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From IT to AI: Analysis of Skill–Biased Technological Change in Europe

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From IT to AI: Analysis of Skill–Biased Technological Change

in Europe

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I. Abstract

II. Introduction

III. Literature Review

IV. Data

V. Conclusion & Policy Implications
1 Abstract

The beginning of the Artificial Intelligence (AI) revolution marks a significant shift in technological advancements, like the Information Technology (IT) revolution of the 20th century. This paper investigates the similarities between the two revolutions, examining evidence of skilled-biased vs. routine-biased technological change (SBTC vs. RBTC) in Europe. This paper examines the impact of information technology on labor markets, productivity, and income distribution by looking at past trends & data. It draws insights from a variety of economists to forecast trends in the age of artificial intelligence.

2 Introduction

The demand for skills has changed due to technological evolution, reshaping labor markets. The new prevalence of artificial intelligence will be no different. To properly navigate the socio-economic impacts of the AI revolution, it's crucial to draw insights from the lessons learned during the IT revolution, particularly in income distribution. Therefore, this study poses a pivotal research question: What insights do the early periods of the IT revolutions offer for understanding the current AI revolution? To answer this question, we will look at data across Europe during its age of IT and review the perspectives of many economists to effectively understand how the labor market will be affected.

To understand how industrial revolutions are viewed it’s important to know the history of them. According to Agrawal, Gans, and Goldfarb (2002), the first industrial revolution started with the use of steam engines, which were used in factories and led to reduced costs. The second was the rise in electricity and its cost reduction. Electricity became a catalyst for technological
change as artificial light created a world that could work at night. The third industrial revolution was seen as a reduction in the cost of arithmetic, specifically in the use of computers. All of these revolutions advance technology, change how economies evolve, and have a major social impact.

This led to the fourth and current industrial revolution: AI, which will make predictions cheaper. Tracing the evolution of technological advancements from steam engines to AI, what makes an industrial revolution so important is its transformative nature and reduced costs.

AI's potential to be integrated into many different industries and have many distinct applications qualify it as a general-purpose technology (GBT). (Trajtenberg, 2018). With machine learning driving advancements in perception and cognition, AI holds immense potential to boost productivity and improve economic welfare like how electricity or the internet have transformed society. (Brynjolfsson, et al. 2017),

This paper focuses on the relationship between artificial intelligence and the labor market and delves into the impact it has on income inequality. This paper will look at how artificial intelligence and the automation of tasks change the classic workflow dynamics. This area of research aims to understand how the job market will be affected differently by the implementation of AI compared to that of the IT revolution. As technological advancements in the past have brought many benefits, it’s also brought increased inequality. This paper goes beyond a mere analysis of trends and challenges as it also promotes the urgent need for policy interventions that come as a response to those whose well-being was affected negatively by this innovation.
Many economists see AI's rise as one of the two extremes: utopian/dystopian, worrying about losing jobs, against the dream of more free time and wealth for everyone (Stevenson, 2017). The changes AI could bring are huge, potentially boosting productivity, sparking innovation, and driving economic growth like never before. But there is a shadow over it: what about jobs, who gets the gains, and how do we all feel about life? Figuring this out is not just for the tech industry, it is crucial for shaping policies that affect us all. And with AI possibly taking over jobs, it becomes imperative that we figure out how to shift smoothly into whatever lies ahead.

Many papers covering artificial intelligence look at the United States economy, as it has been a leader in technological change. Productivity growth in the United States accelerated after 1995, especially in sectors heavily reliant on information technologies, but Europe productivity growth did not experience a similar rebound during the same period. (Etal., 2012). This is due to US companies operating in Europe experiencing a "productivity miracle," achieving higher productivity from IT compared to non-US multinationals, especially in sectors responsible for the US productivity acceleration. (Bloom, 2012). AI is an emerging technology, and there is not as much research focused on Europe. My paper fills this research gap by focusing on Europe and AI.

3 Literature Review

As mentioned in the introduction, many economists have different perspectives on the multifaceted dimensions of technological revolutions, AI, and the future of labor markets. This literature review aims to cover this, particularly within the European market. Specifically, it will investigate the ways these will impact the workforce, the economy, and society. It will also
examine the policies and initiatives that economists have suggested implementing to address the challenges posed by these technological changes.

