Linnæus University
Sweden

Masters Thesis

Artificial Intelligence and Inequality:

Evidence from the OECD Countries

Author: Ibrahim Khan Jabarkhail
Supervisor: Erik Prawitz
Examiner: Hans Gronqvist
University: Linnaeus University
Program: MSc Economics
Term: 2022-24
Subject: Economics

Linnæus University
Sweden

Abstract

This paper explores the relationship between the rise of technology related to artificial intelligence and income inequality in OECD countries. To measure income inequality, the study uses data on the income shares of different population percentiles and employs AI patents as a measure of innovation. Additionally, it incorporates Information and Communication Technology (ICT) patents to assess how ICT compares to AI in terms of its relationship with income inequality. Studying long-run changes 2005-2020 in a long-difference regression, this study finds a positive, albeit insignificant, relationship between AI intensity and inequality.

Furthermore, the study examines the relationship between AI intensity and employment share by skill, revealing a positive relationship for high-skilled individuals and a negative one for low-skilled individuals. Medium-skilled workers are found to be relatively worse off in countries with high AI intensity, especially in the context of low trade union presence. The results this paper got align with the Skill-biased technological change in terms of the AI innovation whereas it aligns with the job polarization and u-shaped or task-based framework in case of the ICT innovation. This suggests the importance of studying the labor market and how it gets influenced by the innovation.

Key words

Innovation, Economics, Income Inequality, Patents, Skills

Linnæus University
Sweden

Acknowledgments

I am very happy that I have completed my master's program in Economics and that I am able to complete my degree project. I would like to thank my supervisor Erik Prawitz whose constant support and guidance helped me discover the patterns in the research problem and complete this paper. I am also thankful to Hans Gronqvist whose guidance helped me choose a good topic. In addition, I am also profoundly grateful to my family, mother, and siblings whose unwavering support and unconditional supports made this academic journey much easier. I am also grateful to the inspiring Afghan youth whose resilience helped me continue striving for excellence in life after the fall of Kabul in 2021.

Linnæus University
Sweden

Table of Contents

LIST OF TABLES AND FIGURES

1 Introduction

In an era where technological innovation is rapidly transforming every facet of our lives, its important impact on economic structures and societal norms is undeniable. This transformation raises critical concerns, specifically regarding the relationship between technological advancement and income inequality—a phenomenon that has garnered renewed interest amidst the swift pace of technological change. There is a growing concern that we may be moving towards a 'jobless future' (Rolf 2021), a scenario that could significantly exacerbate inequality. This future posits a widening economic gap between capital owners and those without, as the latter group loses access to traditional employment opportunities and the associated economic benefits. This study aims to delve into the important dynamics between artificial intelligence (AI) innovation and income inequality within the Organization for Economic Co-operation and Development (OECD) countries, spanning from 2005 to 2020.

There are theoretical reasons to believe that AI has a unique relationship with income inequality, and many observers support this view. For instance, research indicates that AI investment is associated with higher income inequality, particularly benefiting the top income decile while reducing the income share of the bottom decile. Additionally, AI tends to shift income from labor to capital, exacerbating wage disparities (Wang, Cao et al. 2023). Studies also highlight that AI-driven automation disproportionately affects low-skilled workers, further widening the income. The significance of this research lies not only in its academic contribution to the literature, but it is also important from the policy perspective.

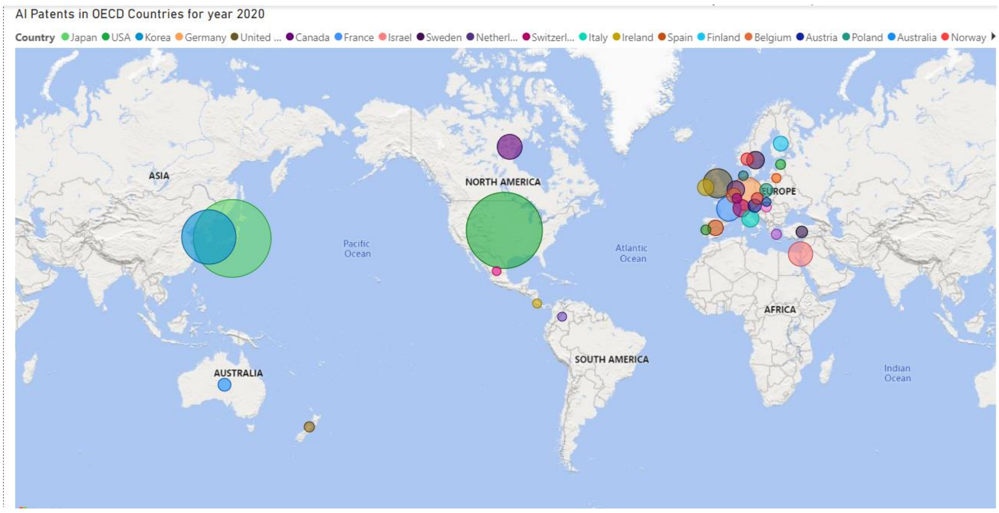

Figure 1: AI Patents growth in OECD Countries as of year 2017.

Technological breakthroughs such as artificial intelligence, robotics, and digital platforms hold the potential to starkly alter labor markets, with profound implications for income distribution (Korinek, Schindler et al. 2021). While these innovations can propel economic growth and productivity, their benefits are not uniformly distributed across the workforce, often favoring skilled workers, and exacerbating existing wage disparities (Acemoglu and Restrepo 2019). It is hence essential to review these claims and concerns and study them thoroughly.

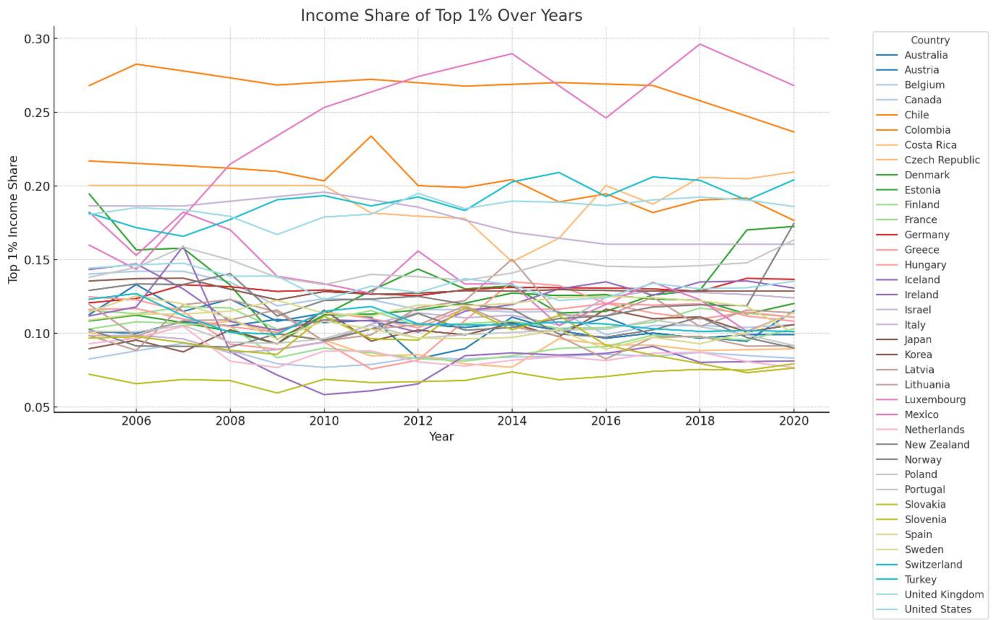

Figure 2: Top 1% income share in the OECD countries over the years.

To address these concerns and to evaluate these claims, this paper delves deep into assessing the relationship between the AI innovation and income inequality and aims to find if there is any linkage between the two. This study uses patent data to measure AI innovation[1]. By doing so, this study posits that unravelling the mechanisms through which technological innovation influences income inequality is pivotal for devising strategies to ensure the equitable distribution of technological progress's benefits across society. The OECD's long-term data indicates that rising inequality is attributable to technological change and rapid globalization (OECD 2003). Theoretical frameworks like the skill-biased technological change hypothesis, as discussed in Acemoglu's work (Acemoglu, 2002), offer a perspective on the impact of technology on labor markets.

[1] Even though it is well known that patents are not a perfect proxy for innovation since all innovation are not patented and since a patent does not necessarily reflect the value of underlying technological innovations, yet patents are probably the best proxy for innovation we have Griliches, Z. (1990). "Patent Statistics as Economic Indicators: A Survey." Journal of Economic Literature **28**(4): 1661-1707.

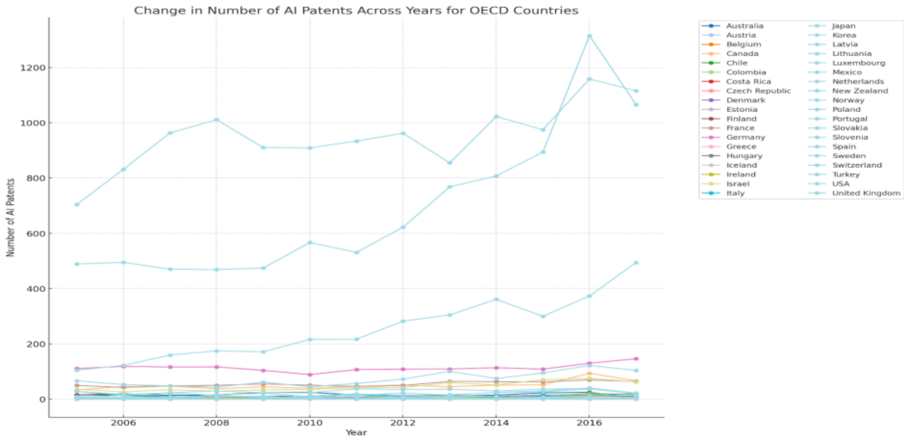

Figure 3: AI Patents growth in OECD countries over the years.

The focus on OECD countries is strategic due to their diverse experiences with technological innovation and varying levels of income inequality, making them ideal for this study. This diversity offers a rich comparative framework for identifying patterns and insights that may apply to a broader range of economies. By concentrating on the period from 2005 to 2020, this research captures a critical insight into the challenges and opportunities presented by the digital age.

The study hypothesis suggests that technological advancements, particularly in artificial intelligence, Information and Communication Technology (ICT) and robotics, which gained prominence in the late 20th century, disproportionately benefit skilled over unskilled workers, thus widening the wage gap between these groups. The advent of artificial intelligence (AI) may further alter this dynamic by threatening higher-skilled jobs, previously considered secure from automation. Additionally, the phenomenon of job polarization, where technology leads to the hollowing out of middle-skilled jobs while both low-skilled and high-skilled jobs experience growth, provides another perspective on how recent technological changes can reshape income distribution. The study also examines the relationship between innovation and employment share, which could indicate the labor market's response to innovation. Whether these technological advances will exacerbate or mitigate income inequality remains an empirical question, highlighting the importance of continued research to understand their widespread impacts.

