Hacettepe University Graduate School of Social Sciences

Department of Economics

IMPACTS OF TECHNOLOGICAL ADVANCEMENTS ON INCOME & WEALTH DISTRIBUTION

Serhat EZEN

Master's Thesis

Ankara, 2024

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ACCEPTANCE AND APPROVAL

The jury finds that Serhat EZEN has on the date of 7/06/2024 successfully passed the defense examination and approves his Master's Thesis titled "Impacts of Technological Advancements on Income & Wealth Distribution".

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I agree that the signatures above belong to the faculty members listed.

Prof. Dr. Uğur ÖMÜRGÖNÜLŞEN

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ETİK BEYAN

Bu çalışmadaki bütün bilgi ve belgeleri akademik kurallar çerçevesinde elde ettiğimi, görsel, işitsel ve yazılı tüm bilgi ve sonuçları bilimsel ahlak kurallarına uygun olarak sunduğumu, kullandığım verilerde herhangi bir tahrifat yapmadığımı, yararlandığım kaynaklara bilimsel normlara uygun olarak atıfta bulunduğumu, tezimin kaynak gösterilen durumlar dışında özgün olduğunu, **Doç. Dr. Onur YENİ** danışmanlığında tarafımdan üretildiğini ve Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Yazım Yönergesine göre yazıldığını beyan ederim.

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ÖZET

EZEN, Serhat. *Teknolojik İlerlemelerin Gelir ve Servet Dağılımı Üzerindeki Etkileri*, Yüksek lisans tezi, Ankara, 2023.

Gelir ve servet eşitsizlikleri insanlık tarihi boyunca devam eden bir olgu olmakla birlikte, işçiler ve kapitalistler arasındaki çatışan çıkarlar nedeniyle daha da artma eğilimi göstermiştir. Bu bağlamda literatür, teknolojik ilerlemelerin gelir ve servet dağılımı üzerindeki etkileri açısından kapsamlı bir şekilde incelendiğinde, çalışmaların iş gücü piyasasındaki tarihsel etkileri ve gelecekteki etkileri kapsamında bir tahmin üretmeye çalıştığı görülmektedir. Tarihsel olarak, endüstriyel teknolojilerin anlamlı oranda bir işsizlik yaratmadığı görülmüştür. Ancak, sermaye getirilerini artırarak gelir ve servet dağılımını etkilediği gözlemlenmektedir. Bu çalışma, gelir ve servet dağılımındaki trendleri inceliyor ve belirli eşitsizlikleri şirketlerin kâr maksimizasyonu hedefleri çerçevesinde teknolojik ilerlemelere bağlıyor. Ayrıca, yeni teknolojilerin tarihsel olarak sınırlı işsizlik eğilimini tersine çevirip çeviremeyeceğini araştırmaktadır. Mevcut veri işaretleri, yeni endüstriyel teknolojilerin etkilerinin geçmişte gözlemlenenlerden farklı olabileceğini göstermektedir. Her yeni endüstriyel teknolojik gelişmede yaşanan kaygılar hâlâ devam etse de bu sefer yetenekli ve eğitimli işçilerin daha fazla etkilenebileceği ihtimali, bahse konu güncel teknolojileri seleflerinden ayırt ediyor. Her işçinin aynı zamanda bir tüketici olduğu kabul edildiğinde, otomasyon nedenli ortaya çıkacak arz fazlalıklarının ve artan verimliliğin, yine otomasyon nedeniyle işsiz kalacak olan ya da ücretlerinde ciddi düşüşler yaşayacak olanlara mutlak bir refah sunamayacağı aşikârdır. Bu zorluklara karşılık olarak, çeşitli siyasi önlemler değerlendirilmekte ve bu çalışma endüstriyel teknolojilerin potansiyel bozucu etkilerini hafifletmek için Yatırım, Yönlendirme ve Tazminat gibi üç temel politika yaklaşımının etkinliğini konu kapsamında değerlendirmektedir.

Anahtar Kelimeler: Gelir ve servet dağılımı, endüstri 4.0, Ar-Ge, emek piyasası, teknoloji, işsizlik, politika uygulamaları

ABSTRACT

EZEN, Serhat. Impacts of Technological Advancements on Income & Wealth Distribution, Master's Thesis, Ankara, 2023.

Income and wealth inequalities have long characterized human history, often exacerbated by conflicting interests between labor suppliers and capitalists. In this context, technological advancements have been extensively studied for their effects on income and wealth distribution, with some studies focusing on historical impacts on the labor market and others predicting future implications. Historically, industrial technologies have not significantly disrupted the labor market but have instead bolstered capital returns, influencing income and wealth distribution without substantial labor market deterioration. This study examines trends in income and wealth distribution, linking certain inequalities to technological advancements within the framework of firms' profit maximization objectives. Additionally, we investigate whether new technologies could potentially reverse the historical trend of limited unemployment caused by technological advances. Current data signals suggest that the effects of emerging industrial technologies may differ from those observed in the past; although concerns persist, this time skilled and educated workers may be more affected. Recognizing that every worker is also a consumer, it becomes apparent that surplus supply and increased productivity, leading to lower product costs, do not necessarily enhance the purchasing power of those displaced by automation. In response to these challenges, various political measures are being considered, and this study evaluates the effectiveness of three primary policy approaches—Investment, Steering, and Compensation—to mitigate the potential disruptive effects of industrial technologies.

Keywords: Income and wealth distribution, industry 4.0, R&D, labor market, technology, unemployment, policy implications

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ARS	**:** Automation Resistant Sector
APS	**:** Automation Prone Sector
ATM	**:** Automated Teller Machine
AI	**:** Artificial Intellegence
BEIS	**:** Department for Business, Energy and Industrial Strategy
CAGR	**:** Compound Annual Growth Rate
CBP	**:** Cloud Based Production
CPS	**:** Cyber-Physical Systems
CPU	**:** Central Process Unit
EBIT	**:** Earning Before Interest and Taxes
EV	**:** Electric Vehicle
FDI	**:** Foreign Direct Investment
FPI	**:** Foreign Portfolio Investment
G7	**:** Group of Seven
GDP	**:** Gross Domestic Product
IC	**:** Integrated Circuit
IFR	**:** International Federation of Robotics
IOT	**:** Internet of Things
IT	**:** Information Technology
LOA	**:** Level of Automation
Ml	**:** Machine Learning
NIT	**:** Negative Income Tax
OECD	**:** Organisation for Economic Co-operation and Development
RFID	**:** Radio Frequency Identification
R&D	**:** Research and Development
STEM	**:** Science Technology Engineering and Mathematics
UBI	**:** Universal Basic Income
US	**:** United States

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INTRODUCTION

Income distribution stands as one of the most captivating and significant subjects in economics, drawing the attention of scholars and policymakers alike. Beyond its conventional considerations, recent technological strides, particularly those emblematic of Industry 4.0 such as automation, artificial intelligence, and machine learning, have profoundly influenced the discourse surrounding income inequality. These technological advancements in industries herald a new epoch of productivity and efficiency, promising unprecedented economic opportunities. However, they also evoke concerns regarding their impact on income distribution. As automation and algorithms increasingly supplant human labor, questions arise about the future distribution of wealth and opportunities.

Historically, growing income inequality has been attributed to the escalating return on capital and the stability of wages relative to capital gains. However, a scenario where wages transition from stagnation to decline could potentially escalate the pace of income inequality. Such a shift raises alarming prospects, widening the chasm between high-earning individuals and those experiencing stagnant or declining wages, thus exacerbating socioeconomic disparities. Moreover, the specter of rising unemployment due to labor-saving technologies amplifies the potential impact, making a significant increase in inequality unsurprising.

As technological advancements and automation reshape industries, there is an urgent call for proactive measures to address these challenges and ensure inclusive economic growth for all members of society. While some argue that technological progress will drive greater efficiency and innovation, benefiting society as a whole, others fear it will widen existing income disparities, particularly affecting low-skilled workers. Furthermore, the advent of automation, artificial intelligence, and machine learning introduces complexities that challenge traditional economic models, reshaping notions of work and compensation.

In light of these developments, policymakers face the formidable task of equitably distributing the benefits of technological advancement. This necessitates proactive measures addressing the root causes of income inequality, including investments in education, training, and social safety nets. Thus, while Industry 4.0 holds immense promise for economic progress, its impact on income distribution remains a subject of intense debate and scrutiny, shaping the economic landscape for generations to come.

The first key research question of this study is whether industrial technological advancements affect income and wealth distribution. The second key question is, if they do, whether these effects can be addressed and how. By reviewing the current literature and updated data, this study aims to contribute to further research and fill existing gaps in understanding the impact of industrial technological advancements on income and wealth distribution. Furthermore, it seeks to provide a new perspective by incorporating a historical viewpoint, thus offering insights into how past economic shifts and technological changes have shaped contemporary socioeconomic structures. This approach not only enriches the current discourse but also lays a foundation for future investigations into policy implications and strategies for addressing income and wealth disparities.

Expanding on the thesis structure, the first section will delve into the transformative role of industrial revolutions and their features in reshaping production processes. It will provide a comprehensive historical overview, tracing the evolution of industrialization and its profound effects on income distribution. By examining the key features and drivers of each industrial revolution, this section aims to lay the groundwork for understanding the complex interplay between technology and income inequality.

Moving on to the second section, the focus will shift to the intersection of technological advancements and income distribution. Specifically, it will explore how capital gains and labor market dynamics have been shaped by recent innovations in automation, artificial intelligence, and machine learning. By analyzing empirical evidence and theoretical frameworks, this section seeks to elucidate the mechanisms through which technological progress influences income distribution, identifying both opportunities and challenges for policymakers.

Finally, the third section will explore potential responses to the anticipated decay in income distribution outlined in the preceding sections, with particular emphasis on political interventions. Drawing on insights from political economy and public policy, this section will evaluate the efficacy of various policy measures in addressing income inequality, from progressive taxation to social welfare programs. By examining case studies and comparative analyses, it aims to inform policymakers about the most effective strategies for mitigating the adverse effects of technological change on income distribution.

CHAPTER 1
HISTORY OF THE INDUSTRIAL REVOLUTIONS

1.1 UNTIL THE INDUSTRY 4.0.

The process of the production has been changed by innovations. Every set of innovations that made ways of producing goods and services more productive and efficient is called industrial revolutions (Landes, 2003). Before the first step of civilization which is known as Neolithic Revolution (i.e. the transition to agriculture), the entire human civilization was trying to sustain their life as hunter-gatherers. At these times, people's capability of making stock was limited, and hence they subsisted their life with instant daily activities. They could not make plans for the future due to uncertainties. The only thing they knew was they were going to migrate (Weisdorf, 2005).

After discovering tilling techniques as part of the agricultural revolution, humans began to live in settled communities, abandoning their nomadic lifestyles. The beginning of the agricultural revolution was not so lucrative for individuals, though (Mazoyer & Roudart 2006). The reason behind that was the fact that people gained fewer calories than the energy they spent in comparison with hunter-gathering. However, the Neolithic revolutions' benefits were more than its shortcomings. First of all, the malnutrition at the beginning was not due to agricultural activities; the problem lay in the productivity and efficiency of these activities. Apart from all of these structural issues, after a while, people started to collaborate among themselves in order to protect their surplus supplies. They established constitutions to promote justice and laid the foundations of statehood to protect themselves from foreigners. Moreover, scientific activities began in order to gather information about nature, such as rain timers, to maintain healthy agricultural operations.

Owing to the improvement in living conditions that came with the Neolithic Revolution, the human population began to increase (Latham, 2013). Due to importance of land in terms of religious, economic, social, military and similar reasons; wars took place, states and empires were established and destroyed (Vayda, 1961). Agriculture had maintained its importance in economies for thousands of years until the 18th century. (Steiner, 2003). But that age was closed when the steam engine was invented by Thomas Savery and implemented in industries. The steam engine was invented in 1698. In the beginning, its usage field was prevalent in the mining sector. Over time, several key developments characterized the first industrial revolution. These included population growth, significant improvements in railways, and the use of steamships for transportation. Additionally, there was an increased pace of immigration driven by urbanization. The period also saw advancements in the mining and steel sectors, the production of capital goods, and the gradual implementation of steam engines in the production process (Hobsbawm, 2010, pp. 27-33). This revolution is one of the most significant milestones regarding the living conditions of the people. It influenced every part of the economic component, from workers and households to employers and governments. Thanks to the first industrial revolution, improvements in many fields were observed such as health, transportation, manufacturing, and so on. It gave rise to many inventions as well (Lucas, 2003).

After the features of the first industrial revolution were integrated into the production process, a series of economic fluctuations occurred, including a notable recession between 1830 and 1840. This pattern is consistent with the theory that innovation is a key driver of economic advancement. Without continuous innovation, economies tend to reach a state of stagnation. Innovations, often driven by research and development (R&D) in the pursuit of profitability, lead to a process known as creative destruction. Creative destruction refers to the emergence of new technologies or business models that displace established industries and economic structures (e.g., the shift from tube TVs to LED TVs) (Schumpeter, 2013, pp. 81-85).

Each wave of innovation increases supply, often surpassing demand, which leads to a decrease in profitability and prices. As profitability declines, capital owners reduce their investment spending, resulting in an economic downturn, or depression period. To overcome these conditions, capitalists resume R&D efforts, spurring new innovations and leading to cyclical economic fluctuations. These cycles of boom and bust are characteristic of industrial revolutions[1].

Under these conditions, the beginning of the Second Industrial Revolution was marked by the discovery of electricity and an important process innovation, i.e., assembly line production. Henry Ford was one of the most significant actors in this process. He used the main features of the second revolution in the automotive sector and started mass production (Donovan, 1997). This movement is known as Fordism. The decrease in the demand for skilled labor with the mass production lines and the division of the workforce to the line stage have been the most significant factors of this trend. During this period, characterized by the ascendancy of the liberal economy and the implementation of a supply-side economics approach, production was conducted based on the preferences of capital owners, with relatively less emphasis placed on demand. In fact, Henry Ford's statement, "Any customer can have a car painted any color that he wants, so long as it is black." serves as a notable example of the extent to which the supply-side economy was embraced (Batchelor, 1994).

Industrialization started to accelerate with a plethora of significant inventions, such as the telephone, airplanes, petroleum refining, chemical fertilizers, and many more. All of these inventions contributed to an increase in production capacity. Consequently, urbanization grew, prompting people to migrate from rural areas to cities. By the year 1900, 40% of the U.S.A.'s population resided in urban areas. In terms of the innovations brought about by the second industrial revolution, we can assert that they paved the way for the features of today's world (Groumpos, 2021).

Following the second industrial revolution, after the discovery of electricity and later the utilization of electronic tools, powered by electricity, gradually expanded and found its way into various industries. The integration of computers and the internet enabled the collection of data and facilitated machine control, thereby laying the foundation for the transition to Industry 3.0, commonly referred to as the automation revolution (Lucas, 2002). The

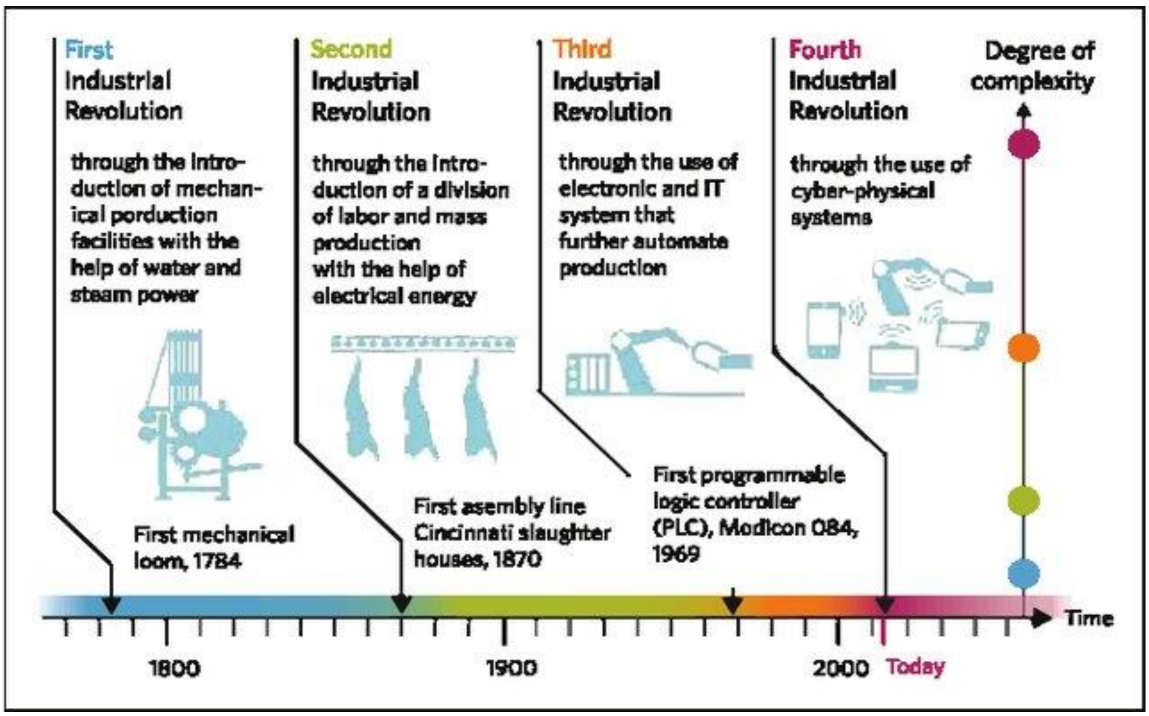
[1] For more on this issue, please see Schumpeter (2013)

terminology that is called the automation age came from the revolution in which the production process began to turn autonomous from analog. The transition from the technology that was ongoing from the second industry revolution, upgraded with robots and the internet connection, meant the production process started to include fewer human interventions. Therefore, this move crucially affected industries (Groumpos, 2021).