### 3.1 IT Revolution

Basu et al. (2003) looks to understand why the United States post-mid-1990s productivity surged while other major economies stagnated most notably the United Kingdom. Basu highlights that it was not merely the adoption of information and communication technology (ICT) that increased productivity—factors like scientific prowess, technological innovation, and a robust venture capital landscape played a large role. The article promotes the idea that significant complementary investments and co-innovations gave the US an edge over everyone as they were prime to adapt to the new technological change. This becomes the case as firms want to take advantage of this new technology, in doing so they invest in learning and innovation to fully utilize ICT. These investments lead to productivity gains over time.

Looking at Europe, the paper discusses how labor and market regulations might have hindered the same investments & innovations. Focusing on the UK, despite its investments in ICT, the high costs of implementation mixed with regulatory barriers hurt its productivity growth. The slowdown of the UK productivity, which was evident in industries like wholesale and retail trade, was a major contributor to the US productivity improvement.

While disruption costs associated with investment might explain part of the measured slowdown, factors like the timing of investments, skilled labor shortages, and regulatory constraints are the differences between the United Kingdom's stagnation and the United States'
rise during the 1990s. The income shares of ICT in the United Kingdom increased from 4.30% to 6.26% between 1990 and 2000.

Autor, et al. (2003), this paper analyzes the relationship between technological change and shifts in skills. Their study reveals that task shifts emerge as the primary driver behind changes in job skill requirements. They find that alterations in task composition significantly contribute to the observed increase in demand for educated workers from 1970 to 1998. The authors find a correlation between computerization and shifts in job tasks. This is seen in a decline in routine tasks with a steep rise in nonroutine tasks. This transformation in task composition is interpreted as evidence of skill-biased technical change (SBTC). They conclude that there is a much higher demand for workers with higher levels of education when there are new technological advances. Autor comes to this idea as these high-skilled workers have an advantage in non-routine tasks.

3.2 AI Revolution

Autor and Dorn (2013) aim to understand employment rate & wage polarization in the United States from 1980 to 2005. They challenge the usual explanation that technology can only benefit or replace people. They argue it’s more complicated as many factors, including evolving consumer preferences and technological innovations facilitate the automation of routine tasks.

Through empirical analysis, they observe a U-shaped pattern in job distribution. They observed a decline in middle-skill occupations and a rise in high and low-skill jobs. What makes this analysis unique is how it presents how low-skill service jobs are resilient to automation. This is because these jobs involve non-routine tasks, like manual labor and interpersonal
communication, that are difficult to automate. This makes logical sense as some occupations may not make sense to automate due to the expensive initial investment coupled with the already cheap labor.

Goos, Et Al. (2014) discusses job polarization in the United States. The paper argues that SBTC has some shortcomings. So instead, the authors offer that RTBC is a more useful explanation of the past labor market. This is because SBTC falls short of explaining polarization in advanced economies. This polarization is due to technology being able to automate more routine tasks and a shift away from jobs that rely heavily on such tasks in specific industries. The takeaway from the countries examined in this study is seen by the jobs at the highest and lowest pay scales have grown. The biggest loser of this polarization is the people with middle income as this has shrunk the most.

Brynjolfsson & and Mcafee (2014) promote the idea that technological progress creates increased wealth yet leads to income inequality. This paper challenges the notion that increased wealth creation and a wider distribution of wealth increase the income for everyone, specifically how economic growth, hasn’t increased the median income proportionally.

“The top 1 percent increased their earnings by 278 percent between 1979 and 2007, compared to an increase of just 35 percent for those in the middle of the income distribution” (Brynjolfsson & Mcafee, 2014). Most of this income being created is going to a small group of winners while the middle and lower class decreased the most. Technology fits into this equation because before the 1970’s the idea that productivity growth with new technology benefitted all workers was true as it led to an increase in productivity. A change occurred in the following
years as those with college degrees and above became increasingly in demand. This increase has led to wage growth.