To investigate these dynamics, this thesis employs a comprehensive analysis of OECD data from 2005 to 2020, using econometric methods such as long difference regression to assess the relationship between technological innovation and income inequality. To capture AI intensity within a country, I divide the number of AI patents by the number of patents during the same time. In addition to different percentiles of income inequality, I also included the Gini coefficient and income shares or unit labor cost. Moreover, this paper used the high dimensional fixed effects regression to study the relationship between the AI & ICT intensity and employment share by skill dynamics across different levels. This method's capability to incorporate fixed effects for both the year and country (or other categories as needed, such as union density settings) ensures that the estimates are robust to omitted variable bias by accounting for both observable and unobservable factors that do not change over time within each unit but vary across units. It is particularly useful when assessing the impact of technology on labor market outcomes across different skill levels, as it allows for a detailed and nuanced analysis of these dynamics while controlling for a broad range of confounding factors.

The results that the study got after evaluating these relationships are divided into two parts. Firstly, the paper reports the impact of AI & ICT innovation on different measures of income inequality and unit labor costs. Later, the paper talks about how the AI intensity and ICT intensity influences the employment share in different skill groups.

Countries with higher AI intensity display a positive, albeit in-significant, increase in inequality measured in terms of share of income attributed to the top 1 percent or 10 percent of the population. A slight decrease in income shares for bottom 50 correlated with AI innovation, although statistically insignificant, suggesting small economic effects on this group. The marginal and statistically insignificant increase associated with a rise in AI patents suggests a weak relationship between AI innovation and broader income disparity. A notable increase linked with AI patent counts, but with high variability that undermines statistical significance, indicating the need for further investigation into how AI impacts labor costs.

Likewise, the ICT Intensity showed A small but statistically significant positive correlation suggests slight income concentration among the wealthiest due to ICT innovation whereas no significant effect of ICT patents on this income group. A significant reduction in income inequality associated with greater ICT innovation, indicating beneficial effects for the less affluent half of the population. In addition, the study finds that ICT patent intensity has no significant effect on the Gini coefficient and only a minor, non-significant decrease in Unit Labor Costs (ULC), suggesting ICT innovation doesn't substantially alter income inequality or labor costs.

The results also showed the regression outcomes that were evaluated after introducing the interaction term of AI Intensity and high & low skill employment shares. The results from the AI innovation confirmed that there are positive effects on high employment share and negative effects on lower employment share which aligns with the skill biased technological change (SBTC) theory of labor economics. Likewise, the ICT innovation when checked in the similar way resulted in showing positive impacts on both higher and lower employment share by skill confirming the u shaped or tasked based framework of labor economics. Moreover, the results showed that medium-skills workers are relatively worse off in countries with high AI intensity and this negative impact is pronounced with the low trade union presence.

The intersection of technological innovation and income inequality has been the subject of extensive scholarly discussion. This paper also relates to the influential body of work documenting the relationship between innovation and income inequality. Key studies like (Acemoglu 2002) explores the skill-biased technological change hypothesis, suggesting that advancements in technology, particularly in ICT and robotics, disproportionately benefit skilled workers, thereby exacerbating wage disparities. This hypothesis is instrumental in understanding the evolving labor market dynamics in the digital age.

In his seminal work, Daron Acemoglu delves into the intricate relationship between technological change and wage inequality, positing that the evolution of technology over the past sixty years has predominantly exhibited a skill-biased nature. Acemoglu argues that the widening wage gap and the increasing returns to education in recent decades can be attributed to an acceleration in skill-biased technological change (SBTC). This acceleration, particularly evident from the 1970s or 1980s onwards, is linked to significant advancements in information technology, marking what some refer to as a "Third Industrial Revolution." Acemoglu suggests that the shift towards skill-biased technology in the twentieth century, as opposed to the skill-replacing technologies prevalent in the early nineteenth century, can be understood through the lens of profit incentives.

The research paper "The Impact of Automation on Income Inequality: A Cross-Country Analysis" by (Gilfoyle 2023)investigates the effects of automation on income disparity across various countries, considering different levels of technology adoption and labor market structures. It uses panel data analysis with data from the World Bank and other sources. The study finds that while automation boosts productivity, its impact on income inequality varies based on a country's labor market and social policies.

In conclusion, this thesis aims to contribute to the ongoing debate on the relationship between technological innovation and income inequality by providing empirical evidence and analytical insights from OECD countries. Through its findings, it seeks to illuminate the complex interplay between technology, labor markets, and income distribution, offering guidance for policymakers in crafting interventions that leverage the benefits of technological progress while minimizing its divisive effects on society. This study's contribution to existing literature lies in its in-depth analysis of specific countries, i.e., OECD countries, which are homogeneous in nature and can be grouped for analysis.

It is hence essential to review these claims and concerns and study them thoroughly. Ultimately, it is an empirical question to determine what kind of relationship exists between income inequality and innovation. In the following chapters the study explores the literature review, data, methodology, results, and conclusion.

2 Literature Review

This paper relates to an influential body of work documenting the impact of technological innovation on labor markets and income inequality. The rapid transformation in the innovation and technology sector over the last decade has expanded internet penetration and increased the adoption of various technologies and applications, enhancing life and work efficiency. However, this shift has also raised concerns about the future of human labor. Significant scholarship has explored how automation and technological advancements impact labor markets, particularly focusing on skill-biased technological change, automation, and income inequality.

Skill-Biased Technological Change

The concept of skill-biased technological change (SBTC) is central to understanding the labor market shifts. (Acemoglu, Autor et al. 2020) analyze the impact of artificial intelligence (AI) on the labor market through an examination of online job postings in the United States from 2010 to 2018. Their findings indicate a significant rise in AI-related job vacancies, especially in sectors compatible with AI capabilities, leading to changes in skill requirements and a reduction in non-AI job postings in AI-exposed establishments. However, they do not find significant impacts on overall employment or wage growth, suggesting limited aggregate labor market effects from AI adoption thus far.

This paper extends the above analysis to the OECD countries, using a broader dataset from 2005 to 2020. By including AI patent counts and unit labor costs, this study provides a more comprehensive view of how AI influences skill requirements across different economic contexts. This contribution offers a more nuanced understanding of the global impact of AI, beyond the U.S. context.

Automation and Labor Displacement

Automation's role in labor displacement has been extensively studied. (Acemoglu and Restrepo 2019)attribute 50-70% of wage structure changes in the U.S. over the last four decades to automation, particularly affecting workers specializing in routine tasks. Their research offers a robust empirical analysis, showing a significant negative relationship between task displacement and wage changes. Similarly, (Kharlamova, Stavytskyy et al. 2018) explores the dichotomy between technological change and income disparity. Key findings indicate that in economically developed countries, technological changes do not significantly deepen income inequality, whereas less developed peripheral countries experience more pronounced effects due to their dependence on larger economies and lack of robust redistribution mechanisms. The study also highlights that increased labor productivity due to technological advancements can exacerbate social inequality in countries with pre-existing high-income disparities.

My research investigates the displacement effects of automation in the OECD countries, incorporating recent data from 2005 to 2020. my study aims to isolate the specific impacts of automation on labor markets in these countries, providing a comparative perspective that enhances our understanding of global trends.

AI and High-Skill Labor

In their working paper (Albanesi eta al. 2023) colleagues investigate how advancements in AI and software have impacted jobs across 16 European countries from 2011 to 2019. Analyzing data on various occupations, they discovered that jobs more involved with AI have seen an increase in employment, especially for younger and skilled workers, supporting the theory of SBTC. This trend varied among countries, influenced by factors like the speed of technology adoption, education levels, market competition, and labor laws. Interestingly, the study found little to no significant effect of new technologies on wages, despite their impact on employment.

My study extends this analysis by covering a longer period (2005-2020) and including a broader range of OECD countries. By integrating novel data sources such as AI patent counts, my research provides deeper insights into the variations in AI adoption and its labor market impacts across different national contexts. This contribution helps clarify the broader implications of AI on high-skill labor markets and wage dynamics.

Job Polarization

Technological change, particularly automation and computerization, disproportionately affects middle-skill jobs that often involve routine tasks. (Autor, Levy et al. 2003) highlights how computer-based technologies substitute for tasks previously performed by middle-skill workers, such as clerical work and repetitive production tasks. This substitution effect shifts the demand towards more abstract, non-routine cognitive tasks typically performed by high-skill workers and some manual tasks in service roles that are not easily automated.

My study builds on this work by examining job polarization trends within OECD countries from 2005 to 2020. Using detailed employment share by skills data and incorporating AI patent counts, my study provides a contemporary analysis of how technological advancements continue to shape task polarization.

Automation and Employment

The impact of automation on employment patterns and income inequality is a critical area of study. (Prettner and Strulik 2020)suggest that while automation displaces some jobs, it also creates new opportunities in sectors that require complex problem-solving and creative skills, which can mitigate some adverse effects on income inequality. Autor's 2015 paper investigates the complex relationship between technological innovation and employment trends, challenging the fear that automation will lead to widespread job losses. He argues that technological advancements complement human labor by increasing productivity, raising earnings, and augmenting the demand for labor, leading to job polarization where middle-skill jobs decline while both high-skill and low-skill job sectors grow.

My research extends this analysis by providing empirical evidence from the OECD countries, utilizing a comprehensive set of indicators from 2005 to 2020. By focusing on the broader implications of automation and AI on employment patterns and income distribution, my study contributes to a deeper understanding of how these technological advancements impact labor markets in diverse economic contexts.

Innovation and Income Inequality

(Fleming 2019) discusses the impact of large language models and generative AI on recent trends. In "Robots and Organization Studies," Fleming challenges the narrative that automation will lead to significant job loss, introducing the concept of "bounded automation" and suggesting an increase in low-wage employment.

The paper "Innovation and Top Income Inequality" by (Aghion, Akcigit et al. 2018) examines the relationship between innovation and income inequality in the United States. Using cross-state data, they demonstrate a significant positive correlation between measures of innovation and the rise in income inequality, specifically focusing on the top 1% of income earners. The study also explores the impact of lobbying intensity, finding that higher lobbying activities dampen the innovation-inequality relationship.

My research builds on this analysis by examining the relationship between innovation and income inequality across OECD countries from 2005 to 2020. By utilizing a comprehensive set of indicators, including AI patent counts and unit labor costs, my study provides new empirical evidence on how technological advancements influence income distribution. This contribution enhances our understanding of the global implications of innovation on income inequality, particularly in economically developed regions.

Empirical Focus on OECD Countries

This research contributes to the existing literature by providing a focused analysis on OECD countries over a critical period (2005-2020), encompassing significant technological advancements in AI and robotics. By utilizing a comprehensive set of indicators, including AI patent counts and unit labor costs, this study introduces new empirical evidence into the debate.