1.2 INDUSTRY 4.0

The cumulative innovations that came from history dragged human civilization to the concept of the fourth industrial revolution (Industry 4.0). This concept was mentioned for the first time in an article published by the German federal government in 2011. In 2011, the concept of Industry 4.0 was introduced at the Hannover Messe trade fair, marking the beginning of discussions on the ongoing automation and digitization of manufacturing processes (Zhou, 2015).

Industry 4.0 enables production ecosystems administrated by smart machines with sensors to make that ecosystem self-configuring, self-monitoring, and self-improving. As a result, Industry 4.0 enables high levels of operational efficiency and accelerate productivity growth (Thames, 2016). Like previous industrial revolutions, Industry 4.0 is characterized not only by improvements in the production process but also in social life. It can be seen as an “Upgraded Industry 3.0” via information and communication technology. These are the reason why Industry 4.0 is called the digital revolution as well (Schwab, 2017). Nevertheless, advancement in the information and communication technologies mainly occurred in the times of Industry 3.0. A question such as “Why should we consider this an industrial revolution?” might come to mind. The answer lies in the implementation of the aforementioned technology improvements in the production process itself. The main difference in Industry 4.0 is the integration of Cyber-Physical Systems (CPS), which encompass all components of the production process, leading to the emergence of smart factories. Consequently, Industry 4.0 can also be regarded as a smart revolution as well as a digital revolution (Groumpos, 2021). Throughout the initial three industrial revolutions, individuals have observed and contributed to the advancement of mechanical, electrical, and information technology with the purpose of enhancing industrial process productivity. The primary industrial revolution boosted efficiency by employing water power, expanding the use of steam power, and creating machine tools. The second industrial revolution introduced electricity and mass production techniques such as assembly lines. The third industrial revolution propelled automation through the application of electronics and information technology. Currently, the fourth industrial revolution is on the horizon, characterized by CPS technology that seeks to seamlessly merge the physical world with the information age for future industrial progress. Figure 1 portrays the four stages of the industrial revolution.



Source: (Wahlster, 2013)

Figure 1. *Industrial Revolutions*

All the structures that include coordination and communication between physical and cyber world are named Cyber-Physical Systems (CPS). One of the main purposes of CPS is to increase all industries' productivity and efficiency and provide agility and dynamic needs (Lu, 2017). Industry 4.0 relies on CPS, which serves as the fundamental infrastructure. CPS enables the connection of all physical devices to the Internet and encompasses five essential functions: computing, communication, precise control, coordination, and autonomy. By seamlessly integrating the virtual and physical realms, Industry 4.0 facilitates the realization of intelligent products and advanced manufacturing processes (Zhou, 2015). CPS are not static systems such as embedded systems. Embedded systems essentially sustain themselves with firmware assigned to them by their creators. Adapting these systems to current trends can be complex. Their functions are limited and cannot be altered without physical intervention from an external source. Examples of such systems include MP3 players, traffic lights, transport vehicles, and medical systems. In contrast, CPS is a dynamic system. Through technologies such as Radio Frequency Identification (RFID), sensors, scanners, and so forth; machines communicate with each other virtually providing monitoring, identification, and management possible at the physical dimension (Gorecky et al., 2014).

One of the most important features of the Industry 4.0 that enables CPS is the Internet of Things (IoT). IoT technology fundamentally provides objects to communicate with each other. This concept has been popular in the 21st century and thought of as a technology that can be a leap from Industry 3.0 to Industry 4.0 by attaching information to products and processes (Trappey, 2017). Technically IoT is an embedded system that makes possible exchange data across objects by using the internet. This feature of the Industry 4.0 is a notional concept that integrates a lot of “things” with each other by labeling what we use both at home and at workplaces by using cheap RFID sensors (Yıldız, 2018).

The data on things that make the IoT concept possible comes from another component of Industry 4.0 which is known as Big Data, or in connection with this, Cloud Technology. Cloud Based Production (CBP) is a paradigm that will make significant additions to the success of Industry 4.0. CBP is indeed an emerging paradigm that holds great potential for the success of Industry 4.0 (Liu and Xu, 2017). CBP leverages cloud computing technologies and concepts to transform the traditional manufacturing processes and enable more efficient and flexible production systems (Gharibvand, et al., 2024). At its core, CBP involves utilization of cloud infrastructure and services to enhance various aspects of manufacturing operations. It enables manufacturers to access and leverage a shared pool of diversified and distributed production resources, which can include machinery, equipment, tools, software, and even expertise, available on-demand through the cloud. Some of the key features and benefits of Cloud-Based Production can be listed as:

- **Efficiency and optimization**: CBP facilitates optimized resource allocation based on real-time demand fluctuations. By leveraging cloud-based resources, manufacturers can dynamically scale their production capabilities to match varying customer demands. This flexibility allows for efficient use of resources and reduces idle time, leading to cost savings (Gharibvand, et al., 2024).
- **Lower product lifecycle costs**: CBP enables manufacturers to reduce the costs associated with the entire lifecycle of a product. With on-demand access to a wide range of production resources, manufacturers can minimize upfront investments in machinery and equipment. Additionally, CBP can help streamline supply chain processes, reduce inventory costs, and enhance quality control through real-time monitoring and data analytics (Talhi, et al., 2019)
- **Ad hoc and reconfigurable production lines:** The cloud-based nature of CBP enables the creation of ad hoc and reconfigurable cyber-physical production lines. Manufacturers can dynamically assemble and configure production systems by integrating different cloud-based resources, adapting to changing product requirements or market conditions. This agility allows for faster response times and facilitates customization.
- **Collaboration and knowledge sharing**: CBP fosters collaboration and knowledge sharing among different stakeholders in the manufacturing ecosystem. Manufacturers can connect and collaborate with suppliers, designers, engineers, and even customers through cloud-based platforms. This enhances communication, facilitates co-creation, and enables real-time feedback loops, leading to improved product development and customer satisfaction.
- **Data-driven decision making:** CBP generates a wealth of data throughout the manufacturing process, which can be collected, analyzed, and leveraged to make informed decisions. By integrating data analytics and machine learning techniques,

manufacturers can gain valuable insights into production performance, predictive maintenance, quality control, and supply chain optimization. This data-driven approach empowers continuous improvement and enhances overall operational efficiency (Ren, et al., 2017).

However, it is important to note that implementing CBP requires careful consideration of cybersecurity, data privacy, and intellectual property concerns. Protecting sensitive manufacturing data and ensuring secure communication between cloud-based resources and on-premises systems is crucial for the success and adoption of CBP. Overall, Cloud-Based Production presents a transformative approach that enables manufacturers to adapt to the dynamic demands of the Industry 4.0 era. By leveraging the power of cloud computing and networked production resources, CBP offers increased efficiency, cost savings, flexibility, and collaboration, ultimately contributing to the success of modern manufacturing (Gharibvand, et al., 2024).

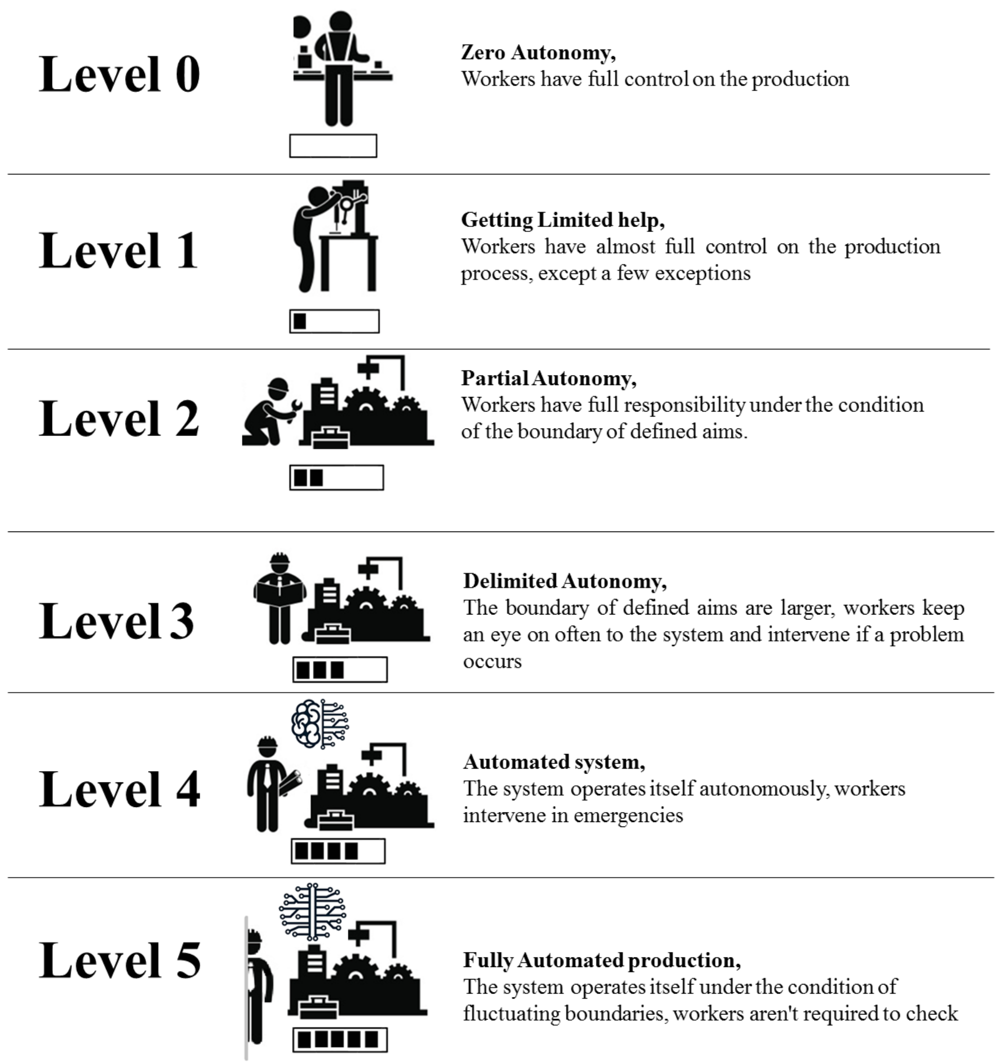
On the other hand, Artificial Intelligence is another advancement in Industries and another feature of the Industry 4.0. Artificial Intelligence (AI) can be broadly defined as a specialized field within computer science focused on the creation and advancement of data processing systems. These systems are designed to execute tasks typically associated with human intelligence, encompassing abilities such as logical reasoning, acquiring knowledge through learning, and enhancing performance through self-improvement. AI serves as a sub-discipline of computer science, delving into the realms of machine cognition and intelligent behavior. It aims to replicate human-like intelligence by constructing algorithms and models capable of comprehending, interpreting, and responding to complex information (Kubsch et al., 2023). By harnessing the power of AI, computer systems can acquire a level of understanding, learning from their experiences and adapting their performance accordingly.

The development of AI systems involves designing sophisticated algorithms, utilizing vast amounts of data, and employing computational techniques to process information in ways that mimic human thinking processes These intelligent systems are capable of performing a wide range of cognitive tasks, such as natural language processing, computer vision, pattern recognition, and decision-making. Furthermore, AI strives for continuous improvement by employing self-enhancement mechanisms. Through iterative processes, AI systems learn from their mistakes, refine their algorithms, and optimize their performance over time. This iterative learning loop enables AI to adapt to new challenges, acquire new knowledge, and refine its decision-making capabilities, leading to increasingly intelligent and efficient systems. Therefore, AI represents a dynamic field of computer science that aims to replicate human intelligence by creating data processing systems capable of reasoning, learning, and self-improvement (AI vs Human Creavity, 2024).

By harnessing the power of AI, we can unlock the potential for intelligent machines to perform complex tasks, revolutionize industries, and augment human capabilities in a variety of domains. As mentioned above, seeds of automation in production processes were sown at the time of the second industrial revolution via the Fordism stream and advancements has been implemented till today. As the level of advancements has improved, automation's substitution of labor in the production process has increased (Chui, 2016). The implementation of AI has carried automation production systems to another level. With the improvements in AI, automation production has started to turn its final shape. Considering the diverse characteristics and applications of industrial systems, it proves advantageous to depict independent actions using a progressive model of autonomy. This approach acknowledges that different levels of autonomy (LOA) can be employed depending on the specific requirements of the application area and individual use cases. For this purpose, the Plattform Industrie 4.0 has introduced an AI-based taxonomy of system autonomy, which outlines a six-level model for automated decision-making within industrial processes. This model provides a comprehensive framework that enables a deeper understanding of the progression towards autonomous systems. Figure 2, which contextualizes the model with real-world industrial scenarios for each level, serves as a visual representation of the various stages of autonomy (BMWi, 2019).

These levels of autonomy are not limited to describing the current state of a system or its components but can also be utilized to articulate future aspirations. By striving to achieve higher LOA, industrial systems aim to become increasingly self-governing and adaptive (Ahlborn, et al., 2019). However, reaching a specific LOA requires integrating industrial systems with additional intelligence, which is acquired through experiential knowledge and advanced technologies such as Industrial AI. Industrial AI plays a vital role in driving the pursuit of higher degrees of autonomy in industrial systems. By harnessing the power of machine learning, data analysis, and predictive modeling, Industrial AI enables intelligent decision-making, optimization of processes, and the ability to autonomously respond to changing conditions. It serves as a catalyst for transforming traditional industrial systems into smart, interconnected entities that can enhance productivity, efficiency, and safety. Despite the progress made in Industrial AI, it is important to note that human involvement continues to be indispensable. Currently, the primary objective of Industrial AI is to augment human performance rather than fully replacing human workers. This symbiotic relationship between humans and AI is likely to persist even as industrial systems evolve to become more autonomous in the future.

Hereby, the adoption of a graduated model of autonomy and the utilization of a taxonomy of system autonomy based on AI facilitate a comprehensive understanding of the development and deployment of autonomous actions in industrial systems. Industrial AI emerges as a core technology that empowers industrial systems with intelligence and enables them to operate with higher levels of autonomy. Nevertheless, human expertise and collaboration remain essential for successful integration and utilization of Industrial AI, ensuring the continued synergy between humans and intelligent machines in industrial environments. (Peres, et al., 2020).



Source: Adapted From (Ahlborn et al, 2019)

Figure 2. *Level of Autonomy*

Cloud Technology, which is one of the most significant features of Industry 4.0 feed off from the concept of prosumption. Etymologically, prosumption is a word that combines 'consumption' and 'production,' encompassing both rather than leaning towards either (Ritzer & Jurgenson, 2010). It is a fact that consumption is related to production and vice versa. Nevertheless, the concept of prosumption is more akin to producing while consuming. For instance, the benefit of a Google search lies in the user consuming the data they need. On the other hand, every search or click of an external link from that search is saved as data to show more accurate advertisements to the user and hence that user who does a search at Google basically produces data. Thus, prosumption activity occurs. The concept of prosumption not only includes final consumers but also encompasses the production process itself. Smart factories in Industry 4.0 contain intelligent machines and systems that use sensors to detect business requirements. They communicate with other production tools through the internet and gather the necessary information for the production process from big data. In smart factories, the interactions and communications between production objects are facilitated through the internet (Alçin, 2016). Therefore, an AI-based production object collects data from cloud systems and generates new ones. In conclusion, the prosumption process is a key area for AI and plays an important role in production.

The conventional approach to production, characterized by large batch production, lacks the flexibility required to meet the individualized demands of customers. To address this limitation, a new era of intelligent factories is emerging, designed to support customizable production modes that cater to diverse requirements. AI plays a pivotal role in this transformation, facilitating the seamless integration of manufacturing with information communication technologies such as computing, communication, and control. This integration enables higher value-added manufacturing by leveraging AI to accelerate processes. Generally, we mentioned the effect of AI on the supply side so far. However, AI affects the demand side substantially as well and prosumption plays a vast role in this. For example, refrigerator that use IoT and AI technologies can track the inventory and order new ones if the owner is running out of a particular item (Gebhard, 2021). Ad-targeting serves as another notable illustration of the concept of prosumption, as previously mentioned. This phenomenon involves users being presented with more relevant advertisements based on algorithms that analyze their internet usage footprints. This tailored approach ensures that users are exposed to advertisements that align closely with their specific needs and preferences, allowing them to make more precise purchases of the items they require. By leveraging these algorithms, individuals can experience a more personalized and efficient online shopping experience (Nalbandyan, 2023).

A customized smart factory possesses distinct characteristics that set it apart. Firstly, it exhibits self-perception, allowing it to gain awareness of its surroundings. Additionally, it optimizes operations through AI-driven techniques, enhancing efficiency and performance. Moreover, dynamic reconfiguration capabilities enable the factory to adapt to changing external needs swiftly. Finally, intelligent decision-making lies at the core of a customized smart factory, enabling it to make informed choices based on extracted process knowledge, including intelligent production, networked collaboration, and extended service models. The implementation of state-of-the-art AI technologies is crucial in achieving these objectives, particularly in the realm of customized manufacturing. Machine learning, multi-agent systems, the IoT, big data analytics, and cloud-edge computing are among the cutting-edge AI technologies employed. Empirical evidence gathered from experiments showcases the potential of AI-assisted customized manufacturing in delivering higher levels of production flexibility and efficiency. The paradigm of large batch production falls short when it comes to accommodating individual customer requirements. The rise of intelligent factories, driven by AI, offers a solution by enabling multivariety and small-batch customized production. The distinctive attributes of customized smart factories, coupled with advanced AI technologies, pave the way for enhanced flexibility, efficiency, and informed decision-making within manufacturing systems. The ongoing experimentation and implementation of AI-assisted customized manufacturing validate its potential for revolutionizing the production landscape (Wan, et al., 2020).