Salomon, Et Al (2014) routine-biased technological change (RBTC) is a concept that examines jobs from a task perspective and identifies whether the tasks done at the jobs are routine or non-routine. It then examines how technology is applied to these jobs and whether the people operating them use it as a substitute for themselves or a complement. Typically, RBTC occurs when new technological advancements disproportionately affect routine tasks, leading to their automation. (Soloman, Et Al, 2014). Non-routine tasks within jobs are harder to perform by computers, which is creating a demand for workers who have the skills to complement and work alongside these machines. With a shift in the market because of the increased nonroutine of tasks, we can expect more people with higher and more advanced skills to be in higher demand.

Skill-biased technological change takes a different approach and looks at the idea that measures workers by their education & skills. This change promotes the idea that people with high skills will be used as compliments to technology, leading to increased demand for highly skilled workers. The theory is that not all jobs will be affected equally as technology progresses; new jobs are created that require a higher level of skills & education. Low-skilled workers have declining employment and wages as their jobs have been automated leading to a skill bias for higher skills. This rise in income inequality occurs as SBTC widens the wage gap between high-skill and low-skill workers. It’s important to note that the job polarization observed in the US and UK challenges SBTC. (Salomons, Et Al, 2014). This is due to polarization referring to the
growth of high-skilled and low-skilled jobs while at the same time having a decline in middle-skilled occupations. (Salomons, Et Al, 2014).

Autor (2015) gives a perspective on the historical context of innovations in the past and their relationship with the jobs market. Autor looks at this relationship between technology, automation, emerging AI, and employment. As technology improved more tasks could be automated, and from the 1940s on, the US shifted away from physically demanding and dangerous work. This being the case many sectors prospered, as agriculture experienced significant gains with the number of agriculture workers decreasing while achieving a considerably higher output.

Looking at how automation affected employment in the IT era Autor looked at jobs by their makeup and breaks the work done into routine and nonroutine tasks. Routine tasks are seen as easy to substitute as they either don’t need much education to do or are codable tasks. Nonroutine tasks are complex and need human judgment that can’t be coded into computers and use skills that can only be learned tacitly.

Autor’s central argument in this paper lies that contrary to popular belief automation is a complement to employment statistics. Autor presents a more nuanced understanding and points out that automation does not necessarily eradicate jobs but rather will change their makeup. Although some positions will be lost to automation with new technological advancements, it will also create new jobs and improve the value of human labor. Lastly, the paper covers how employment polarization is a side effect of automation. This, although not directly responsible for wage polarization, can still worsen wage inequality.
Furman (2017) shows the effects of the AI revolution on the labor market. By arguing against such large reforms as universal basic income and instead reinforcing some of the steps to make sure the growth is shared more equitably. He believes that AI has the potential to increase inequality. He believes that policy can not only advance AI but can also increase the number of people who stand to share the benefits of it. Furman fears that it may be inevitable that AI will take over low-skill jobs but, reasons that they will still exist as people are willing to do them for lower wages.

These fears stem from historically people have patterns of accepting lower wages during technological change. He noted that there has been a decline in wages, and labor force participation in less-educated men. Lastly, Furman argues that AI may be unlike the technological changes of the past. AI could eliminate more jobs than it creates. The concern would shift to what could we do to absorb displaced workers and create new jobs?

His suggestions to protect these workers are to use policies including ideas about expanding aggregate demand, reforming taxes to encourage work, and creating more flexibility for workers. This would create higher wages/ minimum wage and create a stronger collective bargaining agreement. Furman stresses that the public policy goal will be to determine the extent to which the benefits of AI can be fully realized.

Himel and Seamans (2017) provide a perspective on AI rapidly expanding its roles in many sectors like advertising, financial advice, insurance, criminal sentencing, etc. They argued against the concentration of data because it can reduce competition and lead to monopolies and less innovation in the AI data market.
They show the problems with the zero-price nature of digital products and how potential issues can arise. This is due to the focus antitrust agencies have on price-based harm and not nonprice effects. This leads to issues of privacy quality and innovation as there is no one to stand in their way. This is the tradeoff people make for having their services for free. Users of this service end up paying with their personal data and time spent and in turn, will have lower quality content and increased advertisements. Policy solutions that can fix the monopolization of data that are proposed in this article are deferred data sharing, as large datasets could be shared after a period to encourage innovation. The second one is a trusted third party where it can be held by a college or university and accessed by other firms with the purpose of security of the data. Lastly, blockchain was proposed, as it could enable easier control and trading of data, potentially increasing competition.

