(4,514)

Observations	278	270	270	335	321	321
R-squared	0.508	0.530	0.551	0.468	0.493	0.508

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The services sector shows the strongest positive response to AI activity. The fixed-effects model (Column 3) shows that a one-unit increase in AI patents is associated with an almost 9,800 increases in firm jobs (85% of the total increase in employment), and AI investment also has a significant positive effect.

This correlates with the upward trend in AI use within digital services, finance, customer support, and health services — areas that seek AI as an augmentation, not a replacement.

5.4.2 Manufacturing and Industry

Table 9 - AI and Employment in the Manufacturing sector

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	EMPMFG	EMPMFG	EMPMFG	EMPMFG	EMPMFG	EMPMFG
AIPATENT	1.178***	1.310***	1.335***			
	(0.138)	(0.141)	(0.0912)			
INFL		127.0**	177.9**		58.61	149.9**
		(61.90)	(78.64)		(42.56)	(75.13)
GDPGROWTH		-9.005	-199.8		-64.58	-220.3*
		(72.25)	(123.5)		(63.86)	(112.8)
GDPCAP		-0.0171*	-0.0132		-0.0293***	-0.0245**
		(0.00873)	(0.0102)		(0.00815)	(0.00990)
EDUTRY		-67.71***	-61.39***		-8.615	-0.572
		(21.73)	(17.71)		(22.64)	(17.56)
GDPEMP		-63.79	-15.90		-55.81	-22.08
		(92.28)	(116.1)		(82.79)	(106.3)
INVAI				1.46e-07***	1.55e-07***	1.56e-07***
				(3.14e-08)	(3.30e-08)	(1.32e-08)

Constant	2,089***	5,619***	5,393***	1,989***	3,768***	3,285***
	(159.1)	(795.4)	(857.8)	(152.7)	(796.3)	(828.3)
Observations	281	273	273	348	334	334
R-squared	0.371	0.455	0.477	0.258	0.309	0.328

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10 - AI and Employment in the Industry Sector

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	EMPIND	EMPIND	EMPIND	EMPIND	EMPIND	EMPIND
AIPATENT	2.027***	2.226***	2.275***			
	(0.235)	(0.234)	(0.145)			
INFL		109.9**	119.2**		92.59***	144.2**
		(43.95)	(60.51)		(29.69)	(61.43)
GDPGROWTH		42.20	-231.1		-99.95	-329.8*
		(111.9)	(193.6)		(97.18)	(177.6)
GDPCAP		-0.0241*	-0.0214		-0.0537***	-0.0478***
		(0.0139)	(0.0163)		(0.0120)	(0.0157)
EDUTRY		-99.08***	-93.99***		6.029	14.45
		(32.09)	(27.83)		(32.27)	(27.29)
GDPEMP		-145.2	-62.27		-75.53	-11.21
		(145.0)	(184.1)		(129.7)	(170.6)
INVAI				2.64e-07***	2.77e-07***	2.80e-07***
				(5.53e-08)	(5.78e-08)	(2.08e-08)
Constant	3,361***	8,536***	8,664***	3,271***	5,560***	5,236***
	(244.0)	(1,192)	(1,273)	(240.5)	(1,170)	(1,211)
Observations	281	273	273	339	325	325
R-squared	0.415	0.483	0.501	0.320	0.374	0.388

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

When it comes to Manufacturing and Industry, AI and employment are positively correlated. However, the coefficients are smaller than those of the services sector. Manufacturing accounts for a 1300 increase in employment (11% of the total increase), and Industry accounts for a 2300 increase in employment (20% of the total increase).

This suggests that - albeit shyly- AI could contribute to an increase in manufacturing and industry workers by enabling new forms of production, process, and quality control.

5.4.3 Agriculture

Table 11 - AI and Employment in the Agriculture Sector

VARIABLES	(1) EMPAGR	(2) EMPAGR	(3) EMPAGR	(4) EMPAGR	(5) EMPAGR	(6) EMPAGR
AIPATENT	0.144***	0.266***	0.259***			
	(0.0193)	(0.0321)	(0.0415)			
INFL		88.85***	101.8***		84.87***	104.4***
		(31.17)	(17.24)		(23.97)	(17.13)
GDPGROWTH		61.09	92.65		24.58	45.37
		(53.83)	(56.66)		(45.55)	(49.66)
GDPCAP		-0.0291***	-0.0267***		-0.0294***	-0.0269***
		(0.00594)	(0.00518)		(0.00536)	(0.00485)
EDUTRY		-39.38***	-38.59***		-26.81***	-26.92***
		(10.05)	(7.955)		(9.950)	(7.670)
GDPEMP		-73.24	-102.3*		-57.80	-81.88*
		(62.94)	(52.68)		(54.42)	(46.42)
INVAI				1.58e-08***	2.65e-08***	2.61e-08***
				(3.40e-09)	(6.00e-09)	(5.84e-09)
Constant	856.9***	3,590***	3,367***	804.7***	3,051***	2,867***
	(96.73)	(582.0)	(375.2)	(81.49)	(533.3)	(346.8)
Observations	280	272	272	348	332	332
R-squared	0.030	0.406	0.414	0.015	0.316	0.329

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The agriculture sector shows a minimal employment response to AI, with a coefficient of about 260 jobs per AI patent (2% of the total increase). This could possibly reflect the low penetration of AI in agricultural practices across OECD countries as well as the high degree of mechanization that has already shaped labor needs in this sector.