CHAPTER 2
INCOME DISTRIBUTION

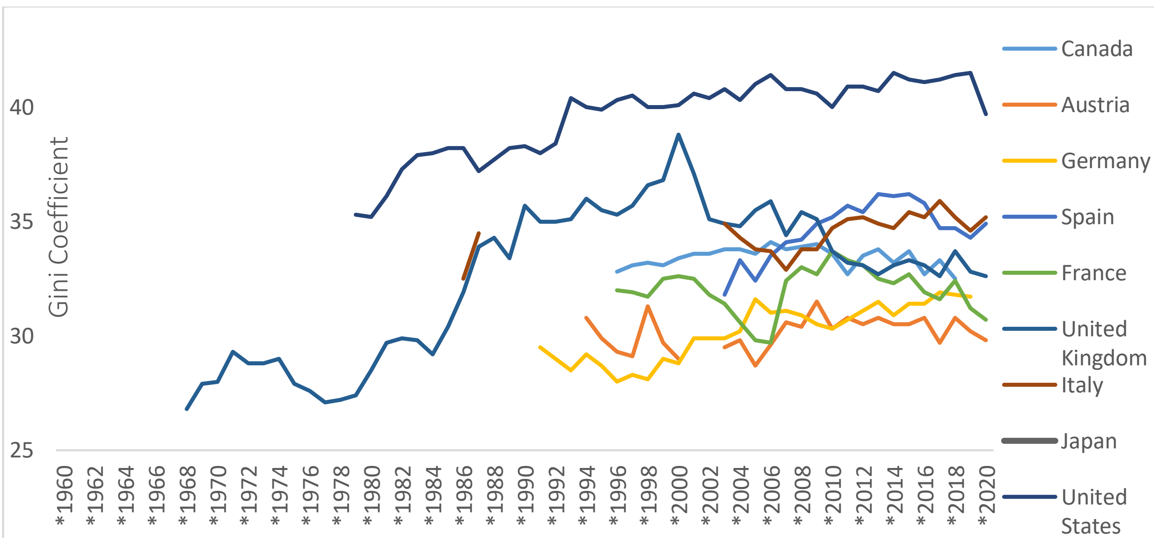
2.1 CONCEPT OF INCOME DISTRIBUTION

Numerous factors, including technological advancements and the emergence of Industry 4.0, are currently influencing income distribution and will continue to impact it (Kharlamova, et al., 2018). Before delving into the effects of Industry 4.0 on income distribution, it is essential to address the concept of income distribution itself. Doing so is crucial to build a proper understanding and place the issue into a reasonable context.

Income distribution plays a paramount role in fostering sustainable development as it profoundly impacts the overall cohesion and stability of a society (Pezzey, 1992, p. 38). By influencing the distribution of wealth, it directly shapes the extent of poverty experienced by individuals, irrespective of the average per capita income. Moreover, a just income distribution also enhances the efficacy of economic growth in alleviating poverty, thereby bolstering its poverty-reducing effects (Kaldor, 1955). Additionally, it should be acknowledged that income distribution holds a significant bearing on the well-being and health of a nation's people. Disparities in income can result in unequal access to healthcare, education, and other vital resources, exacerbating health disparities across various segments of the population. Therefore, addressing income inequality becomes not only an economic imperative but also a critical aspect of ensuring the overall prosperity and welfare of a nation (Stewart, 1999).

Income distribution takes various forms, each shedding light on distinct aspects of economic disparity. Sectoral income distribution, for example, provides insights into how income is distributed across different sectors of the economy (Işık, 2006, p. 123). Regional income distribution, on the other hand, highlights the discrepancies in income across various geographical regions (Alabaş, 2015, p. 225). Another significant category is personal income distribution, which involves dividing the community into scales based on their respective income levels, allowing for a comprehensive examination of income distribution within the society (Karabulut, 2006). Functional income distribution is yet another crucial measure, that reveals the proportions in which factors of production contribute to the national income. This entails analyzing the distribution of income derived from different sources, such as interest, wages, rent, and profit (Black, Hashimzade & Myles, 2012). By understanding how each factor of production contributes to the overall income, policymakers and economists can gain valuable insights into the dynamics of economic growth and inequality (Francese & Granados, 2015).

Economic mobility faces increasingly daunting obstacles due to the exacerbation of income inequality, which is exacerbated even further by a pronounced concentration of wealth. Considering that income is one of the primary sources of wealth and that wealth influences the level of income, it is crucial to examine these factors together (Piketty, 2014). This dual challenge of income and wealth not only hampers the ability of individuals to climb the economic ladder but also underscores the growing disparities in income and hence wealth distribution. Studies and empirical evidence suggest that wealth distribution displays a higher level of concentration than income inequality. Additionally, there is a notable correlation observed between these two variables, indicating a reciprocal relationship (Osakwe and Solleder, 2023). In advanced economies, wealth disparities, as measured by the Gini coefficient, are notably more pronounced than income disparities, with wealth Ginis averaging twice the levels of disposable income Ginis (Derviş & Qureshi, 2016). Take the United States as an illustrative case. According to World Bank data, the wealth Gini coefficient in the U.S. stands at a staggering 0.85. This number reflects an alarming level of wealth concentration, as the Gini coefficient ranges from 0 (perfect equality) to 1 (perfect inequality). A Gini coefficient of 0.85 underscores that wealth is heavily skewed towards a select few in the country. Perhaps even more concerning is the trajectory of wealth distribution over the past few decades. From 1980 to 2010, the share of wealth held by the top 1 percent in the United States increased significantly. In 1980, this elite group controlled 29 percent of the nation's wealth. However, by 2010, their wealth share had risen to 34 percent. This trend signifies a notable shift in wealth distribution towards the upper echelons of society, further cementing the challenges associated with achieving economic mobility for the majority of the population. These statistics emphasize the critical need for policies and initiatives aimed at addressing income and wealth inequality, as they pose significant barriers to economic mobility and social cohesion in advanced economies. Without concerted efforts to rectify these disparities, the gap between the rich and the rest of society is likely to widen, making it increasingly difficult for individuals to attain upward economic mobility and creating a host of social and economic challenges in the process. According to time series of Gini coefficients across developed countries (Figure 3) indicates an upward trend in income inequality. It is evident from the data that a decline in income inequality cannot be substantiated.



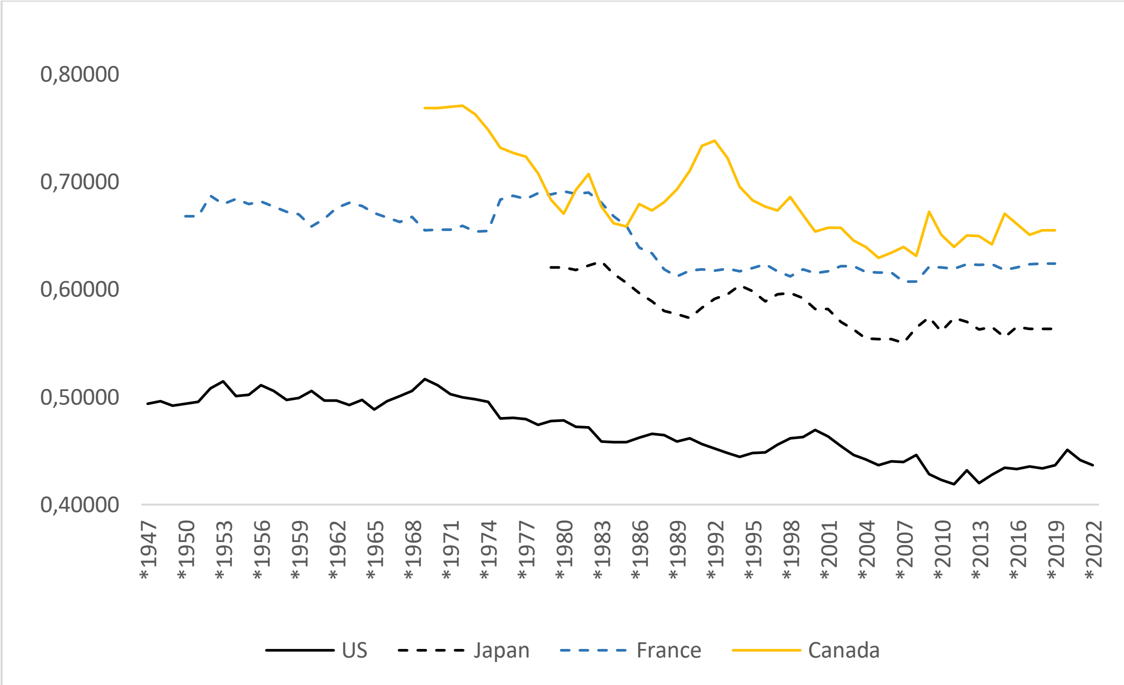
Source: World Bank Data

Figure 3. *GINI Indexes (Developed Countries) (1960-2020)*

In 2006, a year prior to the onset of the financial crisis, Ben Bernanke, the then Chairman of the Federal Reserve, expressed a significant hope. He articulated his aspiration for corporations to allocate a portion of their increasing profits towards addressing the demands for higher wages from the workforce. Similarly, in 2007, Germany's finance minister advocated for European corporations to adopt a more equitable distribution of their profits (Francese & Granados, 2015, p. 37). The financial crisis, once unleashed, injected an accelerant into the already smoldering discussions around these diverging trends. Governments across the globe, donning the mantle of saviors, intervened to rescue beleaguered financial institutions from the precipice of collapse (Grossman & Woll, 2014). However, this narrative of salvation unfolded against a backdrop of sobering realities—rising unemployment rates and the gaping maw of inequality. This paradoxical coexistence of financial sector bailouts and burgeoning inequality underscored the urgency of delving into the intricate interplay of economic dynamics.

To peel back the layers of this intricate economic tangle, we turn our attention to a retrospective analysis of historical data spanning nations constituting four countries. In this comprehensive vista, the labor share of income emerges as a salient protagonist, embarking on a steady descent since the 1970s (Figure 4). The decline, marked by an average contraction of 13 percent (excluding France), sends ripples across the economic fabric.

Intriguingly, standing in stark contrast, the pendulum of income inequality swings in the opposite direction. This facet, encapsulated by the Gini index, captures a disconcerting ascent of 25 percent in some emerged economies within the relatively brief span of three decades. Nonetheless, as we tread into the realm where correlation meets causation, caution is paramount. The apparent concurrence between these two phenomena should not hastily be construed as a direct nexus. Income inequality, a metric emblematic of the unequal allocation of fiscal spoils, rubs shoulders with the labor share of income—a gauge of the proportion of total factor income apportioned to employee remuneration within a fiscal cycle (Oyvat, 2011). Navigating the corridors of economic history, we encounter the notions of nineteenth-century economic philosophers who held steadfast to a stark dichotomy: capitalists as the privileged custodians of wealth through capital returns, juxtaposed against laborers relegated to subsistence on wages, often depicted as the economically marginalized stratum (Lebowitz, 2004).



Source: FED, University of Groningen, University of California

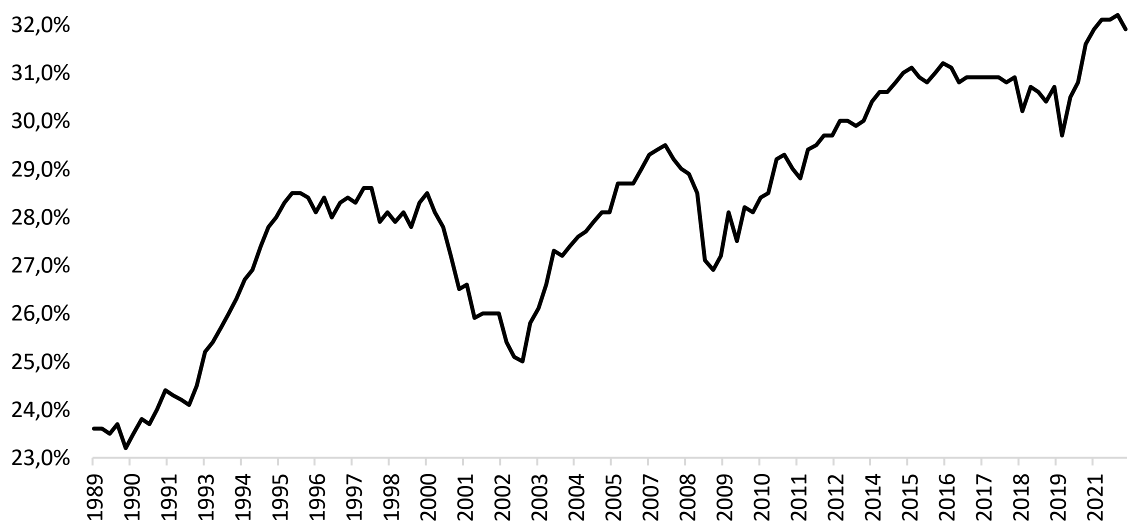
Figure 4. *Wage Share in GDP (1947-2022)*

Data in this section provides a striking visual representation of a concerning trend—nearly all the added value generated in society has become concentrated within a specific segment. Observations are particularly significant in the context of our rapidly advancing technological landscape and the exponential growth in production phenomena. It's evident that this particular segment of society has experienced a substantial increase in wealth.

While minor fluctuations are visible in Figure 5 such as Dot-com Bubble[2], Global Financial Crisis etc. the overarching trend undeniably supports the notion that a significant portion of the added value is disproportionately benefiting a select few. What adds to the intrigue of this figure is the glaring wealth disparity it highlights. The data reveals that the wealthiest fraction of the population, comprising the top 1%, now possesses more than 30% of the total

[2] The bursting of the Dot-com Bubble in the early 2000s led to a sharp decline in stock prices, particularly affecting technology and internet stocks. Many investors experienced significant losses as stock valuations corrected.

wealth in the United States. This means the ratio says that the wealth owned by the top 1% equal the combined wealth of the remaining 99%. Even more astonishing is the fact that this wealth disparity has widened considerably, increasing by a staggering 35% over the span of just three decades.

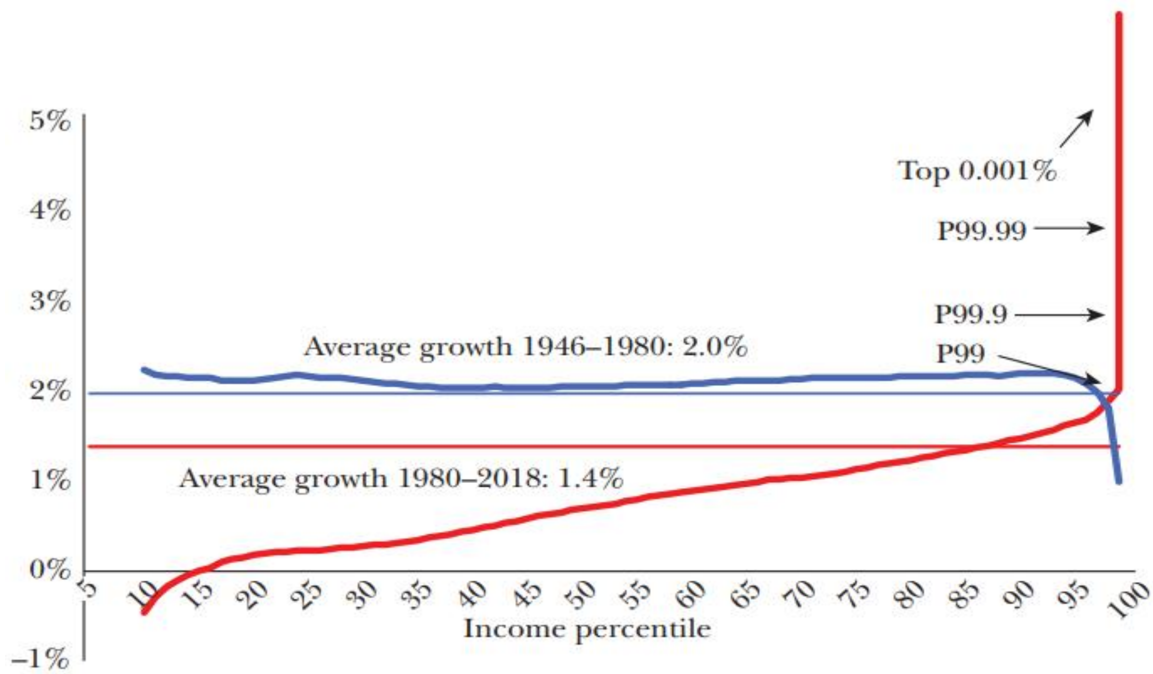


Source: Board of Governors of the Federal Reserve System (US), FRED

Figure 5. *Wealth of the Top 1% to the Wealth of the Remaining 99% (1989-2021)*

In Figure 6, we delve into a detailed comparison of real income growth between two distinct time periods. The graph's horizontal axis thoughtfully segments individuals into twenty distinct income groups, ranging from the lowest earners to the highest. Meanwhile, the vertical axis meticulously illustrates the growth in income over time. This visual representation offers profound insights into the evolving economic landscape.

Upon closer examination of the years spanning from 1946 to 1980 (in blue), a noteworthy pattern emerges. The lower-income groups experienced a remarkable increase in their real income, surpassing an impressive 2%. In stark contrast, the higher income groups witnessed a far more modest growth rate, hovering around a mere 1.5%. This discrepancy signifies a distinct reversal of purchasing power among the upper echelons of income earners during this period, leading to substantial disparities in wealth distribution (Saez & Zucman, 2019).