Brynjolfsson, et al. (2017), look at the discrepancy between optimistic expectations of technological advancements and the lack of corresponding growth in productivity statistics. The contradiction lies as new technologies promise to create many productivity boosts. However, when we look at the historical implementation of these technologies, we see the actual productivity growth has been slow. This is seen as the Solow paradox.

They offer four explanations as to why this could happen. The first explanation is that of false hopes that maybe those receiving the new technology are too optimistic about the new tech's impact. This is dismissed as there is still reason to be optimistic, but to do so cautiously and not to be over-optimism. The second idea is that the measurement of productivity gains is done inaccurately. Brynjolfsson disproves this as he cites studies suggesting mismeasurement isn't the main reason for slow growth. The third explanation is that some groups will monopolize
the benefits of new technologies, essentially blocking others from entering the market leading to benefits not being spread evenly. This is dismissed with the rationale of benefits even though they may not be evenly spread, it is unlikely that they are completely wasted.

The fourth and final explanation is that new technology takes time to adopt and harness fully. This is caused by the more profound the potential technology is the longer the restructuring of time between the invention to the implementation. Building the necessary infrastructure to take advantage of a new technology takes time takes time. They see this as the implementation and restructuring of lags that cause this paradox. GPTs take time to build up the technology's stock and investments need time to realize their benefits. We should see similar patterns of AI and IT in terms of the implementation and restructuring of lags as they are both GBTs.

Varian (2018) provides his opinions on the effects of machine learning vs vertical integration of new technologies for a business or organizational structures. Varian looks at how businesses are changing to increase profits and reduce their costs. Varian provides this information through new pricing methods to allow cloud computing and machine learning to help make price discrimination possible. On the same note, he argues that consumers will have tools to help rebuttal some of these strategies. This is done with the increase with access and understanding of big data. He compares data to the “new oil” in terms of the demand people have for it and the race people are trying to enter first into the industry. The comparison ends when compared with oil, which as a product is rivalrous; when consumed, it reduces its availability. Data is non-rivalrous meaning using it doesn’t diminish the availability of the quantity of data.
He acknowledges return to scale when it comes to machine learning, as there are classical supply-side returns, demand-side returns, and learn-by-doing. When looking at the supply side there are large, fixed costs in developing the software but when distributing it is relatively small. Looking at the demand side when firms with more customers can collect more data, this improves the results of the findings and improves products. Lastly, there is learning by doing which leads to costs declining or quality improving when there is increased production or investment.

Varian argues that some businesses shouldn’t only focus on the ownership of data but instead on sharing allowing for others to access the data. He makes this argument that data for autonomous vehicles should be had by multiple parties for the best possible result as the goal should be to increase overall safety, like that in the aviation industry.

Trajtenberg (2018) provides predictions about the labor market with the prevalence of artificial intelligence and new general-purpose technology (GPTs). By putting in two classes of individuals affected by the change, winners, and losers. The winners are those associated with the new GPT sector deploying the applications, as well as the sectors that are in direct benefit towards the growth such as the VC industry, patent lawyers, and designers. The biggest winners are people in the AI sector who become the early adopters having a first-mover advantage. AI also has the potential to drive innovations across many areas outside the AI sector from healthcare to education leading to a large range of applications.

The losers are the ones who are in industries where the adoption of new GPTS will make losers’ skills obsolete as AI can do them faster and cheaper. This will be challenging for many people as when they get replaced from a role, they might not have the skills to easily change to
a new role. He argues that unlike in the past, there are no new jobs being created as a
counterbalance but instead they are just being completed. Trajtenberg recognizes the change
and characterizes the direction by separating this AI innovation into “Enhancing” or
“Replacing” current roles and tasks.

To combat this Trajtenberg argues that intervention must be taken place to alleviate the
negative effects of AI. Education must play an important factor in teaching skills that are
tailored toward problem-solving, emotional intelligence, and creativity. These skills will
become highly valuable as AI diminishes the significance of knowledge alone decreasing the
need for memorization. Increasing the standards in the personal service industry as seen in the
Nurse Training Act of 1964, to improve quality in many different professions. Lastly, promoting
human-enhancing innovations enhances people's abilities, enabling them to guide machines
effectively instead of replacing them entirely. It is overtly mentioned how the government may
have to have increased responsibilities to handle these losers but in doing so not by slowing
down the pace of technical change.