In conclusion, this literature review synthesizes key studies on the impact of technological innovation on labor markets and income inequality, highlighting the nuanced effects of automation, AI, and innovation on employment patterns and wage distribution. This paper builds on these foundations by offering a detailed empirical analysis of the OECD countries, contributing to a deeper understanding of how recent technological advancements influence income inequality.

3 Theoretical Framework

3.1 Background and Definitions

Innovation, a multifaceted phenomenon, is pivotal in shaping economies and societal structures. It encompasses the introduction of new technologies, processes, and products, such as Artificial Intelligence (AI) and robotics, which play significant roles in modern economies by influencing labor markets and income levels across different socio-economic groups. Importantly, as highlighted by (Aghion and Griffith 2022), innovation can paradoxically both exacerbate and mitigate income inequalities, depending on the distribution of control and benefits from these technological advancements.

3.2 Theoretical Framework

To analyze the relationship between innovation and income inequality, this paper integrates insights from various economic theories, primarily focusing on the perspectives provided by task-based framework and the theories concerning market structures and firm behavior.

3.2.1 Task Based Framework

Building on the framework proposed by (Acemoglu, Aghion et al. 2012), this analysis further explores how innovation impacts the productivity of labor, differentiating between its effects on high-skill and low-skill workers. Acemoglu's model elucidates the dual forces shaping the direction of technical change: the price effect, which promotes innovations that favor scarce factors, and the market size effect, which encourages technological advancements benefiting abundant factors. The elasticity of substitution between these factors is crucial, as it determines the extent to which relative factor prices and technical change respond to shifts in factor supplies.

The task-based framework theory of labor economics provides a comprehensive model for understanding the relationship between AI innovation and income inequality, as well as the employment share by skill. This theory posits that production involves a continuum of tasks, each requiring specific skills, and workers are assigned to tasks based on their comparative advantage. Technological advancements, such as AI, can shift the task composition within occupations, automating routine tasks and increasing the demand for non-routine cognitive tasks that require higher skills. This shift can lead to changes in the wage structure and employment shares across different skill levels. Additionally, AI-enabled automation tends to increase employment in high-skill occupations while reducing the share of employment in low- and medium-skill occupations (Autor 2013). By focusing on the tasks that workers perform rather than the jobs they hold, the task-based framework allows for a nuanced analysis of how AI-driven technological changes impact labor markets, making it a valuable tool for exploring the link between AI innovation, income inequality, and employment shares by skill level.

This study also evaluates the relationship and impact of ai intensity or ict intensity across different skill sets to distinguish how they are impacted contributing to the task-based framework.

3.2.2 Market Structure and Firm Behaviour

Innovations often alters market structures and firm behaviors in ways that can both increase and decrease income inequality. For instance, the dominance of "superstar" firms in certain sectors, as discussed by Autor et al. (2020), can lead to increased market concentration and higher economic rents for these firms. While this could enhance efficiency and consumer benefits through lower prices, it also often leads to higher income inequality as these firms accrue significant portions of the economic surplus. Furthermore, the barriers to entry for new innovators, protected intellectual properties, and lobbying efforts can stifle competition and maintain high-income inequalities (Aghion and Griffith, 2022). This study contributes to this theory by checking the monthly earnings across different skill levels and assesses how it is impacted by the AI or ICT innovation.

3.2.3 Skill-Biased Technological Change

As discussed earlier, the Skill-biased technological change (SBTC) is a pivotal concept in examining the interplay between innovation and income inequality. This theory argues that technological advancements tend to disproportionately benefit workers possessing higher skills, education, or capabilities, which are generally scarcer than less-skilled labor. As technology progresses, it predominantly enhances the productivity of these high-skilled workers, leading to an escalation in their wages and an improvement in their employment prospects relative to their low-skilled counterparts. Consequently, unless there is a parallel increase in the supply of high-skilled workers, the growing demand can significantly widen wage disparities.

3.2.4 Empirical and Theoretical Linkages

The relationship between innovation and income inequality is complex and influenced by multiple factors, including government policies, firm strategies, and the nature of the innovation itself. For instance, public sector innovations often aim at reducing inequalities by improving access to services and lowering costs. In contrast, private sector innovations may not have equality as a primary concern, potentially leading to increased disparities. This paper checks the results for the relationship between skill share and ai innovation across different sectors to evaluate how are the sectors getting impacted by the development of ai and ict innovation.

3.2.5 Policy Implications

Understanding the theoretical underpinnings of how innovation affects income inequality is essential for designing effective policies. Policies aimed at enhancing the benefits of innovation while mitigating its adverse effects on income inequality could include education and training programs, support for technology diffusion in lagging regions, and regulatory measures to ensure fair competition.

4 Data Collection and Methodology

4.1 Sources of Data

The data collection is performed using different platforms and sources. The data on total patents, ICT Patents and AI patents is collected from the OECD Statistics website. The data on different levels of income inequality is taken from the world inequality database (WID). Moreover, the data on the measures related to the GDP per capita and GDP annual growth rate is fetched from the World Bank's World Development Indicators (WDI) database. In addition to this, the data related to employment share was downloaded from the ILOStat (International Labor Organization Statistics) website. Different variables used in this study are now explained in the following lines.

4.2 Definition of the Variables

Top 1% income share represents the proportion of total national income earned by the top 1% of earners. This elite group captures a substantial share of overall income, reflecting their predominant economic status in the income distribution. Top 10% Income Share accounts for the top 10% of the population holding the highest income. Although less concentrated than the top 1%, this group still commands a significant portion of total national income, placing them well above the majority in terms of economic influence and income levels.

Bottom 50% refers to the total national income accrued to the bottom half of the income distribution. It highlights the disparity in income received by this segment compared to the higher income brackets, underlining the extensive income inequality within the population. Unit Labor Cost (ULC) is used to measure how much of firms' production costs goes to labor. If firms replace labor by machines/AI/robots etc, we expect that the labor cost to produce one unit of output decrease. OECD defines Unit Labor Cost as "Unit labor costs measure the average cost of labor per unit of output produced. They are calculated as the ratio of total labor costs to real output. "

Innovation in this study is quantified through the analysis of AI Patents and ICT Patents, which are considered key indicators of technological advancement in their respective fields. To gauge the significance of these innovations within the broader national context, the study measures the number of AI and ICT patents as a proportion of the total number of patents granted in that country for each year. This normalization is performed by dividing the number of AI and ICT patents by the total number of patents issued. This ratio is crucial as it provides a relative measure, highlighting how much a country is investing in these cutting-edge technologies compared to other areas of innovation. By doing so, the study can better understand the prioritization of AI and ICT development within the national innovation ecosystem, as reflected in the patenting trends sourced from the OECD database. The study looked at both the dividends separately to measure the specific impact of AI related innovations because they have unique leverage and are rapidly advancing.

Descriptive Statistics

To begin with, I ran basic exploration of the data and got the descriptive statistics to get a glimpse of how the data looks. The following table demonstrates the results that I got in my descriptive statistics. I have included the data for the years 2005-2020.

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
AIIntensity	494	.009	.021	0	.408	14.825	278.092
ICTIntensity	608	22.042	12.408	0	67.56	.953	3.79
Top1	608	.128	.046	.058	.296	1.534	5.179
Top10	608	.38	.092	.263	.671	1.538	4.545
Bottom50	608	.179	.049	.045	.288	-1.016	3.476
ULC	592	.936	2.639	-9.784	19.732	.491	9.026
GDPPerCapitaGrowth~e	592	1.247	3.611	-14.464	23.305	-.343	7.594
Gini	440	.315	.054	.22	.497	1.069	4.438

Table 1: Descriptive Statistics

The table displays a summary of descriptive statistics for different economic variables, focusing on the distribution of income and the impact of innovation, represented by normalized AI Intensity and ICT Intensity. This shows that, on average, the top 10% earns about 38% of the income, with values ranging from 26% to 67%. The positive skewness indicates a concentration of values towards the lower end but with some exceptionally high-income shares. For the bottom half, the average income share is about 17.9%, with a range from 4.54% to 28.84%. The negative skew indicates that more of the bottom 50% are closer to the higher end of their income share distribution. The top 1% has an average income share of 12.8%, with values ranging from 5.84% to 29.62%. This data is right-skewed, suggesting substantial variability within the top 1% income shares.

The AI Intensity data has an average of 0.009, with a broad range up to 0.408, which indicates a few very high values compared to most. The high skewness and kurtosis reflect a concentration of lower values with sparse extreme high values. The ICT Intensity data, with 608 observations, has a mean value of 22 and a standard deviation of 12.4. It is moderately skewed to the right, indicating some regions with much higher values. The average annual GDP per capita growth rate is 1.25%, with a substantial range from a decline of 14.46% to a growth of 23.30%. The distribution of growth rates is relatively balanced with a slight left skew. The Gini coefficient, with an average of 0.315 and a range from 0.22 to 0.497, indicates moderate to high levels of income inequality, with a right-skewed distribution suggesting some regions have significantly higher inequality.

This table assists in exploring the relationship between income distribution and the level of innovation within an economy, where innovation is indicated by the number of AI patents normalized. The spread and shape of the distribution for each variable provide insights into economic inequality and innovation trends which could be further investigated to understand their interplay.

Distribution of the Variables

After the descriptive statistics, the paper looked at the distribution of the variables of interest.