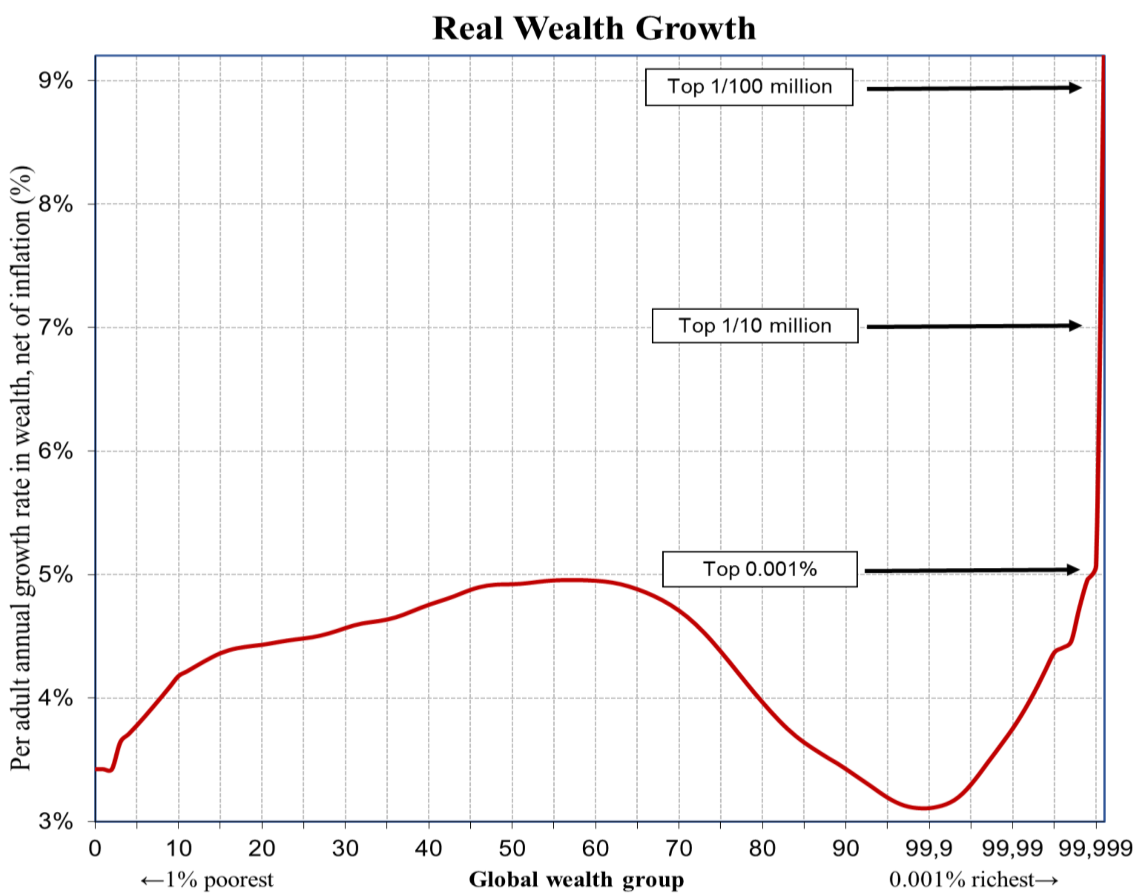
Source: The figure is from Saez & Zucman (2019)

Figure 6. *Real income growth comparison (1980-2018)*

However, a significant paradigm shift occurred between 1980 and 2018 (in red). During these years, the average income of the lower-income groups declined substantially and mediocre growth for the middle group when compared to the higher income strata. Particularly striking is the case of the so-called global elite, constituting a mere 0.001% of the total society. Their income growth curve underwent a remarkable transformation, progressively tilting towards a nearly vertical trajectory, ultimately reaching a staggering 6%. It is essential to emphasize that this data specifically pertains to real income, rendering a 6% increase nothing short of astronomical.

Figure 7 serves as a poignant visual representation of the diverging paths of wealth growth among various societal groups, offering crucial insights into the distribution of wealth and its evolution over time. This data meticulously examines net household wealth, which encompasses the sum of financial assets, such as equities and bonds, alongside non-financial assets like housing and land, after accounting for individuals' debts.

Over the period spanning from 1995 to 2021, the growth rates among the poorest half of the global population ranged from a modest 3% to 4% per year. However, it's essential to recognize that this group initiated their journey from a position of extreme wealth disparity, which inherently limited their absolute wealth growth. Consequently, the poorest half collectively accounted for a mere 2.3% of the overall wealth growth during this time frame.

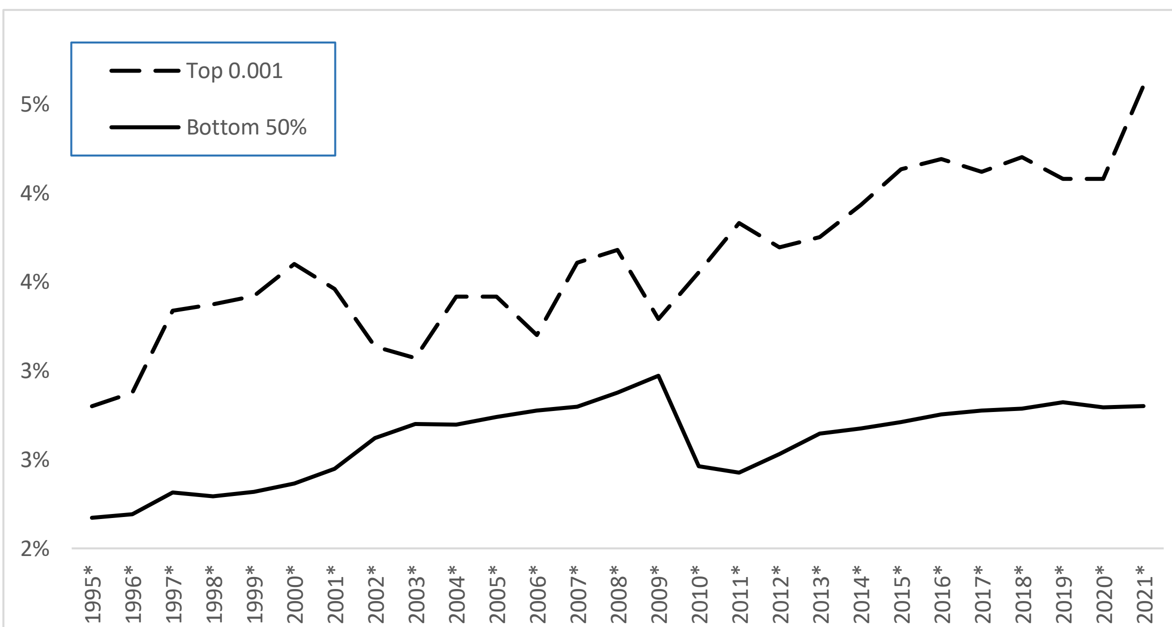


Source: World Bank World Inequality Report (Chancel, et al., 2022)

Figure 7. *Real wealth growth 1995-2021*

Conversely, the top 1% experienced remarkable growth rates, ranging between 3% and an astonishing 9% annually. For a more granular perspective, the top 1/100 million individuals (Top 50) and the top 1/10 million (Top 500) each saw their real wealth expand by approximately 9% and 7%, respectively. These figures vividly underscore the substantial wealth accumulation at the uppermost echelons of society, marking a considerable divergence from the experiences of the majority.

Turning our attention to income growth, intriguing patterns emerge. Between 1980 and 2021, the bottom 50% of the global population experienced substantial income growth, with rates ranging from +50% to an impressive +200%. Simultaneously, the top 1% also enjoyed substantial income growth, ranging from +100% to +200%. In contrast, intermediate income groups registered comparatively modest growth rates (Saez & Zucman, 2022)



Source: World Bank World Inequality Report (Chancel, et al., 2022)

Figure 8. *Wealth share of the global top 0.001% (1995-2021)*

When a group's growth rate outpaces the average growth rate, that group's portion of the total wealth increases. This phenomenon is vividly exemplified among the world's wealthiest individuals. Figure 8 provides a comprehensive overview of the evolution of wealth distribution among the global top 0.001% between the years 1995 and 2021. This exclusive group comprises approximately 55,200 adults as of 2021, and gaining entry into this elite requires amassing a staggering €119 million in wealth, adjusted for purchasing power parity.

If this group's wealth were exactly 100 times the global average, their share of the total wealth would logically be 0.1%. However, the stark reality is that their actual share exceeds 6% of the world's wealth, indicating that their wealth surpasses the average by over 6,000 times. Comparatively, a quarter of a century ago, their wealth was considerably high compared to the average but not nearly as astronomical. At that time, it stood at 3,000 times the average, and their share of the total wealth amounted to 3%. This represents a substantial and alarming escalation in extreme wealth inequality over this period. (Chancel, 2022)

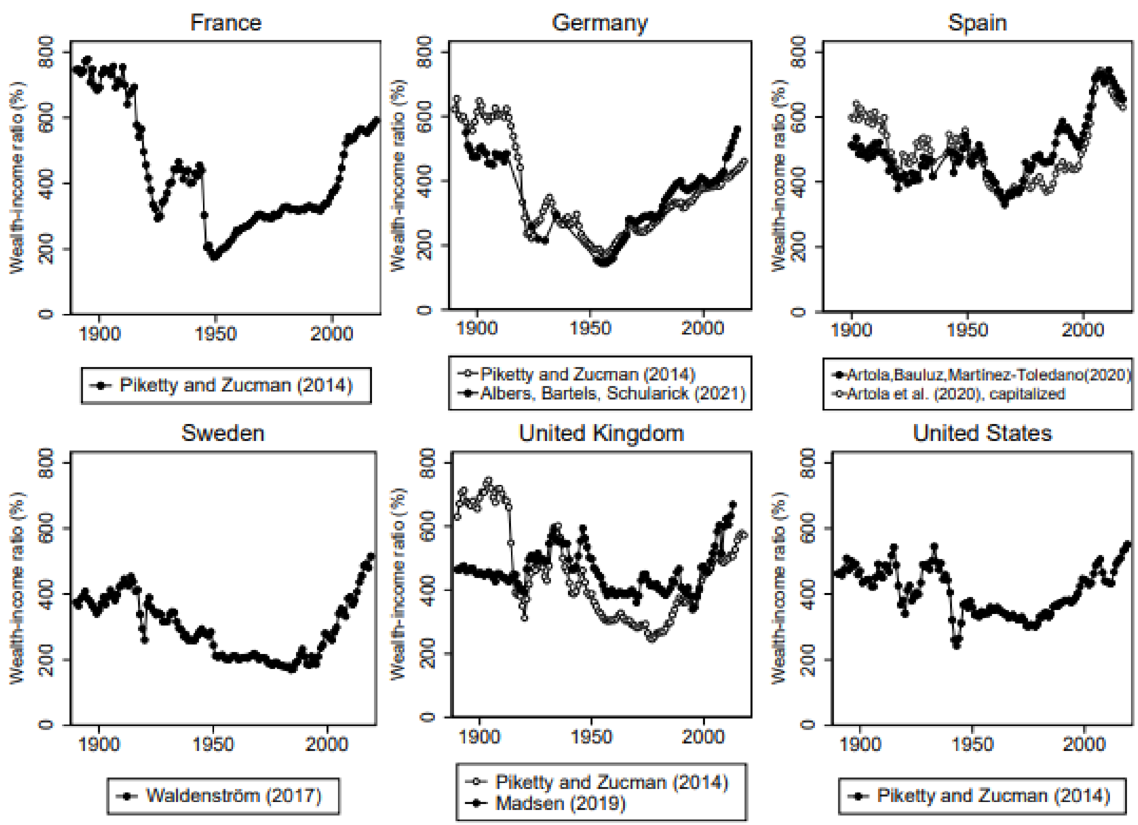
To provide a sobering perspective, consider that the collective wealth of the global bottom 50%, a group 50,000 times larger in population than the top 0.001%, is only three times smaller. While the bottom 50% did experience some growth over the course of several decades (as discussed earlier), their progress was significantly more modest in comparison to the staggering wealth accumulation witnessed among the top 0.001%.

In summation, these trends reveal a nuanced landscape of inequality. While disparities decreased between the bottom and the middle of the global income distribution, they concurrently heightened between the middle and the top. Again, it's worth emphasizing that these growth rates, when interpreted as indicators of real wealth growth, represent truly remarkable shifts in fortunes. In essence, this top percentile managed to capture a staggering 38% of the total wealth growth between 1995 and 2021. These disparities in wealth and income distribution serve as critical markers of our contemporary society. Addressing these imbalances is not merely a matter of economic policy but a fundamental challenge for fostering a fair and equitable global community. The data in Figure 4, 6 and Figure 7 underscore the pressing need for comprehensive measures aimed at ensuring that the benefits of economic growth are more equitably shared, with the ultimate goal of promoting social cohesion, economic stability, and a brighter future for all.

Income distribution, which is one of the main economic policies, has been worsening due to industrial revolutions (Xu, Kim, & David, 2018). These transformative periods in history have, undeniably, exacerbated income inequality. However, delving deeper into the historical context, we find that the period spanning from the agricultural revolution to the advent of the first industrial revolution was marked by numerous conflicts and wars. These wars, undoubtedly grim chapters in human history, carried with them a paradoxical effect – the amelioration of income inequality (The Institute of Economics & Peace, 2015). Each war left in its wake a trail of destruction, but an unintended consequence was the levelling of income disparities. Wars, in their destructive path, indirectly contributed to a more equitable distribution of resources. This peculiar juxtaposition between conflict and income equality underscores a complex facet of economic history.

Furthermore, it's crucial to examine the relationship between capitalism, war, and wealth accumulation. Capitalism, a socioeconomic system underpinned by principles of free trade, appears to discourage armed conflicts. The rationale lies in the understanding that wars can have devastating effects on wealth accumulation, create societal polarization, and engender resource inefficiency. These repercussions are inherently harmful to the tenets of liberal economies, which rely on stability and equitable resource allocation (Vaidya, 2022).

A compelling argument in favor of peaceful coexistence and economic interdependence comes from research conducted by Stanford University. This research demonstrates that commercial alliances, formed through mutual economic interests, exhibit a far higher efficacy in achieving and maintaining sustainable peace when compared to their military counterparts (Jackson, 2014). The underlying principle here is that while military alliances may eventually dissolve, economic ties forged through trade tend to endure and deepen over time.



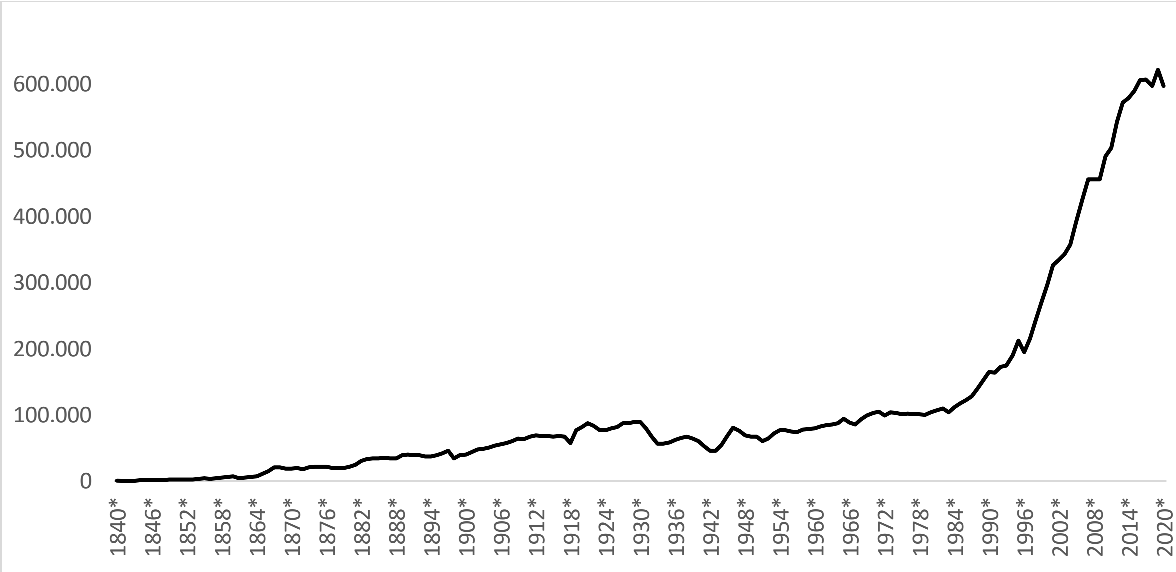
Source: The figure is from Waldenström (2021)

Figure 9. *Historical private wealth-Income ratios of six countries*

Figure 9 vividly presents the private wealth-income ratios of six countries, offering a comprehensive view of their economic dynamics. While variations may exist due to differences in available datasets for some countries, the overarching trend remains discernible. To establish the private wealth-income ratio, a simple calculation involves dividing the value of private wealth by the national income. This ratio serves as a critical indicator of a nation's economic health. Analyzing the graphs, we glean a compelling insight into the impact of global conflicts, such as World War I and World War II, on wealth accumulation. It becomes unmistakably clear that, during the pre-war periods leading up to these monumental conflicts, the conditions for wealth accumulation were markedly more favorable compared to the turbulent periods of war itself and the immediate aftermath (Piketty & Zucman, 2014). These findings underscore the disruptive nature of war on a nation's economic fabric.

During times of conflict, wealth accumulation tends to falter due to the immense economic resources diverted toward war efforts, leaving little room for private wealth growth (Quance & Johnson, 2013). Moreover, the instability and uncertainty that accompany wartime further hinder wealth accumulation. Conversely, during the pre-war periods, economies often experience relative stability and growth, creating an environment conducive to wealth accumulation. Investors and businesses thrive in these conditions, and private wealth tends to accumulate at a healthier pace.