Stevenson (2019) looks at the benefits and potential pitfalls that come with the adoption of
new technology as well as optimistic and pessimistic views of what’s to come. In her research,
she asked 41 top economists if AI could have such large benefits that they could compensate
workers who were negatively affected for their lost wages. The consensus was that no one
disagreed with this thinking, showing that economists are optimistic about the gains from AI.
The question becomes whether we would compensate the losers.

According to these economists' technological change has not historically reduced
employment. This being the case we should expect similar patterns from the IT revolution to
AI. The skepticism of the gains with AI lies with income redistribution in a capital-driven economy, as historical patterns of income are concentrated at the top. In the short term, it is predicted that people might lose their jobs to automation, and there may be uncertainty about how to adapt to these technological changes quickly. In the long term, as people and institutions adapt to new artificial intelligence, fewer hours will be spent working and people can be free to enjoy their lives without the stress of time and money constraints.

4 Data

The source of the data is EUKLEMS available by O’Mahony which provides a comprehensive resource of data combined with national statistics across European countries. This database allows countries to compare factors such as productivity growth, labor composition changes, and many different industries on a standardized classification. The EUKLEMS database provides insights into labor input by skill level by the categorization of high, medium, and low skill levels. To achieve this, the database researchers “cross-classified” hours worked with factors like educational attainment, gender, and age to source the data. To get these reliable statistics they sourced at the industry level using labor force surveys as well as statistics from National Statistical Institutes. (Etal, 2009).

This dataset also provides some productivity trends across Europe, Japan, and the US. In the mid-1990s, European countries during this period experienced a slowdown compared to earlier decades, while the US experienced the opposite, widening the gap. Their research showed the importance of the investments made in IT, changes in labor composition, such as more demand for skilled workers, and the impact of intangible investments such as innovation.
Using this dataset's emphasis on using IT data, we can make informed predictions about the future of artificial intelligence.

Utilizing past data is crucial in forecasting the future of AI. Given that AI is a relatively new field with limited historical data, analyzing past trends and patterns is the most reliable method to predict its future. Using the EU KLEMS data, I looked at four major economic players within Europe, France, Germany, Italy, and the UK, to delve into how the share of total labor compensation has changed through the third industrial revolution.

Figure 1 shows the high skilled labor compensation in Europe and, the findings suggests that technological change led to a greater demand for workers with higher levels of education, due to their comparative advantage in nonroutine tasks, there is an increasing share of the total compensation in Europe. These results show the importance of investing in education and training programs to keep people competitive in the changing future labor market.

Figure 2 shows the low-skilled labor compensation in Europe, these findings suggest that while technology replaces routine tasks performed by low-skilled workers, it does not directly substitute for the core tasks of low-skill service jobs, which include manual tasks and interpersonal communication. As we observe the downward shift in demand for low-skilled services in Europe, it's evident that automation is leading to less demand for such services.

The trade-off with these technological advances is that tasks are being done faster and more efficiently as they have become much easier. The trade-off occurs as the people doing them who used to have well-paying jobs that did not require much training or education have been left without work. On the other hand, this has hurt many people, but it has also created new jobs that did not exist before, leading to new higher-paying opportunities for people with more
advanced skills and education. These Figures support the theory of skill-biased technological change. Because SBTC helps us understand how jobs are changing with the advancement of technology. By analyzing the relationship between technology and tasks, they provide insights into what skills will be in demand in the future job market.

With the data given it's limited to only look at skill-biased technological change because the data is only at the job-level. Having task-level data would provide a more detailed picture. However, it's important to note that we're unsure whether low-skill jobs involve routine or non-routine tasks, especially in terms of interpersonal communication. While the data seems to align with SBTC, further investigation is necessary to determine if it excludes routine-biased technological change. This discussion of routine tasks is tricky due to the absence of relevant data.