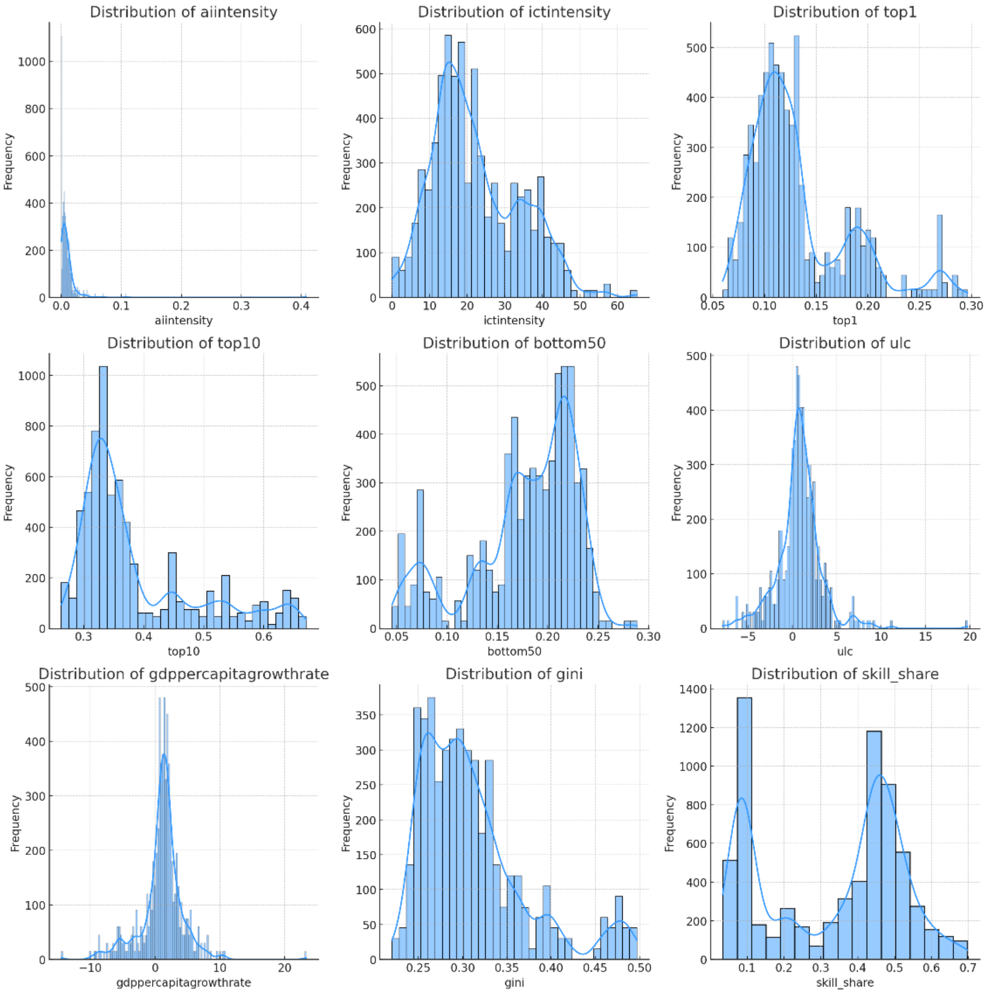

Figure 4: Distribution of the variables of interest.

Overall, these plots reveal a range of distributions across the various measures of income inequality and innovation (patents), as well as economic growth. The skewness in some of the distributions suggests that there are countries that deviate significantly from the majority, potentially due to unique economic conditions or policies. The multiple modes and heavy tails found in some variables may suggest the need for further segmentation of the data or the use of robust statistical methods that can handle such distributions when conducting your analysis.

4.3 Methodology

As discussed earlier, this study uses two methods to assess the relationship between AI innovation and income inequality. Firstly, the study uses the long difference regression to measure the relationship between income inequality and the innovation acknowledging that the impacts of technology on economic disparities may manifest over the long term. Secondly, the study uses the fixed effects year regression measure the employment share against the AI and ICT innovation, the paper uses a robust linear regression framework with high-dimensional fixed effects to control for inherent variations over time and across units. I took the country and year as fixed effects and estimated the relationship between the variables. Therefore, the second method will allow the study to measure that. The disadvantage of this method is that it is left with few observations which gives me low precision.

A novel aspect of this study's methodology is the examination of heterogeneity in the AI-inequality relationship across countries with varying levels of labor rights using the trade union density. I hypothesize that countries with stronger labor protections may experience a different impact of AI on inequality. To test this hypothesis, the study utilizes an interaction term between the AI technology measure and a binary indicator of high labor union density. This approach allows us to capture the differential effects of AI technology in countries with robust labor rights frameworks. The study used trade union density from 2005 and then created dummy variables for higher and lower trade union density based on the mean value.

To refine the analysis, and to control for the confounding drivers of both technology and inequality, the study adjusts for economic size, incorporating GDP per capita growth rate as a control variable. The control variable is also similar to the studies from the literature e.g, that of Aghion et al. The equation for long difference regression in this study is equation 1.

$$\Delta Iit = \Delta\beta AI_{it} + \Delta\delta GDP\_Growth\_{_{it}} + \varepsilon_{it}, \quad (1)$$

where Iit is the change in some measure of income inequality between 2005 and 2020. The main regressor AIit of interest is some measure of AI technology, for example the patent measure at OECD Stat, which varies at the country-year level. Since an increase in AI patents may simply reflect an increase in general innovation, I divide the number of AI patents by the total number of patents, providing me with a measure of AI intensity. I can be income inequality at different percentile levels, gini coefficient or unit labor cost. Next, I just replace ICT intensity with AI intensity to measure for the ICT innovation.

Next for yearly panel with fixed effects firstly because I get more observations, and also the main reason is perhaps that it allows the paper to study how AI relates to different skills.

$$\Delta \textbf{Emp\_Share\_skill}_{it} = \beta AI_{it} + \alpha 1(AI_{it} \times HighSkill\_{it}) + \alpha 2(AI_{it} \times LowSkill\_{it}) + \gamma_i + \phi_t + \varepsilon_{it} \quad (2)$$

In equation 2, Emp_Share_skillit denotes the employment share of a specific skill level for country ii at time tt. The main regressor AI_{sit} represents AI intensity, and its interaction terms with high-skill ($HighSkill_{sit}$) and low-skill ($LowSkill\ s_{it}$) employment shares are denoted by α1 and α2, respectively. The equation includes country fixed effects (γ_i) and year fixed effects (ϕt) to control for time-invariant country-specific characteristics and common time trends, respectively, along with an error term ε_{sit}. Similarly, I performed it for the ICT as well.

Likewise, the study also sees how the income at different skill level to see how that is influence by the AI and ICT innovation and I use the following equations for that. In equation 5 and 6 Log_incomeit represents the logarithm of income for a specific skill level in country ii at time tt. The primary regressor $AIit$AIit is AI intensity, with interaction terms for high-skill and low-skill income denoted by $\alpha 1$α1 and $\alpha 2$α2, respectively. Country and year fixed effects (γiγi and ϕtϕt), along with the error term εitεit, are included to account for unobserved heterogeneity and time trends. Besides skill share, the study also checked the AI and ICT intensity innovation at different skill levels against log of monthly earnings and the equations are below 5 and 6.

$$\Delta \textbf{Log\_income}_{it} = \Delta\beta AI_{it} + \Delta\alpha 1(AI_{it} \times HighSkill\_{it}) + \Delta\alpha 2(AI_{it} \times LowSkill\_{it}) + \gamma i + \phi t + \varepsilon_{it} \quad (3)$$

In addition, the study also checked for the heterogeneity by measuring the impact in high union density and low union density measures. Here is the equation for that

$$\Delta \log(\text{income}_{it}) = \Delta\beta AI\ it + \Delta\alpha 1(AI_{it} \times HighSkill_{it}) + \Delta\alpha 2(AI\ it \times LowSkill_{it}) + \Delta\alpha 3(AI\ it \times UnionDensity_{it}) + \gamma i + \phi t + \epsilon\ sit$$

In this equation, $\Delta\alpha 3$(AIit×Union Densityit) Δα3(AIit×UnionDensity it) is the additional interaction term with union density. Here I also substituted the log income with the skill share to measure it for the employment share level. In addition, I scaled the AI and ICT intensity by deducting the mean and divided with the standard deviation.

5 Results and Analysis

This part of the study explains the analysis performed and the results that were obtained in both methods i.e., long difference regression results and the yearly panel with fixed effects.

5.1 Long Difference Regression Results

The study employs a long difference regression approach, which allows for the analysis of how key variables—AI innovation, and income inequality measures—have changed over an extended period due to increases in AI innovation. This method calculates the differences in the variables of interest between two time points (e.g., 2005 and 2020) for each country, thereby focusing on the overall trend rather than annual variations. It simplifies the analysis by cancelling out effects that do not change over time within each country, such as cultural factors or long-standing economic policies, thus providing a clearer picture of the long-term impact of AI innovation on income distribution. The method is also evident from the recent literature on linkage between innovation and labor market.

The results from the long-difference regressions offer a nuanced view of how advancements in AI, as captured by changes in AI intensity, relate to different strata of income distribution over time. Table 2 below represents the results of long difference regression between the AI intensity and different measures of income inequality.

Change in Income Inequality Due to AI Innovation

VARIABLES	(1) d_Bottom50	(2) d_Top1	(3) d_Top10	(4) d_Gini
d_AIIntensity	-0.013	0.008	-0.006	0.008
	(0.036)	(0.025)	(0.037)	(0.013)
d_GDPPerCapitaGrowthRate	-0.001	0.000	0.002	0.000
	(0.001)	(0.001)	(0.002)	(0.001)
Constant	-0.013	-0.000	0.011	-0.000
	(0.008)	(0.012)	(0.017)	(0.006)
Observations	37	37	37	30
R-squared	0.025	0.004	0.047	0.015

Table 2: Long difference regression results between AI Innovation and Income Inequality

The coefficient of -0.013 in column 1 for d_AIIntensity indicates that a one-unit increase in AI intensity is associated with a 1.3 percentage point decrease in the income share of the bottom 50% of the population. This suggests that as AI innovation intensifies, the income share of the bottom half of the population tends to decline slightly. However, the standard error of 0.036 indicates a relatively high degree of uncertainty around this estimate, suggesting that the effect may not be statistically significant. Similarly, the coefficients for AI intensity in columns 2 and 3, which correspond to the top 1% and top 10% income shares, are 0.008 and -0.006 respectively, with standard errors indicating no strong evidence of a significant effect. In column 4, the coefficient for the Gini index is 0.008, implying a potential slight increase in overall income inequality with increased AI intensity, though this effect also lacks statistical significance given the standard error of 0.013.

The significance of the GDP per capita growth rate's impact on the Bottom 50% income share, with a coefficient of -0.002 and a robust standard error of 0.001, shows that economic growth slightly but significantly negatively affects this group's income share. For gini, the results indicate that a one percentage point increase in AI Normalized Patents is associated with a marginal and statistically insignificant increase of 0.008 in the Gini coefficient, with a robust standard error of 0.013, suggesting no strong or reliable link between the rise of AI innovation and increasing income inequality.

The next analysis explores the impact of ICT innovation on income inequality within OECD countries by focusing on different segments of the income distribution: Top 1%, Top 10%, and Bottom 50%. The dependent variables in each model represent these segments, and the key independent variable is ICT innovation, quantified by normalized patents.

ICT Intensity and Income Inequality

	(1)	(2)	(3)	(4)
VARIABLES	d_Top1	d_Top10	d_Bottom50	d_Gini
d_ICTIntensity	0.001*	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
d_GDPPerCapitaGrowthRate	0.001	0.002	-0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Constant	0.000	0.010	-0.014*	0.000
	(0.012)	(0.016)	(0.007)	(0.005)
Observations	37	37	37	30
R-squared	0.088	0.057	0.082	0.013

Table 3: Long difference results between ICT Intensity and Income Inequality

Top 1% Inequality finds a small but statistically significant positive correlation ($p < 0.1$) between ICT innovation and income inequality in the top 1%, with a coefficient of 0.001. This suggests that as ICT innovation increases, income tends to become slightly more concentrated among the richest or top 1% income holders. Top 10% Inequality shows no significant association between ICT innovation and the income distribution among the top 10%. The coefficient of 0.000 implies that ICT patents do not significantly influence income inequality in this broader rich group. Bottom 50% Inequality indicates a significant negative association ($p < 0.05$) between ICT innovation and income inequality in the bottom 50%, with a coefficient of -0.001. This suggests that greater ICT innovation is associated with a reduction in income inequality among the less affluent half of the population. Additionally, the models control for the GDP per capita growth rate annually which helps to isolate the specific impact of ICT innovation from general economic growth.