Analyzing the broader impact of trade on global relations, it becomes evident that trade has the power to bring people closer together. The pursuit of economic interests and shared prosperity has, historically, reduced the incentives for conflict (Collier, 1999). Consequently, as trade relations expand, instances of armed conflicts have shown a propensity to decrease. In summary, the expansion of trade has played a pivotal role in not only fostering peaceful international relations but also in safeguarding accumulated wealth. This wealth, however, tends to become increasingly concentrated at the pinnacle of the wealth pyramid, raising important questions about wealth distribution within societies. Understanding these intricate relationships between industrial revolutions, wars, capitalism, trade, and income distribution is essential for shaping more equitable and sustainable economic policies in the future.



Source: U.S. PATENT AND TRADEMARK OFFICE Patent Technology Monitoring Team (PTMT)

Figure 10. *Patent applications in US (1840-2020)*

Figure 10 presents a visual representation of patent applications in the United States, offering a valuable glimpse into the trajectory of technological advancements. A cursory examination of the graph immediately reveals a striking trend—an exponential increase in patent applications over the past few decades. While this upward trajectory has been punctuated by occasional fluctuations due to various factors, including conflicts, economic and financial crises, and public health crises, it's noteworthy that in the years following such disruptions, patent applications experienced a remarkable rebound.

However, a closer look at the historical data reveals intriguing patterns during the times of World War I and World War II. During these tumultuous periods in global history, the data shows sharp declines in technological advancements. The reasons behind these declines are multifaceted. Firstly, a substantial portion of the male workforce, essential for driving innovation in the production process, was conscripted and deployed to the war fronts (Boehnke & Gay, 2022). This resulted in a severe shortage of skilled labor within industries that typically fostered technological progress.

Secondly, capitalists and investors, who possessed the capital required for innovation and development, exhibited a certain reticence to invest. The reduced demand for goods and services caused by wartime circumstances and the heightened risks associated with embargoes, invasions, and other war-related activities contributed to this hesitancy. Also crowding out effect due to financing highly costed wars cuts the private investments (Williamson, 1984). These economic conditions and uncertainties led many capital holders to divert their resources away from traditional avenues of investment and towards the booming war industry.

These historical insights highlight the profound impact that global conflicts can have on technological advancement. While wars have historically disrupted the normal course of innovation, they have also catalyzed significant technological breakthroughs in their own right, driven by the demands of the conflict itself. Nonetheless, they serve as a reminder of the importance of fostering a stable and conducive environment for innovation and investment to ensure sustainable technological progress during peacetime.

Conversely, wars have often acted as powerful drivers of technological progress, spurred by the pressing need for enhanced security and strategic advantage. A compelling example of this phenomenon is the rapid development of radar technology, which emerged as an indispensable tool for militaries across the globe during wartime. Radar's adoption brought about significant shifts in military tactics and led to the creation of entirely new warfare strategies.

However, the influence of wartime technology extends well beyond the battlefield. Radar, initially designed for military use, had unexpected and transformative civilian applications. One particularly intriguing discovery born from radar technology was the foundation for the development of microwave ovens, an innovation that revolutionized modern kitchens and cooking (Strickland, 2022).

Moreover, it's crucial to acknowledge the broader impact of wars on scientific and technological progress. The pursuit of military superiority during conflicts has consistently driven innovation in areas such as telecommunications and space exploration. The Internet, which has fundamentally transformed the way we communicate and access information, owes its origins to military research. Similarly, the space race, driven in part by Cold War competition, resulted in humanity's ability to explore the cosmos.

In light of these historical examples, it becomes clear that dismissing wars as entirely unconstructive oversimplifies the intricate relationship between conflict and progress. While wars undoubtedly bring destruction and suffering, they have also, paradoxically, fueled remarkable advancements in technology, scientific discovery, and innovation. This underscores the complex interplay between the destructive and constructive forces inherent in human history.

2.2 EFFECTS OF INDUSTRIAL TECHNOLOGICAL ADVANCEMENTS

2.2.1 Capital Gains

Income inequality has been increasing, especially since the late 1970s (Piketty, 2014, pp. 20-25). However, this doesn't mean that incomes of all people were equivalent in the past. If we cast our gaze back at the early stages of history once again, people were hunter-gatherers, and even during those times, there were strong and weak individuals within communities. Naturally, some people had better living conditions than others (Scheidel, 2017). Nevertheless, the disparity between them was very small. For them, income primarily meant shelter and food, and the concept of substantial wealth was quite different from what we know today.

As time passed, the agricultural revolution emerged, marking a significant shift in human societies (Putterman, 2008). Communities began to adopt settled lifestyles, cultivating crops and domesticating animals. This transition brought about profound changes in social structures. The stronger and weaker individuals who had existed in the hunter-gatherer life now evolved into distinct classes within agricultural societies – the lords and the peasants. The accumulation of wealth accelerated as land became a vital factor in production, further exacerbating income inequality (Carter, 2000).

This transformation not only introduced the concept of private property but also laid the foundation for class-based societies, where access to resources and opportunities was heavily influenced by one's social status (Birdal, 2007). The agricultural revolution not only increased the overall production capacity but also magnified the gaps in income and living standards, setting the stage for the complex economic systems we see today.

While income inequality may have always been present to some degree throughout human history, the agricultural revolution marked a turning point in the scale and impact of these disparities. From simple hunter-gatherer communities with minimal income differentiation to complex agricultural societies with distinct social classes, the evolution of human civilization has been closely intertwined with the changing dynamics of wealth and income distribution (Atkinson & Bourguignon, 2014).

Malthus' theory is fundamentally grounded in the concept of limited land resources. According to his theory, even though resources increase arithmetically, human population growth occurs exponentially. Consequently, famine becomes inevitable when the human population surpasses the sustainable capacity of the land. However, it's clear that Malthus' analysis had its limitations, particularly in terms of predictive accuracy. One of his most significant oversights was failing to account for the effects of the first industrial revolution (Malthus, 1956).

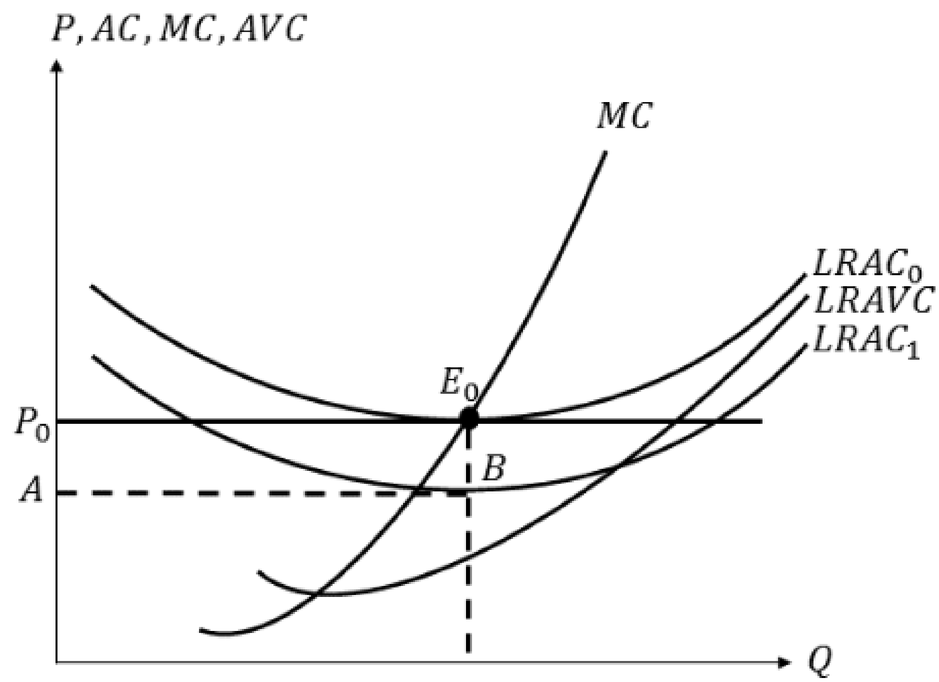
2.2.1.1 Capitalists

Every industrial revolution has made the production process more capital-intensive (Allen, 2005). At this point, the second industrial revolution deserves a mention once again. The key elements of the second industrial revolution are electricity and a low-skilled labor force. In this context, the labor force became an integral part of production through automated production lines that required electricity. Knowledge and human capital were not integrated into the production process, leading to production being carried out by the labor force without a complete understanding of their tasks. Adam Smith's division of labor model played a pivotal role in this type of production system. Production was divided into numerous segments via assembly lines, with each worker performing simple tasks such as tightening screws and assembling pieces.

At first glance, it might seem that a firm's labor costs would be tremendous due to the large workforce required for this division of labor. However, when considering these workers' capabilities within the Fordism system, the labor supply was sufficient to compensate them at minimum wage levels. Therefore, the existence of The Iron Law of Wages provided advantages to these firms. One of these advantages can be counted as massive manufacturing capacity. Production increased substantially, leading to the coining of the term "Fordize," (Pidal, 1998) which means standardizing a product and producing it in large quantities. During these years, a famous slogan from Ford's company echoed: *"Any customer can* have a car painted any color that he wants, so long as it is black."

Another advantage of this system is the reduction in costs. The pricing strategy depends on the price elasticity of goods. However, considering the relatively high price elasticity of cars, decreasing costs allowed the firm to adopt a low pricing strategy to maximize its total revenue and profitability.

Accumulated profits have provided capital owners with opportunities to earn even more profits. Once reaching profit maximization under the current conditions, there are two ways to further increase profit. One of these ways is by reducing costs, which is only possible through R&D expenses at the current optimal production point. With lower costs, firms can either generate grosser and hence operational profits or increase their sales, gaining more market share to become more competitive against other players (Vives, 2008).



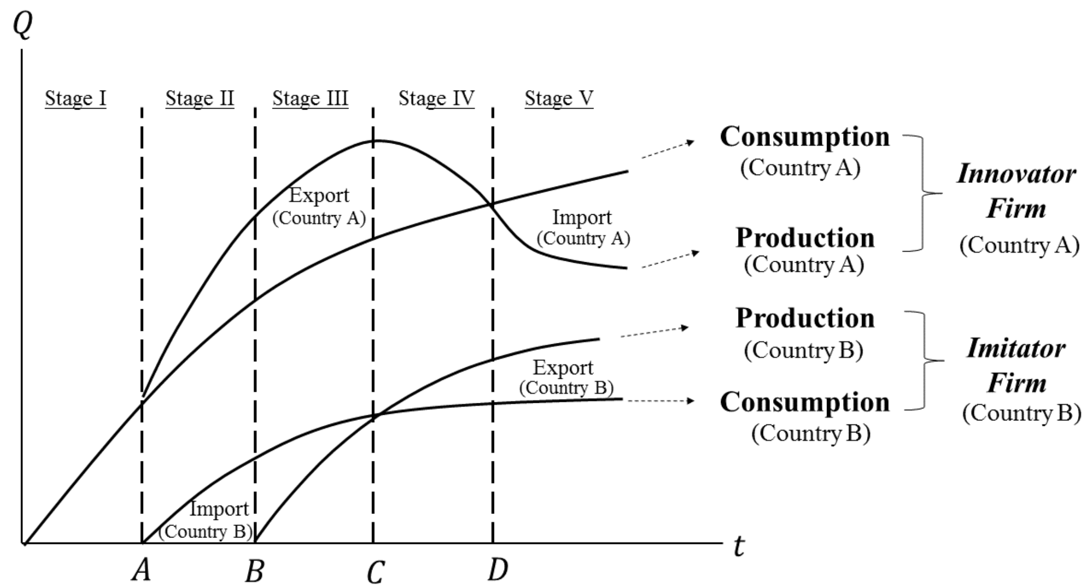
Source: Author

Figure 11. *An effect of innovations on costs and profitability*

This concept is visually represented in Figure 11. In a scenario of perfect competition, one effective strategy for boosting profits is to reduce costs. The condition for profit maximization occurs at point E_0 on the graph. Subsequently, when there is a decrease in costs resulting from a firm's or other firms' R&D efforts, such as implementing mass production techniques, enhancing operational efficiency, or achieving workforce specialization, the average costs curve shifts downward. As a consequence, the firm's profits transition from the zero-profit level to the area enclosed by curves AP_0E_0B

This progress allows firms to enjoy increased profitability for a certain duration, a competitive advantage that persists until other firms adopt similar advancements in their production processes. During this period, the firm that first implements cost-saving innovations gains the upper hand in terms of pricing, quality, or both, attracting more customers and expanding market share (Capozza, et al., 2021). However, as other firms catch up by incorporating similar efficiency enhancements, the advantage gradually erodes, and the industry returns to a state of equilibrium.

The competition among firms to continually improve their processes and reduce costs is a defining characteristic of dynamic market economies. It incentivizes innovation and efficiency gains, ultimately benefiting consumers through better products, lower prices, and improved overall economic growth (Mahardhani, 2023).



Source: (Vernon, 1979)

Figure 12. *Product life-cycle theory*

Another avenue for increasing a company's profitability is through innovation, a concept well illustrated in Figure 12. In the realm of International Economics, the product life-cycle theory, originally derived from Heckscher-Ohlin's factor endowment theory by Vernon (1979), provides valuable insights. Even though this theory is based on countries and takes into account economic development and production based on firms, we can revise this theory with a focus on two specific firms in different countries. First of all, according to this theory, akin to the pursuit of reduced costs, creating added value necessitates robust R&D operations.

This dynamic process involves firms in developed countries engaging in innovative endeavors and crafting new products through substantial R&D investments.

Upon closer examination of the figure, we observe a clear progression. After the introduction of an innovative product, the firm embarks on Stage One, a phase where it predominantly focuses on producing the innovative goods to meet domestic demand. This is a pivotal stage for the firm, as it benefits from the close proximity to domestic consumers, who provide valuable feedback.

Advancing to Stage Two requires dedication and learning by doing. Continued R&D operations contribute significantly, as the firm's product matures through the know-how process. It is at this juncture that the firm's products gain international appeal, and exports to foreign markets commence. The period between Stage Two and Stage Three often witnesses a surge in exports from the innovating firm in Country A, driven by high demand overseas. Simultaneously, domestic demand for the product remains strong. Throughout these stages, the innovating firm enjoys a robust production capacity, and it's essential to emphasize that the manufacturer retains a monopoly over the technology, yielding monopolistic profits.

In contrast, during these phases, imitating firms in Country B and others transform into importers (Can call that Country C, D etc.). As the production process gradually standardizes, both producers and consumers become well-acquainted with the features of the innovative product. Stage Three marks the initiation of standard production. The innovator firm may find it advantageous to sell licenses or patents for the new product, opting to reduce its own production. Alternatively, it might shift the entire production process to another country via offshoring where labor costs are lower compared to its home country. This relocation is driven by the qualifications of the labor force. R&D operations, which originate in developed countries, require a skilled yet expensive workforce. However, once the production process is standardized, the innovator firm can dispense with the cost of R&D, making the move to a more cost-effective location an appealing option.

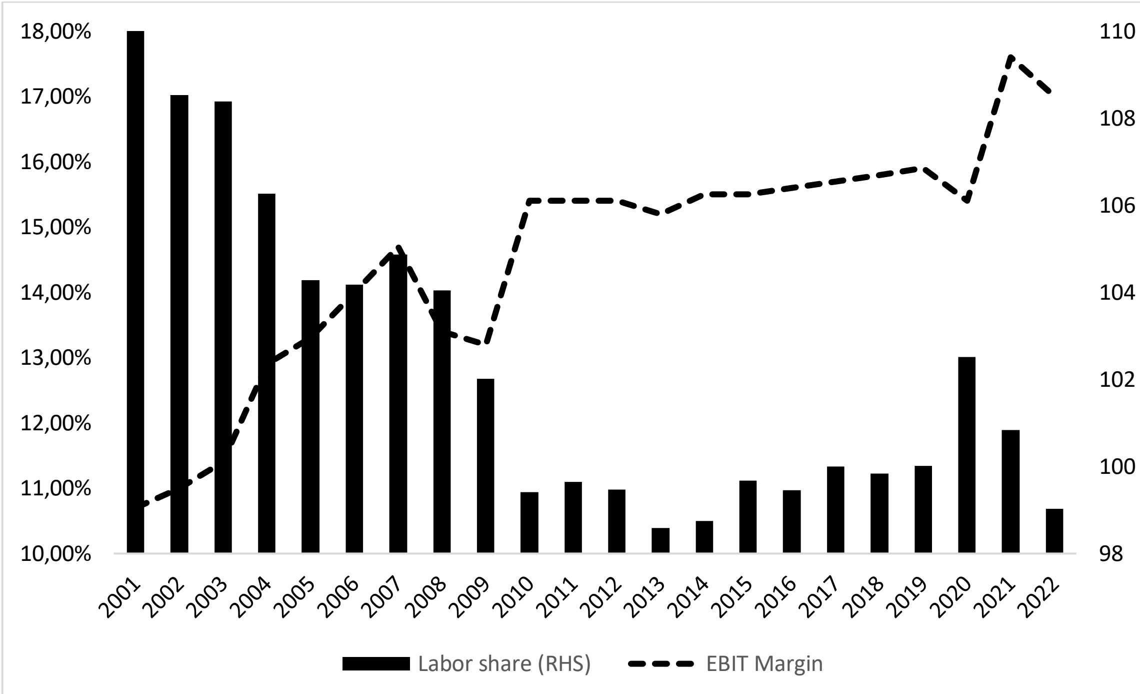
Upon closer scrutiny of Figure 12, it becomes evident that the firm continues to produce, albeit to a lesser extent, during Stage Four. However, firms that secure licenses and patents from the innovator firm begin manufacturing the products initially developed by the innovator, exporting them to developed countries. Over time, the innovator country transitions into an importer of the product, and the innovator firm loses its monopolistic profit until it ushers in a new innovation through R&D operations. As a result, R&D operations are geared towards generating technological advancements aimed at enhancing profits from new products or reducing costs. Given that labor costs are a constraint within the profit maximization objective function, it is anticipated that technological innovations might prioritize labor-saving mechanisms even more.