5.8 Limitations of the Study

Although the data results provide valuable insights, there are important limitations to be taken into consideration:

1. Measurement of AI: There exists no specific indicator for artificial intelligence, therefore, the proxies used may not fully capture the effect of AI. For example, the growth in the number of AI patents suggests a growth in research and development related to AI innovation, however, this does not necessarily reflect the actual implementation of AI in the workplace and its corresponding actual magnitude. Moreover, private investment in artificial intelligence reflects interest in artificial intelligence by investors; nevertheless, this does not guarantee that businesses are integrating AI usage in their tasks.

2. Endogeneity and Causality: The model establishes correlation, not causation. Therefore, possible problems could be present:

- Reverse causality: In general, developed countries experiencing economic growth (paired with a consequent increase in employment) may be engaging in research related to AI, thus increasing AI patents and investing in AI as well.

- Omitted variables could have an impact on both AI and employment, such as digital infrastructure and labor union strength.

Endogeneity remains a risk even with the usage of year-fixed effects and control variables, therefore more advanced techniques should be implemented in order to make causal claims.

For example, in future studies, including countries, fixed effects would allow for to reduction of some of the omitted variable bias, and would also allow for exploration of within-country variation over time, which strengthens the internal validity of the estimates.

3. Time Lags and Data Reporting: As noted in Chapter 3, the data related to AI patents and investment may involve time lags related to reporting, especially after 2020. This may understate AI’s recent growth and its most current employment effects.

4. Time Horizon Limitation: The emergence of AI remains a recent technological advancement; therefore, it is too early to infer conclusions on its impact in only 10 years, especially with AI’s exponential growth, specifically with the growth of generative AI, post-2023.

CHAPTER 6

DISCUSSION

Using OLS and fixed effect regressions, the model studies the association between AI and employment in OECD countries over a 10-year period, with a focus on variations across gender, age, and sectors. The results depict a positive association between the national interest in AI and overall employment outcomes, reflecting combined labor market dynamics. This supports the labor augmentation theory discussed in the literature.

The findings illustrate that both men's and women's employment benefited from AI adoption, with men's employment experiencing a slightly larger effect. This could be explained by the fact that AI innovation creates a lot of tech and software-related jobs, which are mostly sectors dominated by male labor.

On another note, upon testing for any specific bias towards seniors or youths, results showed that the middle-aged population experienced the highest employment gains. This may be attributed to the maturity, creativity, and experience of middle-aged workers who are still able to learn and adapt to the new technology (unlike the seniors) and also have well-established careers that allow them to stay and advance in their jobs, with a priority over the entry-level youth.

When looking into the different sectors, the results suggest that the job creation effect was mostly witnessed in the services sector. The services sector is the most reliant on non-routine cognitive tasks, as it relies heavily on human contact and communication with clients. In this sense, AI technologies represent a complement to human skills rather than a replacement. Unlike manufacturing or agriculture, which are dominated by routine tasks, the services sector encompasses occupations where AI tools can boost productivity without fully substituting human labor, such as finance, healthcare, education, and information technology. These results are consistent with the labor augmentation theory, which holds that industries with a high degree of knowledge-intensive work are more likely to see both technological adoption and job growth

CHAPTER 7
CONCLUSION

This thesis investigates the association between AI and employment across OECD countries. The findings show that AI innovation could be linked to a positive impact on labor market dynamics. This is in line with the labor augmentation theory that illustrates that the employment gains are a result of productivity growth, and the realignment of job tasks towards tasks that focus on cognitive capabilities, in addition to the creation of new types of jobs.

The results show minimal differences in employment growth between men and women, with the absence of bias towards seniors or youth. Additionally, the services sector demonstrates itself to be the sector that is mostly benefiting from the development of artificial intelligence. Our study provides cross-country evidence from the OECD and examines demographic and sectoral heterogeneity, contributing to a more nuanced understanding of AI’s labor market effects.

Having said that, these results should be interpreted with caution. The thesis highlights the impact of AI on a macro level, without diving further into the micro-effect. In addition, Artificial intelligence is exponentially growing, and its effect is still ambiguous, and it would ultimately depend on the economic systems, the ability of societies to adapt to the technology and the response of institutions and education systems.

Artificial intelligence should hence not be treated as a shock, but rather as a force slowly being integrated into the core of a country’s economic system. Therefore, further research should be done to closely monitor how AI is shaping the economy and society. At this point, then, the main question is not “Will AI replace us?”. The question is “How can we make AI our servant, and not our master?”.

CHAPTER 8

POLICY IMPLICATIONS

AI adoption has been shown to generate productivity gains that benefit the workplace. Nevertheless, there is a need for policy interventions to ensure that the labor market benefits are inclusive and sustainable.

One of the main targets of governments should be education, where there must be a focus on reskilling programs that adapt to the evolving skill demands with the new technology. Specifically, since most of the employment growth is on the services sector, there must be a focus on human soft skills such as creativity, leadership and interpersonal skills. Additionally, to ensure the adaptation of workers to the new technology, emphasis should be on developing technical skills, such as data analysis, software development, and machine learning. This ensures that workers will be able to keep up with the new technology, and artificial intelligence will continue developing in a manner that keeps its productivity gains evolving.

Policy frameworks must target underperforming sectors, such as agriculture and manufacturing, where the productivity gains of AI adoption were minimal. This shall ensure that growth will be present in all sectors and not dominated by one. This will thus create new job categories and contribute to the modernization of the traditional sectors.

An important factor to be considered is the inclusive AI deployment across countries and population groups. This includes ensuring equal access to artificial intelligence technologies and the creation of opportunities for all demographic segments.

Finally, since most of the development in AI is in private institutions, there must be effective public-private partnership to ensure the fair and ethical usage of artificial intelligence.

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