For the Gini coefficient, which measures income inequality, the coefficient for ICT patent intensity is 0.000, indicating no significant effect from changes in ICT patents on the level of income inequality within the data set. This suggests that increases or decreases in ICT patenting activity do not substantially alter the distribution of income as measured by the Gini coefficient.

I also used unit labor cost against the AI and ICT intensity and the results are provided in the appendix. In the analysis of Unit Labor Costs (ULC), which reflect the average cost of labor per unit of output, the coefficient for ICT patent intensity is -0.064. The detailed results can be found in table 20 and table 21.

5.2 Fixed Effects Panel Regression Results

Next, this study performed assessment on the relationship between skill share data and the innovation intensity. Here is also where the second method of this study i.e., yearly panel with fixed effects comes into work. The plot in figure 5 visualizes the distribution of employment share across three distinct skill levels—high, medium, and low—over the years from 2005 to 2020. Each line represents one of the skill levels.

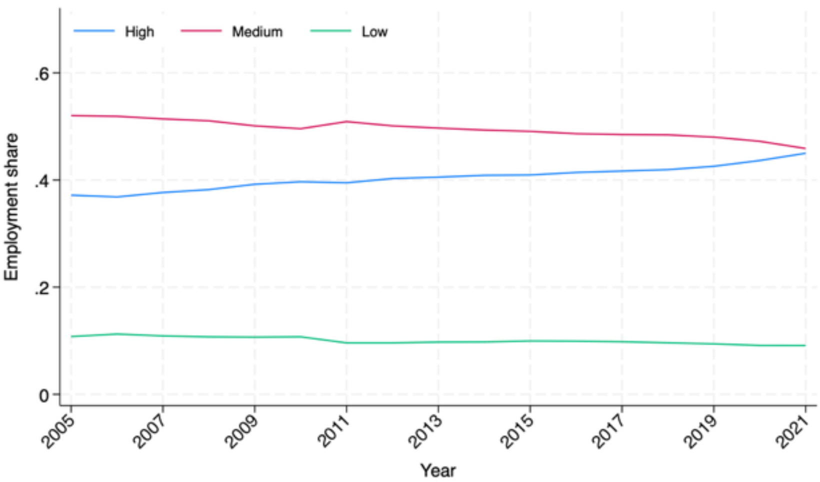

Figure 5: Skill share over the years across different level of skills.

The blue line represents individuals with high skill levels. It shows a generally stable trend with a slight increase towards the end of the period. The red line represents individuals with medium skill levels. The employment share for high skill appears to be increasing on the expense of medium skill. The green line represents individuals with low skill levels. This line remains relatively flat and low throughout the period, suggesting that the share of low-skilled workers in employment has remained consistently minor compared to other groups.

In this part of the study, the relationship between AI Intensity and employment share is studied. Utilizing a high-dimensional fixed effects model, the analysis incorporates both year, and country to control for unobservable heterogeneity over time, ensuring robust estimates.

In the model, which includes the fixed effects the results show that the coefficient for the interaction between AI intensity and high skill levels is at 0.08 and is statistically significant, reinforcing the positive relationship between AI and the skill share of high-skilled workers. It shows that a 1 SD increase in AI patents is associated with a 0.8 percentage point increase in the high-skill employment share (or about a one percentage point increase. The coefficient for the interaction between AI intensity and low skill levels is negative and statistically significant (-0.002, suggesting a clearer negative impact of AI intensity on the skill share of low-skilled workers when sectoral variations are controlled for. that a 1 SD increase in AI patents is associated with a -0.2-percentage point decrease in the high-skill employment share.

Change in Employment Share by Skill to AI Innovation

VARIABLES	(1) skill_share
ai_intensityXhighskill	0.008***
	(0.002)
ai_intensityXlowskill	-0.002***
	(0.001)
_Ihighskilla1	-0.114***
	(0.003)
_Ilowskilla1	-0.403***
	(0.002)
Constant	0.506***
	(0.002)
R-squared	0.837

Table 4: Change in Employment Share by Skill Due to AI Innovation

Next, the study explores the differential impacts of ICT (Information and Communications Technology) intensity on employment skill share across high-skill and low-skill groups. Utilizing a robust econometric framework that incorporates high-dimensional fixed effects (HDFE) to control for both time and unobservable heterogeneities within groups, the study provides insightful evidence into how technological advancements in ICT influence labor market dynamics.

The regression output reveals a positive and statistically significant relationship between ICT intensity and the share of high-skill employment. The coefficient for the interaction between ICT intensity and high-skill workers is 0.033, which is statistically significant at the 1% level ($p<0.01$), with a standard error of 0.003. This indicates that 1 SD increase in the ICT intensity is associated with a 3.3 percentage point increase in the employment share of high-skill workers. In contrast, the coefficient for the interaction between ICT intensity and low-skill workers is 0.002, which is not statistically significant and has a standard error of 0.003, suggesting no meaningful impact on the employment share of low-skill workers. Therefore, ICT innovation appears to favor high-skill employment relative to medium skilled, potentially widening the employment gap between high-skill and low-skill workers.

Change in Employment Share Due to ICT Innovation

VARIABLES	(1) skill_share
ict_intensityXhighskill	0.033***
	(0.003)
ict_intensityXlowskill	0.002
	(0.003)
_Ihighskilla1	-0.105***
	(0.003)
_Ilowskilla1	-0.401***
	(0.002)
Constant	0.502***
	(0.001)
R-squared	0.834

Table 5: Change in employment share by skill due to ICT innovation

The substantial and significant increase in high-skill employment share linked with AI and ICT intensity suggests that industries heavily invested in new AI and ICT technologies may be shifting towards more skill-intensive production processes. This shift not only reflects the higher productivity associated with high-skilled employment but also may signal a broader transformation in economic structures favoring more complex job roles that leverage advanced technological capabilities.

For low-skill employment, the absence of a significant effect might indicate that while innovations are not directly displacing low-skilled jobs, they are not contributing to their growth either.

In addition to above, this study also looked at how the monthly earnings across different skill levels are impacted by the AI intensity and the ICT intensity. The below figure 6 shows how log monthly earnings have varied across different years and in different skill levels. The income is seen fluctuating for all the skills over the years. The results for regression are provided in table 8 and table 9.

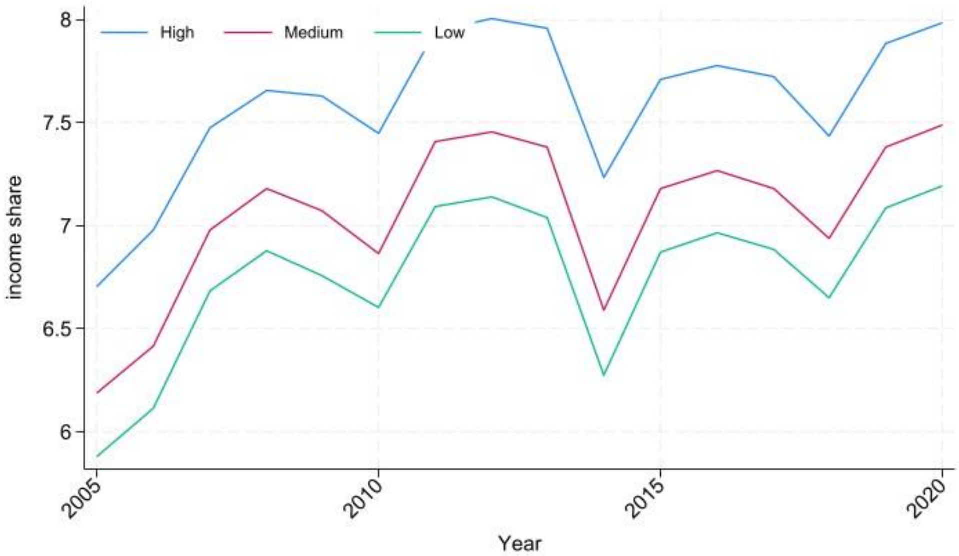

Figure 6: Monthly earnings by skill over the years.

The analysis of the impact of AI innovation on income inequality shows that AI intensity significantly affects income among both high-skill and low-skill workers relative to medium-skill workers. Specifically, the coefficient for the interaction between AI intensity and high-skill workers is 0.217, which is statistically significant at the 5% level ($p<0.05$), indicating that 1 SD increase in the AI intensity is associated with a 21.7 percentage point increase in income for high-skill workers compared to medium-skill workers. Similarly, the coefficient for the interaction between AI intensity and low-skill workers is 0.191, significant at the 10% level ($p<0.1$), suggesting a 19.1 percentage point increase in income for low-skill workers relative to medium-skill workers. The control variables indicate that, independent of AI intensity, high-skill workers have a substantially higher log income (0.531) while low-skill workers have a lower log income (-0.306) compared to medium-skill workers.

Change in Income Share Due to AI Intensity

VARIABLES	(1) log_income
ai_intensityXhighskill	0.217**
	(0.101)
ai_intensityXlowskill	0.191*
	(0.111)
_Ihighskilla1	0.531***
	(0.066)
_Ilowskilla1	-0.306***
	(0.067)
Constant	7.080***
	(0.047)

Observations	444
R-squared	0.848

Table 6: Change in income share by skill due to AI intensity.

In contrast, the impact of ICT innovation on monthly earnings appears to be small, as the coefficients for the interactions between ICT intensity and both high-skill (-0.011) and low-skill workers (-0.008) are not statistically significant in response to the 1 SD change in the ICT intensity. This suggests that ICT intensity does not meaningfully affect the log income of either high-skill or low-skill workers relative to medium-skill workers. However, the control variables show that high-skill workers have a significantly higher log income (0.525) and low-skill workers have a significantly lower log income (-0.301) compared to medium-skill workers, independent of ICT intensity.