Technological innovations and the patent creation process typically advance cumulatively as we discussed. According to Archibugi (1997), technological accumulation is driven by technological capability. This encompasses parameters such as institutional structures within firms, inter-firm relationships, external factors, as well as knowledge, skills, and experience (Miyazaki and Sato, 2018). These parameters are closely intertwined with technical advancements, including major investments in new plants and equipment, as well as incremental adaptations and improvements to existing production capacity. Furthermore, production capacity factors, such as the skills and know-how of the labor force, the organization of production processes, and operating procedures, are intricately tied to the concept of fixed capital. Fixed capital plays a critical role in both expanding production capacity and facilitating technical change (Corrado et al., 2005). As previously discussed, each industrial revolution has progressively transformed the production process into a more capital-intensive endeavor. In fact, we can extend this argument to assert that every technological advancement inherently necessitates more capital investment. This is due to the increasing complexity and sophistication of technology, which naturally demands greater financial resources (Xu et al., 2022).

To summarize, firms are driven by the pursuit of profit maximization, motivating them to innovate in order to reduce costs and create new products that can yield monopolistic profits (Teng et al., 2023). The pursuit of these goals invariably requires substantial investments (World Investment Report, 2023). Consequently, these factors perpetuate a cyclical system characterized by the investment-profit loop, ultimately leading to the accumulation of wealth in the hands of a select majority within society (Kapelle & Lersch, 2020). It is reasonable to categorize this elite group as capital holders. Historical data reveals a significant trend – the portion of total real GDP attributed to capitalists has been on a consistent decline since the era of the Great Depression (Piketty, 2014). This observation prompts a critical question: "Who, then, benefits from the capital relinquished by these capitalists?"

The answer lies in the historical context. The aftermath of major global conflicts and the establishment of international institutions promoting free trade, such as the World Trade Organization, has ushered in an era where entrepreneurship has gained considerable prominence (Sobel et al., 2007). Entrepreneurial activities can be viewed as a form of capital gains, effectively redistributing wealth.

To further support this shift, let's consider the data from the Department for Business, Energy and Industrial Strategy (BEIS). According to their statistics, the compound annual growth rate (CAGR) of businesses in the United Kingdom has seen a robust increase, standing at 2.8% from 2000 to 2018. In contrast, self-employment, another form of economic activity, has experienced a CAGR of 1.3% (Chiripanhura & Wolf, 2019). And the total labor force has grown at a slower pace, with a CAGR of 0.7% (World Bank, 2019). While it might initially appear that this shift could be indicative of improved income equality between capital and labor earnings, a closer examination reveals a broader trend. Capital gains are, in fact, on the rise. This implies that wealth is being increasingly accumulated within the realm of entrepreneurship, further expanding the divide between capital holders and the labor force. The upcoming section will delve into the dynamics of the labor market side to shed more light on this complex interplay between capital and labor.



Source: Bloomberg, FRED. (2001-2022)

Figure 13. *Median Operating Income of S&P 500 & Labor Share of Income in US*

In delving deeper into the implications of Figure 13, which displays the dynamics between companies' Earnings before Interest and Taxes (EBIT) Margin and the labor share in income within the S&P 500, a more nuanced understanding of the transformative impact of automation on the economy emerges. The visible inverse relationship between increasing profits and decreasing labor share underscores a critical shift in the distribution of income, prompting an exploration of the underlying drivers and potential consequences.

As companies witness a surge in profits, the diminishing labor share in income becomes a focal point of discussion. This trend becomes particularly pronounced when viewed in the context of capital spending aimed at accelerating automation (Sprovieri, 2023). Companies strategically prioritizing operational efficiency stand poised to reap increased returns on investment, as exemplified by the observable rise in operating margins within the S&P 500 from 2021 to 2022.

The historical context, exemplified by the transition from manual labor to mechanized agriculture, provides valuable insights into the transformative nature of automation (Wickenberg, et al., 2022). The switch from horses to tractors revolutionized farmingg practices, leading to heightened productivity and efficiency. Without these technological advancements, a substantial portion of the US population might still be toiling in labor-intensive agricultural roles (Basha & Newisar, 2023). This historical perspective serves as a harbinger of the impending transformation in the manufacturing sector, where automation is anticipated to drive down labor's share of revenue to unprecedented levels (Sharma, et al., 2022).

The intricate interplay between technology, labor, and income distribution remains a complex and evolving landscape (Awosusi et al., 2022). While automation promises heightened efficiency and increased profitability for companies, it simultaneously raises concerns about the equitable distribution of wealth. The observed trend in the S&P 500 serves as a microcosm of broader economic shifts, inviting further exploration into the potential ramifications of this evolving dynamic on both corporate success and individual livelihoods (Ahmed, Jeon, & Piccialli, 2022). As we navigate these changes, an in-depth analysis of historical parallels and future implications becomes integral to crafting informed policies and strategies that foster a balance between technological progress and societal well-being.

2.2.1.2 Automation, offshoring & reshoring

Offshoring on the other hand, boosts profits by relocating a company's operations internationally, a practice frequently used by international firms (Kedia & Mukherjee, 2009). This method involves moving parts of the value chain to other countries to reduce costs. Since the 1960s, companies have relocated manufacturing from high-cost to low-cost countries, a trend well-documented by Dunning and Lundan (2008). Vernon's product life cycle model that we have mentioned initiated the academic study of offshoring, responding to the trend of U.S. companies shifting labor-intensive processes to developing regions (Jensen & Pedersen, 2012).

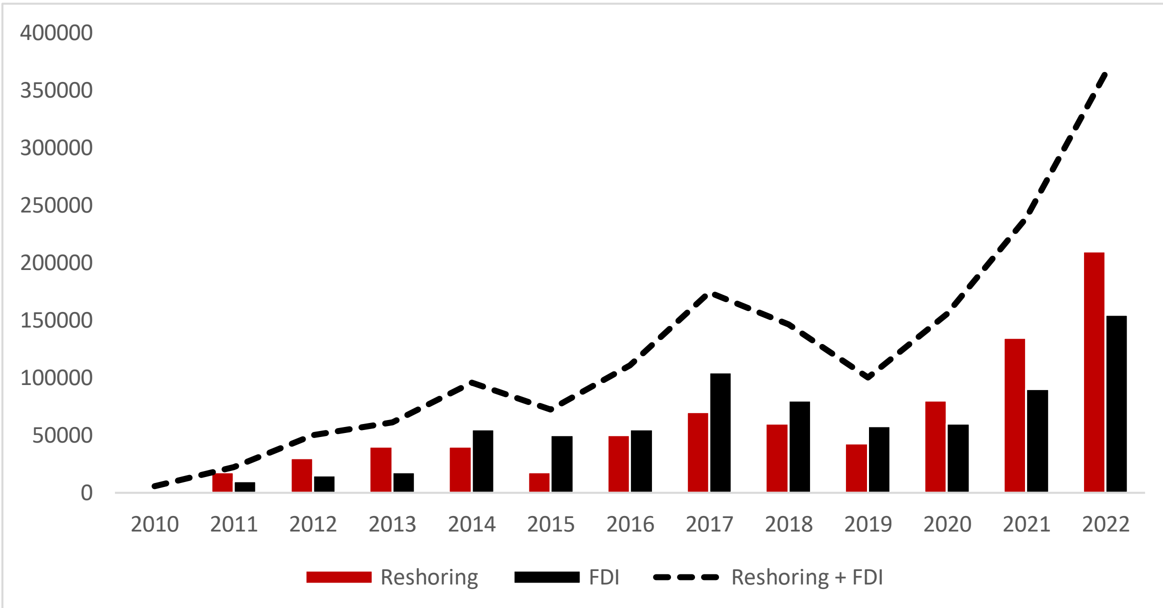
Offshoring and outsourcing have transformed global business operations, particularly in the services sector, due to trade liberalization and rapid technological advancements (Goos, Manning & Salomons, 2014; Nwani et al., 2022). These changes have expanded business horizons across various sectors, significantly impacting the services industry. Traditionally associated with manufacturing, offshoring has recently become a dominant practice within the services sector, leading to discussions about its effects on the economic futures of outshorer countries (Beckert, 2021).

To sustain and enhance living standards, outshorer countries must improve productivity, maximizing the value of their workforce and exploring innovative economic solutions (Fitoussi, Sen, & Stiglitz, 2011). Offshoring critics argue it exports jobs, calling for protective measures. However, a comprehensive view shows offshoring can enhance organizational capabilities and allow global expansion, leveraging comparative advantage (Lipai et al., 2021). Restrictions on offshoring would amount to protectionism, potentially hindering economic progress (Wang, Jiang, Li, & Wang, 2022).

In recent years, offshoring has surged in Asian countries like India, Singapore, and China, drawing considerable interest (Alkhalidi et al., 2019). Despite favorable conditions for offshoring, reshoring and insourcing activities are rising. Reshoring involves transitioning production back to the home country or nearby regions, reflecting a strategy for localizing manufacturing (Bals et al., 2016). According to the Reshoring Initiative 2022 Report, there has been a significant increase in reshoring and Foreign Direct Investment (FDI) over the past thirteen years. This trend results from companies recognizing that offshoring costs can exceed those of domestic sourcing, influenced by policy changes and trade disputes. Figure 14 illustrates the fluctuations in reshoring and FDI trends over this period.

Between 2020 and 2022, reshoring resurged, driven by supply chain disruptions, geopolitical events, and advancements in robotic technologies. Investments in critical areas like semiconductor chips and electric vehicle (EV) batteries contributed to job creation in the U.S.

in 2022. This trend reflects deeper structural shifts in business strategies towards reshoring and increased domestic investment.



Source: Adapted from Reshoring Initiative (2022)[3]

Figure 14. *Job announcements of Reshoring and Foreign Direct Investments in USA*

Between 2020 and 2022, reshoring resurged, driven by supply chain disruptions, geopolitical events, and advancements in robotic technologies. Investments in critical areas like semiconductor chips and electric vehicle (EV) batteries contributed to job creation in the U.S. in 2022. This trend reflects deeper structural shifts in business strategies towards reshoring and increased domestic investment.

As Figure 14 shows, this trend has not been linear; it experienced significant fluctuations due to specific occurrences, such as the spike in 2017 driven by tax and regulatory changes, and the subsequent declines in 2018 and 2019 due to trade disputes. However, the overall trend indicates a robust underlying movement towards reshoring, with an estimated continuation of around 350,000 job announcements annually forecasted for 2023 and 2024. Even as this

[3] For more on this issue, please see Reshoring Initiative (2022)

trend is partly influenced by short-term government policies, it is expected to incentivize further investments in EV batteries and attract more Foreign Direct Investments for EV assembly plants. Increased investments in semiconductor chips are likely to bring more electronic product assembly back to domestic soil. Geopolitical uncertainties are also compelling companies to consider reshoring additional product categories. Moving work from Asian countries to the U.S. and neighboring areas is expected to drive nearly 40% of value addition within the U.S. economy. The ongoing trend in U.S. manufacturing employment, highlighted in the Reshoring Initiative 2022 Report, shows a significant shift from offshoring towards reshoring and increased FDI. This trend is analyzed using a regression study from 1997 to 2006, showing that without the reshoring trend, U.S. manufacturing employment would be significantly lower by about seven million jobs. During past recessions, manufacturing employment fell below the trend line, but the 2020 recession saw an increase above the trend line, which expanded in 2022 (Reshoring Initiative, 2022).

Reshoring has consistently outpaced FDI for three consecutive years, evident in alliances between domestic and foreign entities like GM and the LG battery plant. These joint ventures allocate job assignments based on contract specifics or evenly distribute them between the original equipment manufacturer (OEM)/contract manufacturer or reshoring/FDI. The trend favoring reshoring reflects the cresting of globalization and responses to changing economic and geopolitical dynamics, along with U.S. government incentives encouraging reshoring initiatives. This shift underscores U.S.-based companies' growing realization of localized production advantages, a concept long understood by many foreign entities.

Globalization manifests in two primary forms: the traditional single-source model, with production concentrated in one location for global markets, and the localization model, advocating manufacturing tailored to specific market demands. The shift towards localization, driven by geopolitical tensions, is reducing the dominance of the single-source model, driving substantial FDI into the U.S. due to its large, stable market, economic incentives, and reduced geopolitical risks. Considering a conservative two-year timeline from announcement to hiring, around one million people have been employed due to these manufacturing shifts. This accounts for about 70% of the 1.43 million increase in U.S. manufacturing jobs since February 2010. These new jobs represent approximately 8% of total U.S. manufacturing employment as of December 31, 2022 (Reshoring Initiative, 2022).

The shift towards reshoring indicates the decline of offshoring, with potential implications for labor-intensive economies like China, impacting their growth trajectory (Lipai et al., 2021). This shift represents a larger global economic reconfiguration, suggesting a substantial economic shift with capital returning to developed nations, altering the global balance between labor and capital. Automation and Industry 4.0 advancements drive this trend, accelerating reshoring in capital-intensive nations and transforming global production and economic dynamics (Santhi & Muthuswamy, 2023). The next section will explore income distribution issues within the labor market.

2.2.2 Labor Market

Technological advancements exert a considerable influence over various economic facets, notably casting a significant impact on the labor market. The potential ramifications of these changes on employment have been a longstanding concern, reflecting a historical continuum of worry. Throughout history, societies have witnessed protests, strikes, and even rebellions triggered by fears and real consequences of technological shifts causing job displacement (Mokyr, et al., 2015). This ongoing debate continues to underscore the delicate balance between progress and its implications for the workforce, prompting ongoing discussions and actions aimed at managing the evolving landscape of employment in the face of advancing technology.

Centuries before the onset of the initial industrial revolution, there existed apprehensions regarding the capacity of advanced technologies to replace human labor. This concern about automation was notably articulated in the late sixteenth century, during the time of Queen Elizabeth, when William Lee sought a patent for his stocking frame knitting machine. In response to Lee's request, Queen Elizabeth expressed her reservations, cautioning him about the potential implications of his invention. (Acemoglu & Robinson, 2012).

She remarked, *“Thou aimest high, Master Lee. Consider thou what the invention could do to my poor subjects. It would assuredly bring to them ruin by depriving them of employment, thus making them beggars.”*

Even the term "sabotage" itself bears a connection to this issue, notably exemplified in the theory surrounding the invention of the Jacquard loom by Frenchman Joseph Marie Jacquard in 1801. This pioneering loom revolutionized the textile industry by utilizing punch cards to automate the intricate process of manipulating warp threads, surpassing the weaving capacity of human hands. While this innovation marked a significant technological leap, it also displaced numerous textile workers from their jobs. According to one theory, some of these workers, in an act of protest or resistance, resorted to throwing their wooden clogs (referred to as "sabots" in French) into the sophisticated machinery, causing deliberate disruption and damage (Oxford English Dictionary, n.d.).

During the Glorious Revolution of 1688, the craft guild in Britain, while still prevalent on the Continent, experienced a decline, losing much of its former political influence and sway (Nef, 1957). Subsequently, with Parliamentary supremacy solidified over the Crown, legislation was enacted in 1769, deeming the sabotage or destruction of machinery a capital offense (Mokyr, 1990). Despite these legislative measures, resistance to mechanization persisted. Notably, the "Luddite" riots between 1811 and 1816 were partly a reflection of workers' apprehension toward technological advancements, especially as Parliament rescinded a law from 1551 that prohibited the use of gig mills in the wool-finishing trade. In response to these riots, the British government adopted a more stringent approach, mobilizing a force of 12,000 men to suppress these anti-mechanization movements (Mantoux, 2013).

Many economists addressed the effects of the technological advancements on the labor market. In the wake of the Luddites resorting to the destruction of machinery out of fear for their job security, economist David Ricardo, once optimistic about the universal advantages of technological advancement, crafted an abstract model to explore the prospect of technological unemployment in greater detail. This conceptual framework postulated a scenario wherein the equilibrium wages for workers might decline to a level insufficient for basic subsistence. The underlying concept revolves around the idea that, at a certain point, rational individuals would be disinclined to accept employment at wages below their minimal needs. Consequently, this reluctance to engage in low-paying work could lead to widespread unemployment, with machines assuming the responsibilities instead. Ricardo's model thus underscored the potential societal impact of technological progress, revealing a nuanced dimension where advancements could inadvertently contribute to economic imbalances and workforce displacement (Ricardo, 2005).

Furthermore, G. Clark's insightful exploration, as documented in his 2006 book, not only sheds light on the historical dynamics of the working horse population but also underscores the intricate consequences of industrialization. The scenario he presents unfolds with a vivid narrative, illustrating the persistence of horses in diverse roles even after the Industrial Revolution had transformed various sectors. The year 1901 serves as a pivotal point in this narrative, marking the pinnacle of the working horse population in England at 3.25 million. Despite the evolving landscape favoring rail and steam engines for transportation and machinery, these equine laborers continued to plow fields, transport goods over short distances, navigate canals, toil in mines, and contribute to military efforts. Their resilience in the face of evolving technology showcases the complexity of the transition from traditional to industrial practices. However, the tide turned with the introduction of the internal combustion engine in the late nineteenth century. This technological leap rapidly rendered horses obsolete in many of their roles. By 1924, their numbers had dramatically dwindled to less than two million, marking a profound shift in the labor landscape.

Clark's narrative poignantly highlights a crucial economic aspect – the existence of a wage level that could have retained these horses in employment. Regrettably, this wage was economically unviable, falling below the threshold necessary to cover their basic sustenance, let alone facilitate the breeding of successive generations. In this manner, the fate of working horses becomes a poignant early example of how industrialization not only transforms labor dynamics but also presents challenges in reconciling economic sustainability with technological progress (Clark, 2006).