When looking at a specific industry occasionally you can find an unexpected outcome when it comes to employment. Looking at how financial intermediaries faired in the 1970s with the rise of IT and ATMs one would think they would simply be a substitute. Instead, the introduction of ATMs reshaped their roles, as cash handling tasks which were once done by bank tellers and taken over by ATMs, indirectly increased the demand for tellers. (Autor, 2015).

This happened for multiple reasons, ATMs reduced the operational costs of bank branches leading to opportunities for tellers to participate in newly created customer-facing roles. This new technology allowed these tellers to change into the relationship banking sector where they could build a relationship with customers and promote additional banking services beyond basic simple cash transactions. (Autor 2015).
When looking at Figures 4, 5, and 6 it’s evident that this upgrade to a new technology didn’t lead to massive unemployment among bank tellers as initially feared and instead did the opposite. These graphs showed the percentage of labor composition in financial services in four European countries, utilizing data sourced from the EUKLEMS database. This was done to look at a specific industry and see how automation and technological improvement affected it. Automation can displace certain tasks, but in doing so it can also create new jobs. Looking at this example it can lead to skill upgrades as it changed the nature of their work toward nonroutine value-added tasks.

It is important to note the EU KLEMS dataset is a great resource for cross-comparison of job composition and growth in various metrics across European countries. It's vital to keep in mind that the information we have may not be perfect and there could be some limitations that we should consider when analyzing the results. The most important potential issue is the accuracy of the data. This being due to the collection of it being sourced in many different countries and sectors, it could lead to some errors. The issue lies in the quality of the data in the EU KLEMS dataset, which can occasionally be inconsistent, which can ultimately impact the accuracy and dependability of the results. Also, data coverage within countries can pose a challenge in analyzing the data for comparisons (Etal, 2009). Therefore, while the EU KLEMS dataset can provide great insights on composition & growth, it is important to be aware of its limitations for research or policy purposes.

5 Conclusions/ Policy Implications

This thesis looks to explore parallels between the IT revolution and the current AI revolution. It does this by looking at trends and technological advancements to see what their
impact is on labor markets, productivity, and income distribution in Europe. It builds upon the historical content by looking at how AI is considered a GBT and could follow past revolutions by redefining work and productivity. Income inequality was discussed heavily as the relationship between AI and the labor market drew insights from many economists with many unique perspectives. This data was done using the EUKLEMS data and looked at concepts such as skilled-biased vs. routine-biased technological change. The insights from the data led us to believe there was evidence of skilled biased technological change.

The data analysis utilizing the EU KLEMS dataset provided valuable insights into past trends in labor composition and productivity growth across European countries. Examining the impact of automation and technological advancements on specific industries; it became possible to understand some of the complex dynamics of job creation, displacement, and skill upgrading that come with automation and technology advancements.

In the literature review, economists had different opinions about AI's future impacts, with some expressing concerns about job displacement and income inequality. Nevertheless, other economists argued for the potential of AI to boost productivity and increase innovation. This brings us to the proposed policy implications by economists to counteract the potential adverse impacts of AI on labor. The aim is to ensure a more equitable distribution of AI benefits, rather than them being concentrated among a few.

As seen in the data technological advancements favor high-skilled workers leading to income inequality. A response to this is to expand or make education and training more accessible for skills complementing innovations. This could lead to a skill upgrade for high-skill labor. From an outside influence, government intervention could take place, with the
implementation of more progressive taxes on companies utilizing AI. This would incentivize companies to prioritize the employment of human workers over fully automated systems. Another potential solution could be helping low-skilled workers with institutional support for a higher minimum wage, and a stronger collective bargaining agreement could be reached to help those displaced from AI.
References


Figure 1:

High-skilled Labor Compensation in Europe
(The Share of Total Industry Labor Compensation)
Figure 2:

Low-skilled Labor Compensation in Europe
(The Share of Total Industry Labor Compensation)
Figure 3: Medium-skilled Labor Compensation in Europe (The Share of Total Industry Labor Compensation)
Figure 4:

High Skill Labor Composition In Financial Services

Italy  Germany  UK  France
Figure 5:

Medium Skill Labor Composition In Financial Services

Italy
Germany
UK
France
Figure 6: Low Skill Labor Composition In Financial Services