Change in Income Share Due to ICT Intensity

VARIABLES	(1) log_income
ict_intensityXhighskill	-0.011
	(0.068)
ict_intensityXlowskill	-0.008
	(0.069)
_Ihighskilla1	0.525***
	(0.063)
_Ilowskilla1	-0.301***
	(0.064)
Constant	7.134***
	(0.044)
Observations	549
R-squared	0.812

Table 7: Change in log income due to ICT Innovation

5.3 Studying Sector Level Variations

The regression results indicate that the effects of AI intensity on skill share are consistent across various sectors, with AI intensity for high-skilled workers generally showing a positive and significant impact on skill share with 0.008 value in response to 1 SD increase in the AI intensity, while the effect on low-skilled workers is either negative or insignificant in construction sector as shown in table 9. This uniformity across sectors suggests that the impact of AI innovation on skill share does not vary significantly by sector, implying a general trend where AI benefits high-skilled workers' share more consistently across different industries. Thus, it can be concluded that AI's effects on skill share are general and do not substantially vary across sectors. Other sectors resulting tables are provided in the appendix.

Skill Share Due to AI Innovation in Construction sector.	
	(1)
VARIABLES	skill_share
ai_intensityXhighskill	0.008**
	(0.004)
ai_intensityXlowskill	-0.002
	(0.002)
1.highskill	-0.114***
	(0.006)
1.lowskill	-0.403***
	(0.005)
Constant	0.506***
	(0.004)
R-squared	0.837

Table 8: Impact of AI intensity in the Construction Sector

5.4 Heterogeneity Checks by Including Higher and Lower Union Density

Next, this paper performed heterogeneity checks by looking at how are the changes occurring at different union densities. For AI intensity, in high union density environments, AI intensity significantly increases the skill share for high-skill workers, as indicated by the positive and statistically significant estimate, while its effect on low-skill workers is smaller and less significant. In low union density environments, the impact of AI intensity on both high-skill and low-skill workers is relatively small and not statistically significant. Relative to medium-skill workers, these results suggest that in high union density settings, AI innovation disproportionately benefits high-skill workers, potentially exacerbating skill-based disparities. Conversely, in low union density environments, AI innovation does not significantly alter the skill share for either high-skill or low-skill workers, indicating a more neutral impact across skill levels. This underscores the importance of union density in moderating the effects of technological advancements on workforce skill composition.

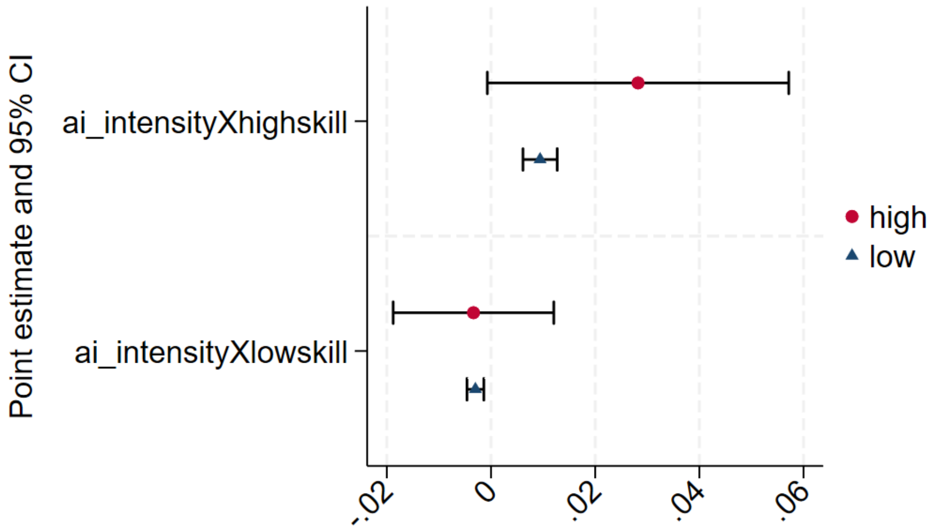

Figure 7: AI Intensity and its effects on different skill level across different union density.

Next, I made similar plot for ICT intensity across different union density and got results as shown in the figure 8. In high union density settings, ICT intensity has a small positive effect on the skill share of high-skill workers, but this effect is not statistically significant. Similarly, the effect on low-skill workers is minimal and not significant. In low union density settings, the effects of ICT intensity on both high-skill and low-skill workers are also small and statistically insignificant. This indicates that ICT innovation does not significantly impact the skill share of either high-skill or low-skill workers relative to medium-skill workers in both high and low union density environments. Overall, the results suggest that ICT innovation has a neutral effect on skill share across different union densities, implying that ICT advancements do not exacerbate skill-based disparities in either context. The tables for results are provided in appendix.

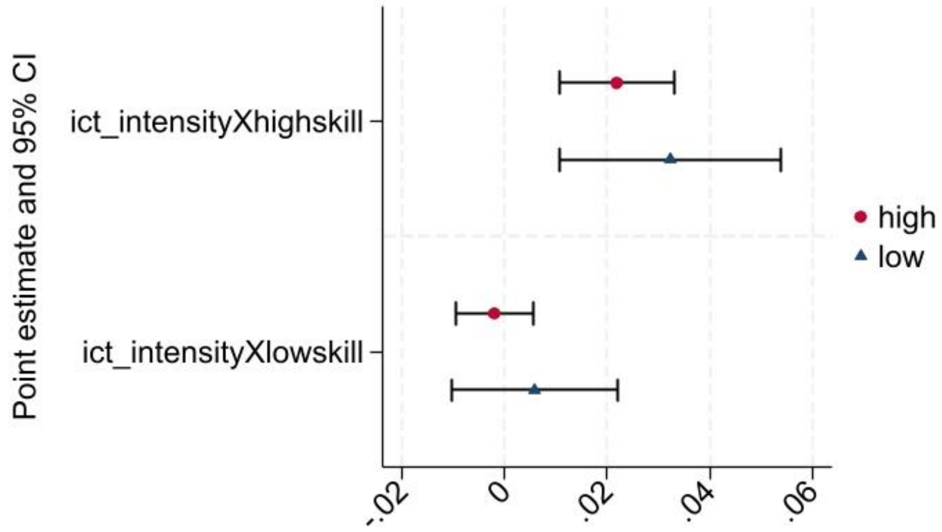

Figure 8: ICT Intensity and employment share across different union densities.

Interestingly, the omitted category, which represents medium-skilled workers, appears to be relatively worse off in countries with high AI intensity, especially in countries with low union presence. This aligns with the theory of skill-biased technological change (SBTC), which posits that technological advancements, including AI, tend to favor high-skilled workers while displacing low-skilled workers. Medium-skilled workers, whose tasks might be automated or require upskilling, find themselves at a disadvantage. The lack of significant differences in high union density countries suggests that strong unions help mitigate these effects by providing better wage negotiations, job security, and retraining opportunities, thus protecting medium-skilled workers from the adverse impacts of AI.

Overall, the results imply that AI innovations are associated with a shift towards higher-skilled employment in industries where AI is more intensively used, potentially leading to a polarizing effect on the labor market where high-skilled workers benefit while low-skilled workers might not experience the same positive impact. This underscores the need for policies aimed at mitigating the adverse effects on low-skilled workers, such as through training and education programs tailored to the demands of an increasingly automated economy.

Next, the following plot depicts the relationship between ICT intensity and income earnings for high and low skill workers across different union density settings. For high skill workers, ICT intensity has a similar positive effect on income earnings regardless of the union density, as indicated by the overlapping confidence intervals. For low skill workers, the impact of ICT intensity on income earnings is also positive but shows little difference between high and low union density settings.

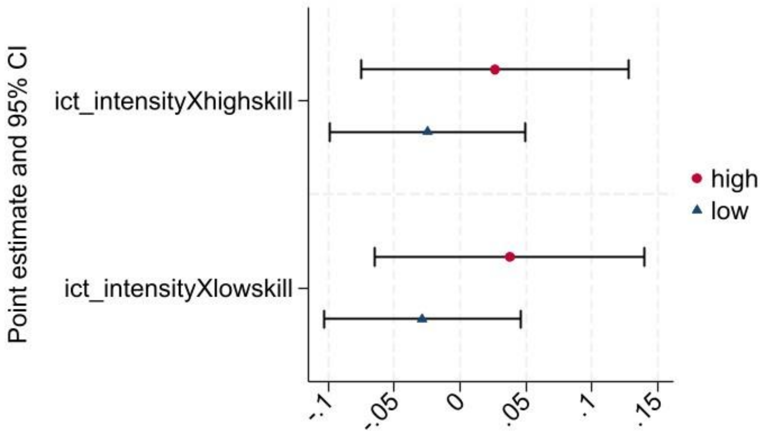

Figure 9: ICT intensity and income earnings for different skills across different union settings.

In high union density regions, the coefficient for AI intensity on high-skilled log income is positive but statistically insignificant, indicating no clear impact, while for low-skilled log income, the coefficient is negative and similarly insignificant. In low union density regions, the coefficient for AI intensity on high-skilled log income is also positive and statistically insignificant, suggesting a similar lack of impact, while for low-skilled log income, the coefficient is positive and significant, implying that AI intensity increases log income for low-skilled workers in these regions.

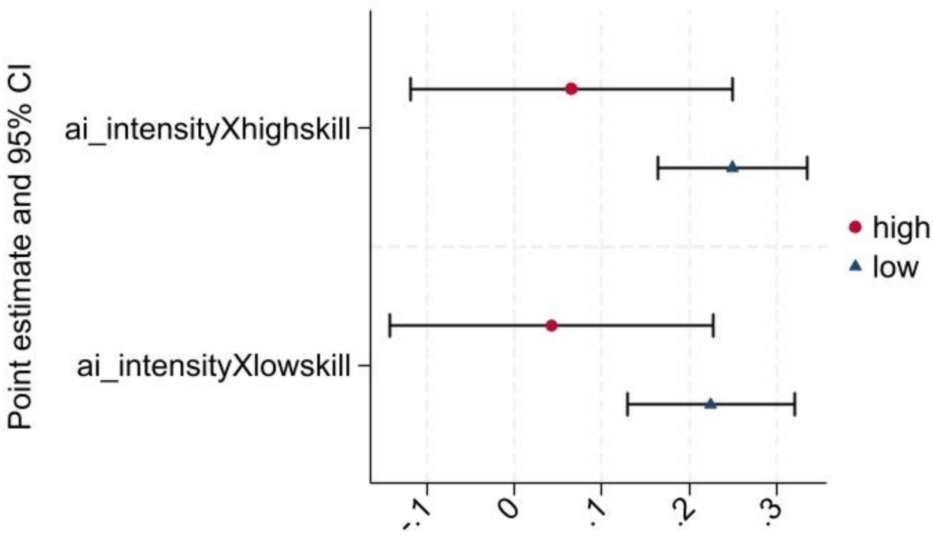

Figure 10: AI Intensity and Log Income at different density levels.

5.5 Robustness Checks

The study also performed robustness checks to look at the results. To check robustness, I replaced the log income with the income instead and the results were like what I had got with the log income. Similarly, the significant positive effect for income was considered for both high and low skill just like when I used the log income before. For example, in the case of ICT innovation, there is insignificant positive with the ai intensity for high skill and negative insignificant effect for low skill like table 8 and 9.