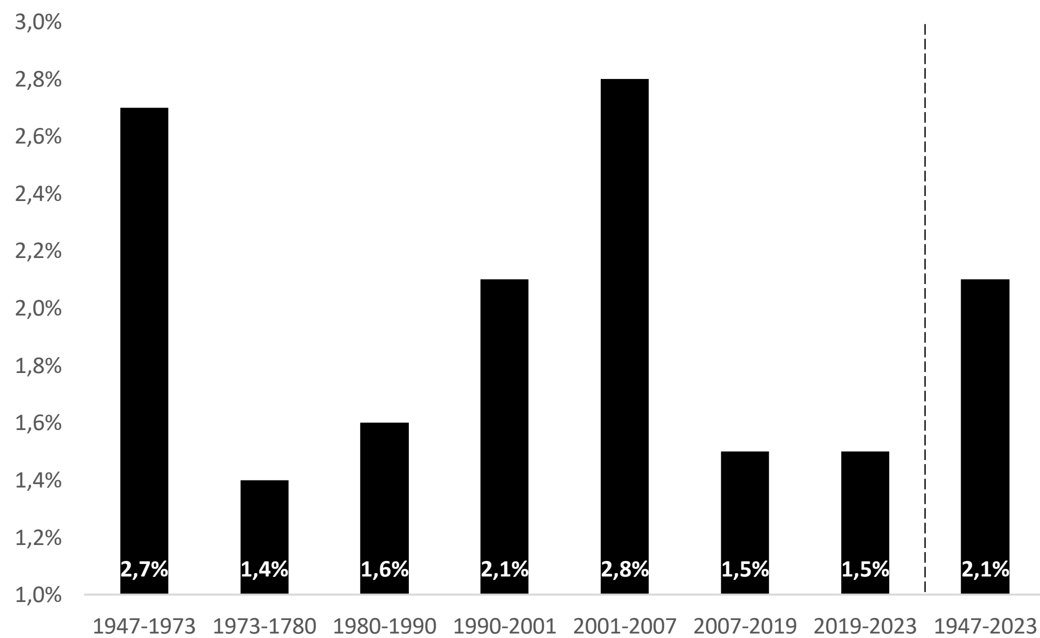
In his exploration outlined in the essay "Economic Possibilities for Our Grandchildren" Keynes (1930) envisioned a future where individuals, in the span of a century, would engage in work for merely three hours a day while still enjoying a satisfactory standard of living and overall contentment. This forecast stood in stark contrast to the prevailing pessimistic sentiments of that era, where the predominant belief was in an unavoidable and continuous economic downturn which a sentiment not unlike today's.

His quote in the aforementioned book goes like this: *"We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come—namely, technological unemployment. This means unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour."* (Keynes, 1930).

Related to these, among the extensive array of economic metrics, one assumes particular prominence: productivity growth. Defined as the measure of output per unit of input, with a specific focus on labor productivity gauged by output per worker or output per hour worked, this metric stands as a critical determinant for the trajectory of rising living standards. Robert Solow's groundbreaking work, "*A contribution to the theory of economic growth"* recognized with the Nobel Prize, elucidates a pivotal concept—that economic growth emanates not merely from heightened labor exertion but, more significantly, from intelligent work practices. This involves the adept utilization of novel technologies and production methodologies to generate heightened value without proportional increases in labor, capital, and other resources. Even marginal increments in productivity growth, a mere percentage point or two annually, can yield substantial differentials in wealth accumulation over time.

In historical contexts where labor productivity exhibited a modest 1% growth, a prevalent trend during much of the 1800s, the doubling of living standards took approximately 70 years

(Brynjolfsson & McAfee, 2011). Conversely, a robust 4% annual growth, as witnessed in 2010, resulted in living standards soaring 16 times higher over the same period. While such exceptional growth is noteworthy, the past decade stands out as notably favorable for labor productivity—the most robust since the 1960s. Figure 15 shows that, with an annual average growth surpassing 2.5%, it outpaces the rates observed in the 1970s and 1980s, even surpassing the performance of the 1990s in US.



Source: Bureau of Labor Statistics

Figure 15. *Productivity Growth (1947-2023)*

A significant consensus among economists has coalesced regarding the catalyst behind the surge in productivity since the mid-1990s, pinpointing Information Technology (IT) as the primary driver (Jorgenson, Ho, & Stiroh, 2005). Despite the encouragement drawn from official productivity metrics, they remain inherently flawed, grappling with the comprehensive measurement of qualitative attributes, variety, timeliness, customer service, and other intangible aspects of output. The conventional ease of quantifying tangible goods such as bushels of wheat and tons of steel sharply contrasts with the intricacy of evaluating the quality of teaching, the value of diverse cereal options in a grocery store, or the convenience of 24/7 access to an ATM.

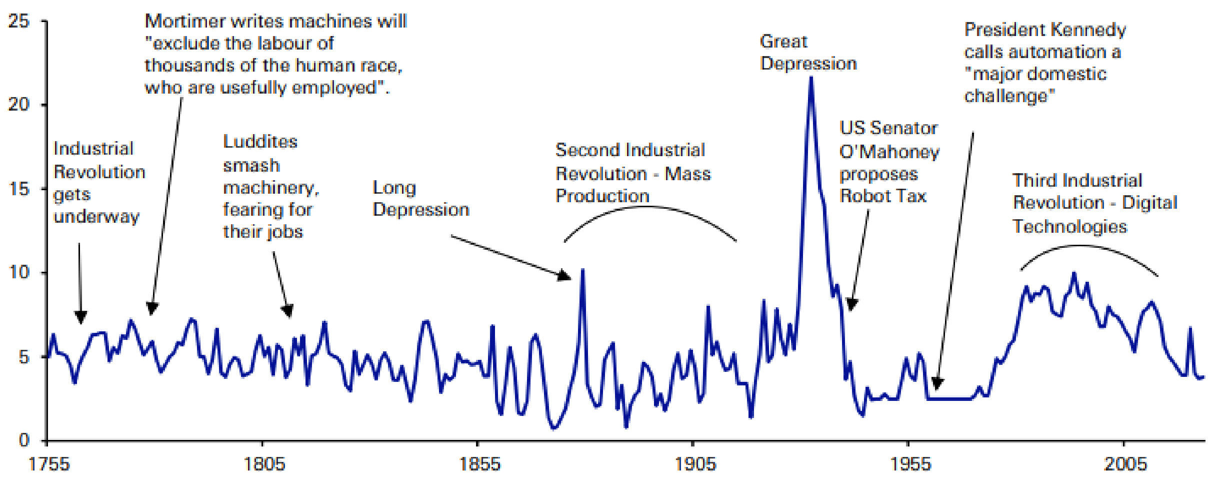
Adding to this measurement complexity is the absence of free digital goods, like Facebook, Wikipedia, and YouTube, in productivity assessments. As the Internet and mobile telephony expand, offering a growing array of free services that occupy more of people's daily lives, this source of measurement discrepancy becomes increasingly relevant. Moreover, a significant constraint lies in the valuation of most government services at cost, implicitly assuming zero productivity growth for the entire sector, irrespective of whether genuine productivity aligns with the broader economic trajectory (Brynjolfsson & McAfee, 2011).

An additional source of measurement error arises from the inadequate assessment of health care productivity, a substantial and critical segment of the economy. Despite often being assumed as stagnant, health care productivity fails to account for the significant increase in life expectancy, with Americans living, on average, about 10 years longer today than in 1960. While this represents an invaluable gain, it remains unacknowledged in productivity data. According to Nordhaus (2002), the economic value of increased longevity over the twentieth century approximates the value of measured growth in non-health goods and services. Historical eras also witnessed significant unmeasured quality components, such as the welfare gains from telephones or disease reductions from antibiotics. Conversely, productivity statistics might overstate growth in certain areas, neglecting factors like increased pollution or heightened spending on crime-deterring goods and services prompted by an uptick in criminal activities. In summary, the official productivity data likely underestimate the genuine improvements in our living standards over time when considering the myriad complexities and unaccounted dimensions within the economic landscape. The existing body of scholarly literature on the effects of automation and digitalization can be broadly categorized into two perspectives. Firstly, there exists an optimistic viewpoint that perceives these technological changes as part of the normal course of market dynamism. Proponents of this stance argue that technological change has been an integral aspect of "modern economic growth" since the Industrial Revolution. Disruptive innovations have consistently generated what Mokyr et al. (2015) term as "technological anxiety," a phenomenon observed since the advent of the steam engine and the power loom. Nobel laureate Kuznets (1971) highlighted, in his Nobel lecture that the hallmark of modern economic growth lies in a combination of a high rate of aggregate growth with disrupting effects and new problems. This disruption pertains specifically to the changes in economic and social structures triggered by technological innovation.

Key theorist Joseph Schumpeter introduced the concept of "creative destruction" to describe the continual revolutionizing of the economic structure through technological innovation. He regarded this process as the "essential fact about capitalism" (Schumpeter, 1943). Notably, Schumpeter's perspective predated the neoclassical standard growth model put forth by Solow. Solow's model once again, attributed unaccounted-for output growth to a broad category of "technical change" in his aggregate production function Key theorist Joseph Schumpeter introduced the concept of "creative destruction" to describe the continual revolutionizing of the economic structure through technological innovation. He regarded this process as the "essential fact about capitalism" (Schumpeter, 1943). Notably, Schumpeter's perspective predated the neoclassical standard growth model put forth by Solow. Solow's model once again, attributed unaccounted-for output growth to a broad category of "technical change" in his aggregate production function. Scholars aligned with this optimistic tradition underscore the historical adaptability of market economies to innovation and change, with minimal emphasis on temporary or permanent 'losers' in the process. They argue that automation, by taking over repetitive, dangerous, and unhealthy tasks, not only enhances the quality of work and products but also brings about public health benefits (Acemoglu & Restrepo, 2018, p. 1489).

2.2.2.1 Optimists vs Pessimists

Crucially, proponents of the optimistic perspective contend that automation reduces production costs, leading to lower prices in a competitive market—a boon for all consumers. Additionally, they argue that automation, by decreasing wages relative to the rental rate of capital, encourages the creation of new labor-intensive tasks, generating a self-correcting force toward stability. For instance, according to Acemoglu & Restrepo (2018), the equilibrium between the outcomes of productivity enhancements and displacement ramifications defines the overall impact on total employment. Inevitably, the adoption of new technologies will result in a reduction in the demand for certain jobs and tasks. However, it will also enhance firm productivity, thereby augmenting the demand for labor in tasks that are not subject to automation. Optimists often advocate for skills development within the labor force to foster a synergistic relationship between human and non-human work. This aligns with the concept of the "race between technology and skill supply" proposed by Goldin and Katz (2007), drawing on Tinbergen (1974)'s thesis. Furthermore, they might propose reducing taxes on labor to enhance labor competitiveness compared to robots. In essence, the optimistic perspective emphasizes the positive outcomes of automation and digitalization, envisioning a future where innovation leads to overall societal benefits and increased stability.



Source: GFD, Deutsche Bank.

Figure 16. *Median G7 unemployment (%) rate with annotations around technological breakthroughs and big events*

The optimistic perspective looks to history as a foundation and envisions the future as a continuation of past trends. According to analysts at Deutsche Bank, history indicates that technology does not lead to unemployment. Examining long-term unemployment data, particularly the median of the G7 countries, reveals that unemployment has fluctuated based on economic cycles rather than technological shifts. The current median G7 unemployment rate of 3.8% is lower than the 5% rate in the UK at the series' inception in 1755 (Reid & Allen, 2023).

Despite the disappearance of nearly all jobs from 1755, the automation of various tasks did not result in an escalating unemployment spiral. Technology consistently generates wealth, freeing up labor for alternative and more productive employment, giving rise to industries and jobs that were previously unforeseen.

The question is raised: "Could this time be different?" The answer suggests that there are valid arguments supporting the possibility, considering the rapid adoption of AI and the types of jobs it may jeopardize. However, even in the face of short-term disruptions to labor markets, the much-needed productivity boost from AI is crucial. This, in turn, is likely to create more opportunities, jobs, and wealth for society. The nature of work will evolve, as it always has, but AI is anticipated to ultimately generate more jobs than it eliminates.

According to Brynjolfsson & McAfee (2011), analysts propose three alternative interpretations: cyclical patterns, stagnation, and the concept of the "end of work." The first two could be seen as optimistic viewpoints. The cyclical interpretation suggests that the persistently high unemployment rate in America is merely a result of insufficient economic growth to absorb unemployed individuals back into the workforce. Paul Krugman advocates for this perspective, asserting that "All the facts suggest that high unemployment in America is the result of inadequate demand—full stop" (Krugman, 2010). Former Office of Management and Budget director Peter Orszag concurs, stating that "the fundamental obstacle to reemploying jobless Americans is weak economic growth" (Orszag, 2011). According to the cyclical explanation, a sharp decline in demand, such as the Great Recession, is expected to be followed by a gradual recovery. Thus, the economic conditions experienced by America since 2007 can be viewed as another instance of the business cycle in motion, albeit a particularly severe one.

A second interpretation of the current economic challenges perceives stagnation rather than cyclical patterns. Stagnation, in this context, refers to a prolonged decline in America's capacity to innovate and enhance productivity. Economist Tyler Cowen articulates this perspective in his 2010 publication, The Great Stagnation. He argues that America has been reliant on easily accessible opportunities for at least three centuries, and over the past four decades, those opportunities have become scarcer. Cowen attributes the slowdown in median income growth to reaching a "technological plateau." The stagnation argument implies that the sluggish recovery and high unemployment have deeper roots—a slowdown in the emergence of impactful new ideas that drive economic advancement.

This slowdown predates the Great Recession, tracing back to the 1970s when U.S. productivity growth decelerated, and the median income of American families ceased to rise as rapidly as before. Advocates of this viewpoint, including Cowen and Nobel Prize-winning economist Edmund Phelps, argue that a higher pace of innovation and technological advancement is essential to overcome the current economic challenges.

A variation of this explanation suggests that while America has not stagnated, other nations such as India and China have caught up. In a globalized economy, American businesses and workers must maintain higher productivity levels than their counterparts in other countries. Technological advancements have removed barriers, resulting in a convergence in factor prices like wages and compelling American labor to compete under different conditions (Phelps, 2010).

The pessimistic perspective on the other hand, on the current wave of automation and digitalization, often characterized as the "digital revolution," extends beyond economic concerns to encompass profound societal and labor market transformations. Advocates of this viewpoint contend that the present technological advancements are fundamentally distinct from prior industrial revolutions, signifying a paradigm shift in the relationship between humans and machines (Marengo, 2022). Unlike earlier revolutions that primarily replaced human muscle, the digital revolution is deemed capable of supplanting cognitive functions, marking a departure from the traditional complementary role of technology to a more substitutive one. The digital revolution introduces an array of intelligent, adaptive, and versatile technologies with unprecedented capabilities, expanding their influence beyond routine tasks to intricate, skill-intensive endeavors. Activities traditionally deemed immune to automation, such as complex tasks like stitching, are now within the purview of automated systems. This shift in the nature of work has implications for the labor market, as the evolving dynamics between human and non-human work become increasingly substitutive, challenging the conventional understanding of technology as a complement to human skills (Brynjolfsson & McAfee, 2011).

The Executive Office of the President of the United States commissioned a comprehensive report in 2016, echoing concerns about the potential erosion of skills traditionally associated with human expertise. The report, endorsed by Barack Obama, warns that as AI and advanced technologies advance, skills historically dominated by humans may diminish. This raises questions about the adaptability of the workforce and the potential emergence of a skills gap, contributing to social and economic inequalities. Drawing historical parallels, DeLong (2015)'s analogy of "peak human" suggests that, akin to the decline of horses' economic significance, human labor may have reached its zenith. This hypothesis prompts a reevaluation of the role and value of human labor within the economic landscape, suggesting transformative changes in societal structures and support systems.

Economically, pessimists underscore the dual impact of automation on wages and profits. The downward pressure on wages, leading to stagnant real wages, is attributed to the displacement of certain categories of labor by automation. Simultaneously, automation is seen as exerting upward pressure on the rate of profit from capital investment, potentially redistributing economic gains in favor of capital owners as we have said in the previous section. The observed divergence between productivity gains and wage growth since the 1970s in many OECD countries serves as empirical evidence supporting these assertions.

Furthermore, pessimists express concerns about the nature of job creation in the era of automation. The prospect of "technological unemployment" suggests that the jobs replaced by automation may not be replaced on a one-to-one basis, resulting in a net reduction in employment opportunities. The concept of "premature deindustrialization" raises the possibility that jobs created in sectors dominated by automation might be less desirable and productive, contributing to a qualitative decline in the labor market (Schlogl & Sumner, 2018). In essence, the pessimistic perspective on automation and digitalization extends beyond economic considerations to encompass broader societal implications, urging a nuanced examination of the transformative forces at play in the digital revolution.

The third and the last alternative explanation of Brynjolfsson & McAfee, (2011) (first two were optimistic) called “End of the Work”, was presented by Jeremy Rifkin in his book with the same name in 1995. Rifkin proposed a theory suggesting a new era in global history, wherein fewer workers would be required to meet the needs of the world population. He attributed this transition to the advancement of sophisticated software technologies, potentially leading towards a future with minimal reliance on human labor. Rifkin contended that all sectors of the economy were witnessing technological displacement, resulting in significant unemployment. Addressing this displacement, according to Rifkin, was likely to emerge as the primary social challenge of the upcoming century. Similar sentiments have been expressed by various individuals, including economist Wassily Leontief. In 1983, Leontief anticipated a reduction in the significance of humans as the primary factor of production, drawing parallels to the diminishing role of horses in agricultural production due to the introduction of tractors (Leontief, 1983). Martin Ford, a software executive, echoed similar sentiments in his 2009 book, "The Lights in the Tunnel," envisioning a future where machines would gradually assume the roles of a considerable portion of the workforce, potentially leaving many individuals without opportunities for alternative employment (Ford, 2009).