Change in Income by Skill Due to ICT Innovation

VARIABLES	(1) income
ict_intensityXhighskill	206.558**
	(85.567)
ict_intensityXlowskill	-90.559
	(58.362)
_Ihighskilla1	1,407.339***
	(77.798)
_Ilowskilla1	-545.752***
	(56.379)
Constant	2,067.603***
	(29.422)
Observations	549
R-squared	0.875

Table 9: Robustness for income with the ICT innovation

In addition, I also checked by removing the United States to see if that has any impact in the long difference regression between AI intensity and the income inequality. Excluding the United States from the analysis does not significantly alter the relationship between AI intensity and income inequality, as the coefficients for AI intensity on the bottom 50% income share, top 1% income share, top 10% income share, and Gini coefficient remain largely similar and statistically insignificant in both scenarios. The primary differences are minor variations in the coefficients: the bottom 50% income share changes from -0.013 to -0.015, the top 1% income share from 0.008 to 0.009, the top 10% income share from -0.006 to -0.004, and the Gini coefficient remains at 0.008.

Change in Income Inequality Due to AI Innovation - Excluding US

VARIABLES	(1) d_bottom50	(2) d_top1	(3) d_top10	(4) d_gini
d_aiintensity	-0.015	0.009	-0.004	0.008
	(0.035)	(0.025)	(0.037)	(0.013)
d_gdppercapitagrowthrate	-0.001	0.000	0.002	0.000
	(0.001)	(0.001)	(0.002)	(0.001)

Constant	-0.011	-0.001	0.009	-0.000
	(0.007)	(0.012)	(0.017)	(0.006)
Observations	36	36	36	30
R-squared	0.021	0.003	0.043	0.015

Table 10: Robustness for checking long difference regression excluding U.S

6 Discussion and Conclusion

This thesis examined how advancements in technology, specifically AI and ICT patents, affect income inequality among OECD countries. It reveals that the relationship between technology development and income inequality is complex and not straightforward. This research shows that while technological innovation does not significantly decrease the income of the lower 50% of earners, it also suggests that the richest 1% and 10% might benefit from it in the long run, although these findings are not strong enough to be definitive.

The concept of Skill-Biased Technological Change (SBTC) is supported in the study. This theory suggests that technological improvements usually benefit those who are already skilled, which might increase the income gap between different skill levels. This idea ties in with the small and inconclusive signs seen in growing income gaps driven by technology advancements over time.

For high-skill employment, both ICT and AI intensity exhibited a positive and statistically significant impact, especially in environments with low union density. This correlation underscores the increased demand for advanced skills capable of leveraging new technologies, indicating a shift towards more skill-intensive roles within technologically advancing industries.

Conversely, the effects of technological intensities on low-skill employment were not statistically significant, suggesting that these advancements do not directly displace low-skill jobs. However, they also do not contribute to the growth of low-skill employment shares, highlighting a potential risk of job stagnation or obsolescence in sectors less influenced by technological innovation.

The role of union density proved to be a significant factor in moderating these effects. Medium-skilled workers are found to be relatively worse off in countries with high AI intensity, particularly in environments with low trade union presence. This negative impact is more pronounced in the settings, where the lack of strong labor protections exacerbates the challenges faced by medium-skilled workers.

Future research should explore these dynamics in high union density environments to offer a fuller picture of how different labor protections influence the relationship between technology and employment. Longitudinal studies could also clarify the long-term effects of these technological shifts across various industries.

Comparing results with the previous work

The results of this study are in line with the previous work like that of Innovation and Inequality: A comparative study by (Włodarczyk 2017) that did not find any relationship between innovation and income inequality. The results of this study also align with and expand upon the findings of previous works on the relationship between technological innovation and income inequality. Like Acemoglu's skill-biased technological change hypothesis, this research demonstrates that AI and ICT advancements tend to disproportionately benefit high-skilled workers. The significant positive impact of AI and ICT intensity on the employment share of high-skilled workers corroborates the earlier findings by Acemoglu, Autor, and others who highlighted that technological progress favors those with advanced skills, thereby widening the wage gap between high-skilled and low-skilled workers. Moreover, the minimal and statistically insignificant impact on the Gini coefficient and unit labor costs echoes the nuanced view presented in studies like those by Gilfoyle and Prettner & Strulik, which suggest that while technology drives productivity, its effects on broader income inequality measures can be complex and varied.

However, this study also provides new insights, particularly regarding the moderating role of union density in mitigating the adverse effects of technological innovation on low-skilled workers. The analysis reveals that high union density can buffer the negative impacts of AI on low-skilled employment and earnings, a factor not extensively covered in previous research. This finding highlights the importance of labor protections in addressing income inequality, suggesting that strong labor unions can play a crucial role in ensuring that the benefits of technological advancements are more equitably distributed. Additionally, the study's focus on OECD countries and the specific period from 2005 to 2020 provides a contemporary perspective, capturing the effects of rapid AI and ICT innovations in the digital age, thereby contributing to a more current understanding of these dynamics compared to earlier works that may not have fully encompassed these recent technological developments.

Future research could use the updated data specifically after the recent advancements in the field open AI and how that is impacting the employment or the income inequality. The more research done in the field could be helpful in forming the policymakers of the trends that are occurring and hence can contribute to better decision making that could help reduce the inequality and promote sustainable employment opportunities for all skills.

7 References

Acemoglu, D. (2002). "Technical Change, Inequality, and the Labor Market." Journal of Economic Literature **40**(1): 7-72.

Acemoglu, D., et al. (2012). "The Environment and Directed Technical Change." American Economic Review **102**(1): 131-166.

Acemoglu, D., et al. (2020). "Ai and Jobs: Evidence from Online Vacancies." SSRN Electronic Journal.

Acemoglu, D. and P. Restrepo (2019). "Automation and New Tasks: How Technology Displaces and Reinstates Labor." Journal of Economic Perspectives **33**(2): 3-30.

Aghion, P., et al. (2018). "Innovation and Top Income Inequality." The Review of Economic Studies **86**(1): 1-45.

Autor, D. H. (2013). "The “task approach” to labor markets: an overview." Journal for Labor Market Research **46**(3): 185-199.

Autor, D. H., et al. (2003). "The Skill Content of Recent Technological Change: An Empirical Exploration*." The Quarterly Journal of Economics **118**(4): 1279-1333.

Fleming, P. (2019). "Robots and Organization Studies: Why Robots Might Not Want to Steal Your Job." Organization Studies **40**(1): 23-38.

Gilfoyle, A. (2023). The Impact of Automation on Income Inequality: A Cross-Country Analysis.

Griliches, Z. (1990). "Patent Statistics as Economic Indicators: A Survey." Journal of Economic Literature **28**(4): 1661-1707.

Kharlamova, G., et al. (2018). "The impact of technological changes on income inequality: The EU states case study." Journal of International Studies **11**: 76-94.

Korinek, A., et al. (2021). "Technological Progress, Artificial Intelligence, and Inclusive Growth." IMF Working Papers **2021**(166): A001.

OECD (2003). Emerging Risks in the 21st Century.

Prettner, K. and H. Strulik (2020). "Innovation, automation, and inequality: Policy challenges in the race against the machine." Journal of Monetary Economics **116**: 249-265.

Rolf, S. (2021). "Working in the end times." New Technology, Work and Employment **36**(1): 114-117.

Wang, L., et al. (2023). "Are artificial intelligence dividends evenly distributed between profits and wages? Evidence from the private enterprise survey data in China." Structural Change and Economic Dynamics **66**: 342-356.

Włodarczyk, J. (2017). "Innovations and income inequalities – A comparative study." Journal of International Studies **10**: 166-178.

8 Appendix

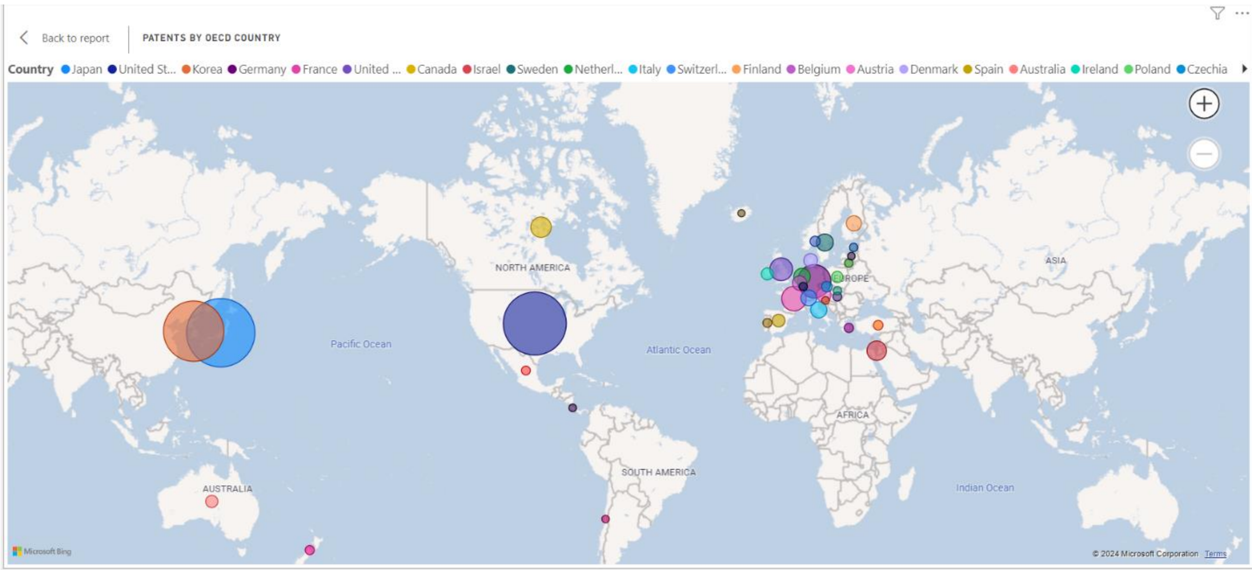

Figure 11: Total patents by country

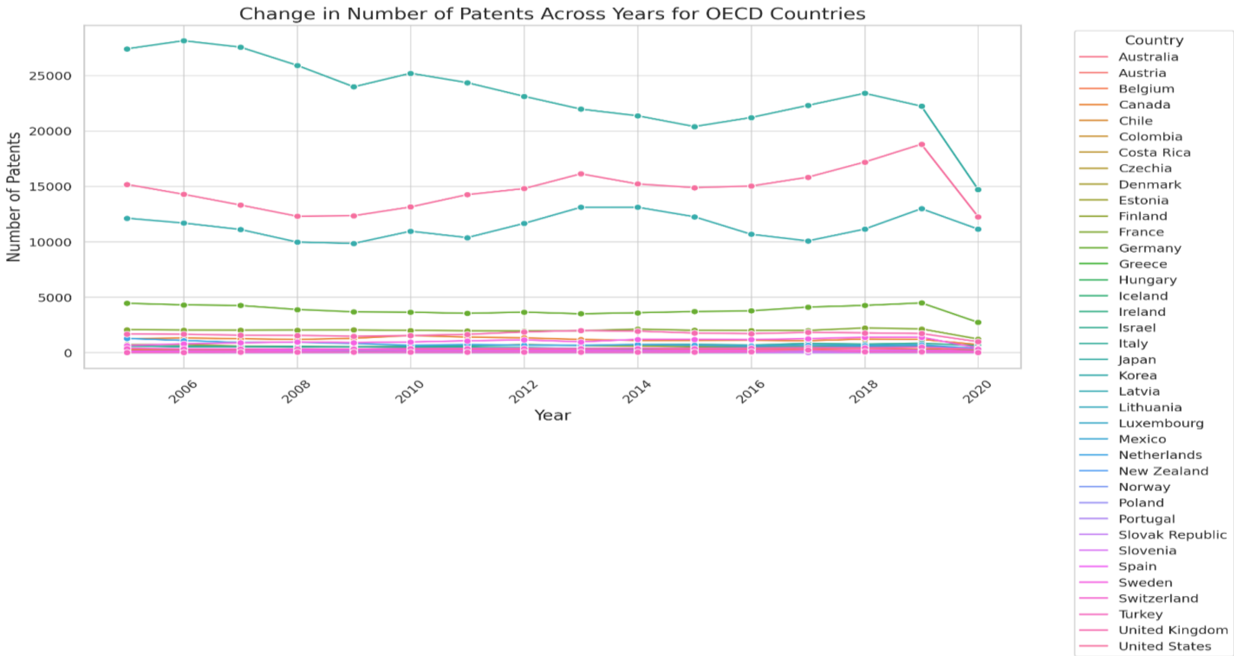

Figure 12: Change in number of patents over the years in OECD Countries

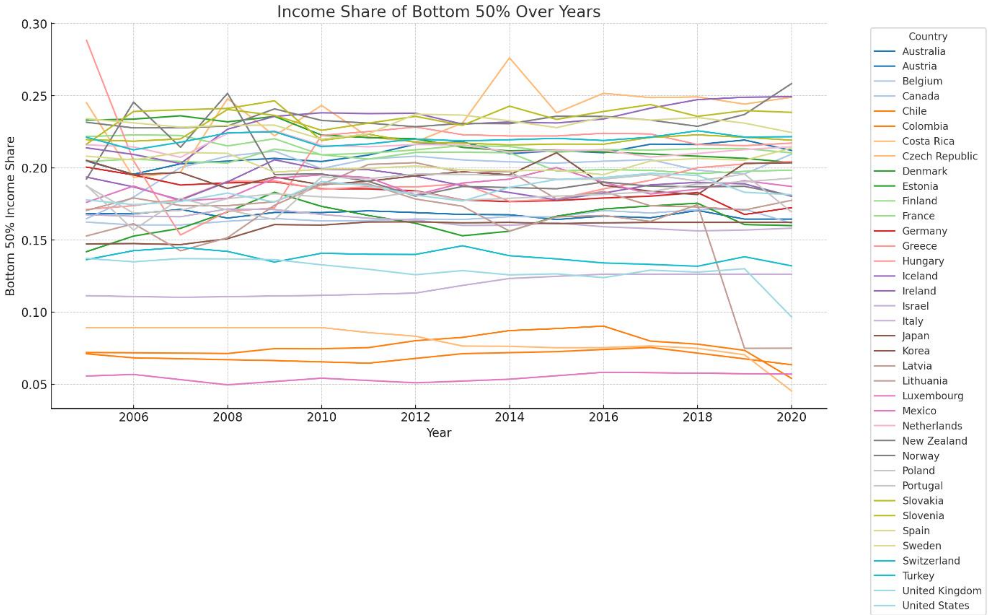

Figure 13: Income share of bottom 50% over the years

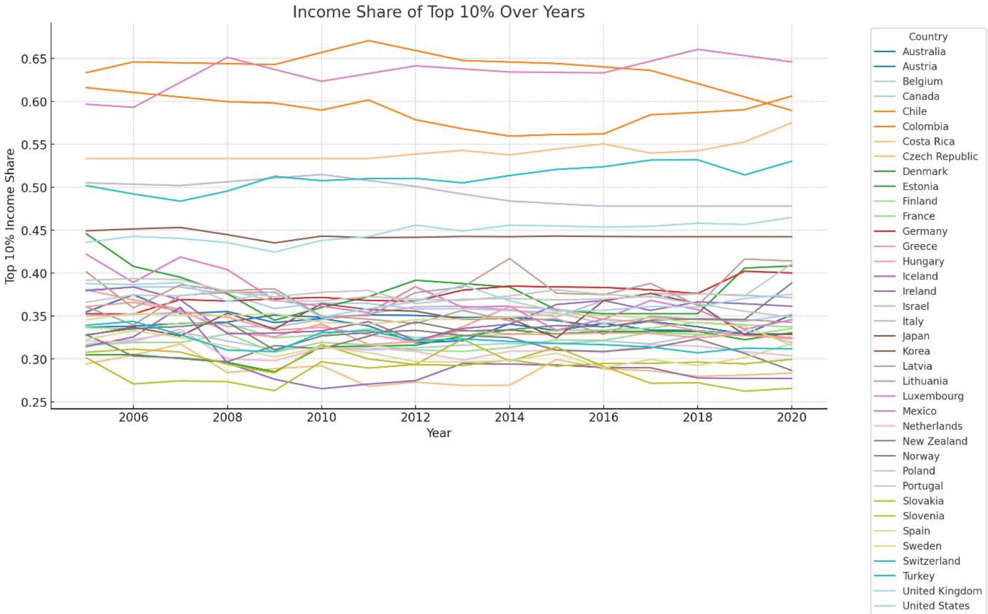

Figure 14: income share of top 10% over the years

Change in Employment Share due to AI Intensity in Low Union Density

	(1)
VARIABLES	skill_share
ai_intensityXhighskill	0.009***
	(0.002)
ai_intensityXlowskill	-0.003***

	(0.001)
_Ihighskilla1	-0.161***
	(0.004)
_Ilowskilla1	-0.403***
	(0.003)
Constant	0.521***
	(0.002)
Observations	3,300
R-squared	0.811

Table 11: Change in employment share by skill in low union density context

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Change in Employment Share Due to AI Innovation in High Density Context

	(1)
VARIABLES	skill_share
ai_intensityXhighskill	0.028***
	(0.006)
ai_intensityXlowskill	-0.004
	(0.003)
_Ihighskilla1	-0.045***
	(0.003)
_Ilowskilla1	-0.403***
	(0.002)
Constant	0.483***
	(0.002)
Observations	2,275
R-squared	0.924

Table 12: Change in employment share by skill in low union density context

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Change in Employment Share Due to ICT Innovation in Low Union Density

	(1)
VARIABLES	skill_share
ict_intensityXhighskill	0.022***
	(0.002)
ict_intensityXlowskill	-0.002
	(0.002)
_Ihighskilla1	-0.035***
	(0.003)

_Ilowskilla1	-0.398***
	(0.002)
Constant	0.477***
	(0.002)
Observations	2,815
R-squared	0.915

Table 13: Change in employment share by skill due to ICT innovation in low union density context

Change in Employment Share by Skill Due to ICT Intensity	
	(1)
VARIABLES	skill_share
ict_intensityXhighskill	0.032***
	(0.005)
ict_intensityXlowskill	0.006
	(0.004)
_Ihighskilla1	-0.154***
	(0.004)
_Ilowskilla1	-0.404***
	(0.003)
Constant	0.520***
	(0.002)
Observations	4,050
R-squared	0.811

Table 14: Change in employment share by skill in high union density context

Change in log income in High Union Density Due to ICT Intensity	
	(1)
VARIABLES	skill_share
ict_intensityXhighskill	0.022***
	(0.006)
ict_intensityXlowskill	-0.002
	(0.004)
_Ihighskilla1	-0.035***
	(0.007)
_Ilowskilla1	-0.398***
	(0.005)
Constant	0.477***
	(0.005)

Observations	564
R-squared	0.915

Table 15: Change monthly earnings in in High Union Density Due to ICT Innovation

Change in Skill Share in Low Union Density Due to ICT Intensity

	(1)
VARIABLES	skill_share
ict_intensityXhighskill	0.032***
	(0.011)
ict_intensityXlowskill	0.006
	(0.008)
_Ihighskilla1	-0.154***
	(0.008)
_Ilowskilla1	-0.404***
	(0.006)
Constant	0.520***
	(0.004)
Observations	810
R-squared	0.811

Table 16: Change monthly earnings in in low Union Density Due to ICT Innovation

Skill Share Due to AI Intensity in Public Administration

	(1)
VARIABLES	skill_share
ai_intensityXhighskill	0.008**
	(0.004)
ai_intensityXlowskill	-0.002
	(0.002)
1.highskill	-0.114***
	(0.006)
1.lowskill	-0.403***
	(0.005)
Constant	0.506***
	(0.004)
Observations	1,116
R-squared	0.837

Table 17: Skill Share Due to AI Innovation in Public Administration

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Skill Share Due to AI Intensity in Mining and Quarrying

VARIABLES	(1) skill_share
ai_intensityXhighskill	0.008**
	(0.004)
ai_intensityXlowskill	-0.002
	(0.002)
1.highskill	-0.114***
	(0.006)
1.lowskill	-0.403***
	(0.005)
Constant	0.506***
	(0.004)
Observations	1,111
R-squared	0.836

Table 18: Skill Share Due to AI Innovation in Mining and Querying

Skill Share Due to AI Intensity in Trade

VARIABLES	(1) skill_share
ai_intensityXhighskill	0.008**
	(0.004)
ai_intensityXlowskill	-0.002
	(0.002)
1.highskill	-0.114***
	(0.006)
1.lowskill	-0.403***
	(0.005)
Constant	0.506***
	(0.004)
Observations	1,116
R-squared	0.837

Table 19: Skill Share Due to AI Innovation in Trade

Change in ULC Due to AI Intensity

VARIABLES	(1) d_ULC
d_AIIntensity	4.877

	(5.378)
d_GDPPerCapitaGrowthRate	0.498*
	(0.270)
Constant	0.874
	(2.193)
Observations	36
R-squared	0.140

Table 20: ULC against AI intensity

ICT Intensity and Unit Labor Cost	
	(1)
VARIABLES	d_ULC
d_ICTIntensity	-0.079
	(0.105)
d_GDPPerCapitaGrowthRate	0.516*
	(0.254)
Constant	1.112
	(2.099)
Observations	36
R-squared	0.154

Table 21: ULC against ICT intensity