Furthermore, Brian Arthur posits the existence of a vast yet largely imperceptible "second economy" driven by digital automation. While the argument for the end of traditional work is compelling, evidenced by everyday tasks such as ATM withdrawals and automated airport kiosks replacing human labor, the relatively low unemployment rates in the United States during the 1980s, '90s, and the early years of the new millennium have mitigated concerns regarding displacement (Arthur, 2011). Nonetheless, the end-of-work thesis has not gained significant traction in mainstream discourse surrounding the current job market recovery. Notably, a report from the Federal Reserve Bank of Richmond by Hornstein and Lubik (2015), titled "The Rise in Long-Term Unemployment: Potential Causes and Implications," avoids explicit references to terms such as computer, hardware, software, or technology. Similarly, research papers published in 2011 by the Federal Reserve, including "New Evidence on Cyclical and Structural Sources of Unemployment" by Chen et al. (2011) and "Has the Great Recession Raised U.S. Structural Unemployment?" by refrain from delving into the role of technology. To encapsulate the prevailing sentiment, technology journalist Farhad Manjoo (2011) remarked in the online magazine Slate that "Most economists are not giving much weight to these concerns. The notion that computers could significantly disrupt human labor markets—and consequently further weaken the global economy—remains on the periphery.

2.2.2.2 Jobs, wages & technology

Before delving into the impacts of technological advancements on the labor market, it is essential to categorize jobs. According to the task model proposed by (Autor, Levy, & Murnane, 2003), this model scrutinizes whether computers act as substitutes or complements for workers in executing specific tasks, and how these tasks may substitute for one another. The authors elucidate these scenarios by examining the integration of computers into routine and nonroutine cognitive and manual tasks.

Autor, Levy & Murnane (2003) also indicate that the rapid and sustained decrease in the actual cost of symbolic processing offers significant economic inducements for executives to replace expensive labor with information technology for workplace tasks. Altogether, it provides substantial benefits for workers whose skills become more productive as computing costs decline. Despite the ubiquitous presence of computers, they have specific capabilities and limitations, relying on programmers to script instructions for task execution. For a computer to autonomously perform a task, it must be well-defined, allowing a machine lacking flexibility or judgment to successfully execute the task by following the programmer's steps (Ashenfelter & Card, 2010). Computers and computer-controlled equipment excel at tasks that can be scripted, such as routine or codifiable activities, as described by Autor, Levy, and Murnane. Routine tasks, not necessarily mundane (e.g., washing dishes), are sufficiently understood to be fully specified as a series of instructions for machine execution (e.g., adding a column of numbers) (Acemoglu & Autor, 2011).

Many jobs that require middle-level cognitive and manual skills involve regular tasks such as bookkeeping, clerical duties, repetitive manufacturing, and monitoring. Because of the clear and systematic procedures involved, these tasks are progressively being encoded into computer programs, allowing machines to perform them or outsourced to overseas locations. The decreases in office tasks and managerial roles noted in the study conducted by Acemoglu & Autor (2011) are likely due to the reduced cost of machine alternatives for these responsibilities. It's noteworthy that the economic significance and prevalence of tasks in these fields have not diminished with automation. Instead, tasks involving the organization, storage, retrieval, and manipulation of data—common in middle-level managerial, office jobs, and production positions—are increasingly being automated. Additionally, advancements in technology have notably reduced the expenses associated with relocating information-based tasks to foreign locations via offshoring (Blinder and Krueger, 2008). This automation and offshoring of routine tasks boost the demand for workers capable of performing complementary non-routine tasks. The mentioned Autor, Levy, & Murnane (2003) classify non-routine tasks into two main types: abstract and manual tasks. Abstract tasks, which involve problem-solving, sentience, convincing, and creativity, are prevalent in professional, administrative, technical, and creative roles. Individuals proficient in these tasks usually possess high levels of education and analytical skills. The authors discuss that these analytical occupations complement computer technology, as they heavily rely on information as an input. With the decreasing cost of accessing, organizing, and manipulating information, abstract tasks are further supported.

Tasks that are non-routine and involve adaptability to various situations, as well as the recognition of visual cues and language, along with in-person interactions, are heavily concentrated in activities such as driving, meal preparation, and manual labor. Individuals skilled in non-routine manual tasks possess physical dexterity and, in some instances, proficient oral communication skills. Typically necessitating minimal formal education, these tasks hold significant importance in service-oriented roles, as highlighted by Autor & Dorn (2010). Occupations such as meal preparation, customer service, sanitation, facility maintenance, landscaping, healthcare support, security, and protective services heavily rely on non-routine manual tasks. The fundamental responsibilities within these professions demand adaptability in interpersonal interactions and environmental conditions, rendering them resistant to automation due to the need for spontaneous responses to unscripted situations—both environmental and interpersonal. Although these occupation tasks are often impractical to relocate offshore due to their requirement for physical presence and execution, it's crucial to highlight that they typically don't necessitate formal education beyond a high school diploma or extensive training (Autor & Dorn, 2010).

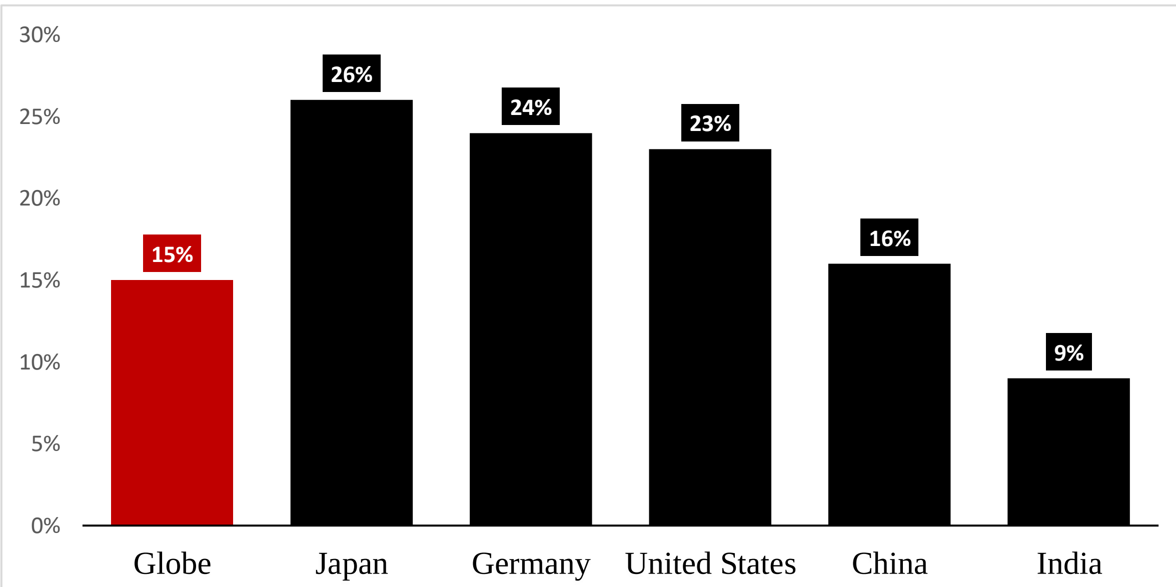
To summarize, the shifting of employment away from roles focused on repetitive tasks might have influenced the division of labor by limiting job options in middle-tier positions such as clerical, managerial, manufacturing, and operational roles. However, roles that emphasize abstract thinking or non-repetitive manual tasks are less affected due to the demand for problem-solving, decision-making, and innovation in the former, and adaptability and physical dexterity in the latter. These roles typically span across the skill spectrum, ranging from professional and managerial positions to service and labor roles, potentially leading to a partial fragmentation or division of employment opportunities. Frey & Osborne, (2017) discuss the topic, building on the job categorization framework established by Autor, Levy, & Murnane, (2003) as we have spoken. In addition they use manual and cognitive job categorization from Autor & Dorn (2013) as well. According to their perspective, the consistent decline in the real cost of computing has generated significant economic incentives for employers to replace labor with computer capital, a phenomenon known as ‘capital deepening’. However, the capabilities of computers in performing tasks are ultimately contingent upon the proficiency of a programmer in crafting a set of procedures or rules that effectively guide the technology in various scenarios. Frey & Osborne (2017) suggest that computers prove to be relatively productive compared to human labor when a problem can be precisely specified, indicating that success criteria are quantifiable and easily assessable Acemoglu & Autor (2011). Therefore, the extent to which job computerization occurs is determined by technological advancements that facilitate the adequate specification of engineering problems, thereby defining the boundaries for the scope of computerization. The continual evolution of technology further tightens the constraints highlighted by Frey and Osborne. In essence, the concepts of machine learning (ML) and artificial intelligence (AI) play a pivotal role in dismantling these limitations. For instance, the groundbreaking work of Zhu et al. (2023) exemplifies the transformative potential of AI, with their report on China's AI-powered 'robot chemist' successfully devising a method to generate oxygen on Mars. This not only demonstrates the expanding capabilities of AI but also underscores its efficiency, surpassing what would have taken a human 2,000 years to achieve the same outcome. The trajectory of technological advancements, particularly in the realms of ML and AI, continues to redefine the scope and possibilities of job computerization, heralding a future where human-machine collaboration reaches unprecedented levels of sophistication and efficiency.

Frey & Osborne (2017) assert that the rise of big data is a central factor driving the automation or computerization of a wide range of non-routine cognitive tasks. The scalability of computers, especially when networked, gives them a significant advantage in handling complex computations associated with extensive datasets. Machine learning (ML) algorithms running on computers outperform humans in pattern recognition within big data. Algorithms, devoid of certain human biases and designed for specific tasks, contribute to the acceleration of computerization in various industries. Notably, healthcare, legal, financial services, and education are witnessing transformations as computers take on tasks traditionally performed by humans. The integration of sensing technology and ML algorithms further expands the scope of automatable tasks, ranging from condition monitoring to supply chain management. Advancements in user interfaces enable computers to respond directly to human requests, automating certain jobs and augmenting highly skilled labor. Occupations requiring nuanced judgment, including those in intensive care units and financial trading, are increasingly susceptible to computerization. Software engineering is also evolving, with algorithms optimizing parameters and automatically detecting bugs.

While not all impacted occupations are fully computerizable, estimates suggest that sophisticated algorithms could substitute for a substantial number of knowledge workers worldwide. The overarching trend indicates a gradual encroachment of computers on human labor in diverse cognitive tasks, marking a departure from historical technological progress primarily focused on the mechanization of manual tasks. Despite some tasks remaining outside the realm of full computerization, the trajectory is clear: computers are progressively challenging human labor across various cognitive domains.

In the section on the Industry 4.0, we briefly examined the features and effects of the new technology. Now, let's attempt to analyze its impact on jobs. As technology evolves, more jobs are at risk. Algorithms optimize objects based on statistics and mathematics, whereas people make mistakes. Many of the unpleasant issues are human-made. According to a study at Stanford University, nearly 50% of workers emphasized that they are quite sure they made an error at their workplace, which could have led to security issues in their company. Additionally, 88% of data breaches are caused by human error. Considering these facts, we can conclude that automation is a reasonable alternative to human power.

Machine learning and, consequently, artificial intelligence have the potential to contribute to unemployment and the elimination of jobs from the labor market (Ford, 2013). Consider the healthcare sector, which demands significant human capital. Doctors prescribe medicines based on limited samples, and despite their significance, these samples often do not represent the entire population (Röhrig et al., 2010). Shockingly, 128,000 people succumb to the adverse effects of prescribed drugs (Light, 2014). The complexity arises from the fact that there are usually multiple drugs available for a specific illness. Within the constraints of cost and time, researchers and doctors may inadvertently make mistakes. Artificial intelligence and machine learning emerge as crucial tools in this context. An artificially intelligent robot can access patients' microbiome maps, enabling it to prescribe the optimal drug and significantly minimizing the error rate.



Source: Statista, 2017

Figure 17. *Job under risk due to automation by countries till 2030*

Another sector experiencing transformation is law, particularly advocacy, deemed a high-skilled job. Similar to other professions, advocacy has its share of successful and unsuccessful practitioners, potentially causing disruptions in the judicial system. Artificial intelligence offers a solution by enabling a robot to meticulously scan all laws, precedents, and exceptional cases, optimizing the error rate. Additionally, the idiosyncrasy of judges' sentences, influenced by their hunger, introduces another layer of variability. Judges tend to deliver harsher sentences before and after lunch (Danziger & Levav, 2011). Research suggests that hunger-induced nervousness influences quicker and potentially biased judgments before lunch. An artificially supported robot would operate without succumbing to such effects. Figure 17 provides a visual representation of jobs under threat from automation, aligning with the arguments presented. This projection underscores the transformative impact artificial intelligence and automation may have on various professions and industries.

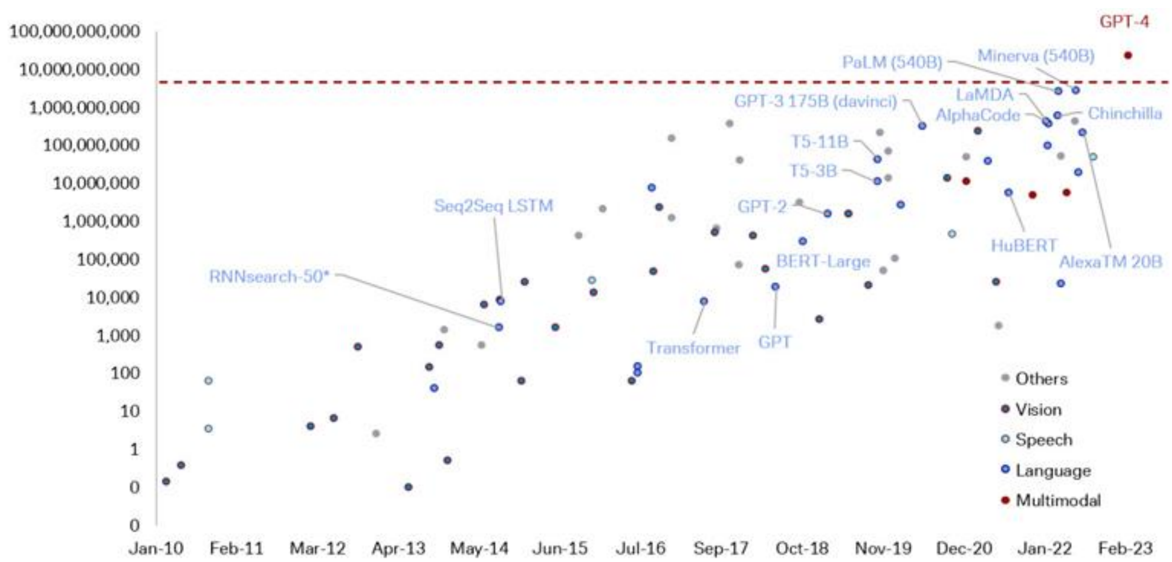
Another job field under risk is education. While the advent of AI and robots in education sparks concerns about privacy, attachment, deception, and the erosion of human contact and control accountability, it is crucial to recognize that these technological advancements also pose a potential threat to human teachers' job security. The utilization of tele-operated android robots, exemplified by SAYA, adds a layer of complexity to the evolving dynamics of education (Hashimoto et al., 2011). As AI-driven robots demonstrate capabilities in mimicking human expressions and engaging in communicative functions, there is a growing perception among educators and students that these technologies could eventually serve as substitutes for human teachers. This perception raises questions about the future role of human educators in a landscape increasingly dominated by technological interventions. One aspect worth exploring is the impact of AI on teaching methodologies. Some educators express curiosity about AI's ability to emulate human teaching methods, questioning whether technology can replicate the nuanced qualities that make human instruction unique. On the other hand, students express concerns about the potential devaluation of teachers if traditional teaching methods persist in the face of technological advancements (Chan and Tsi, 2023).

Based on a study from Organisation for Economic Co-operation and Development (OECD) in 2022, artificial intelligence (AI) is projected to significantly impact highly skilled professions such as those in medicine, law, and finance, potentially causing significant disruptions in employment dynamics. A report by the OECD highlights that occupations in finance, medicine, and legal sectors, which typically necessitate extensive education and rely on accumulated expertise for decision-making, may face sudden threats of automation from AI technologies. The OECD's research, surveyed the responses of workers amidst the emergence of AI in various industries. The survey, encompassing 5,300 individuals across 2,000 companies in manufacturing and financial sectors across seven OECD member nations, revealed that three out of five workers expressed concerns about the possibility of job displacement due to AI within the next decade (Lane, Williams & Broecke, 2022). As specified by Bouchrika (2023)'s study at the Research gate, the premise of the Frey & Osborne (2017) is straightforward: if a machine (such as AI, machine learning, robotics, computers, etc.) can automate a job, then that job is susceptible to being taken over by machines. Utilizing predictive modeling, the study categorized 702 jobs into high, medium, and low risk of computerization, ultimately determining that 47% of them could be replaced by machines.

According to the findings of Frey & Osborne (2017), the first sectors to be affected by automation are transportation and logistics, office and administration, and production labor. The study also identified a high probability of automation in the service, sales, and construction sectors. Other sectors listed as high-risk for replacement by machines include farming, fishing, forestry, installation, maintenance, and repair. Some science, technology, engineering and mathematics (STEM) careers may also be at risk, particularly where hazardous materials are involved, and could benefit from automation and robotic maneuvers.

Contrary to the Frey & Osborne (2017) claim of a 47% job-loss risk, two studies present significantly lower estimates. A ZEW Mannheim study asserted that only 9% of jobs are likely to be lost to automation when considering the full range of variables in occupations (Arntz, M., et. al, 2017). The Mannheim researchers emphasized the importance of task heterogeneity, suggesting that factors like gender, age, educational level, and income influence the risk. However, Frey & Osborne (2017) disagreed, maintaining that a machine capable of doing the job would not discriminate based on demographic variables. On the other hand, one of the previous studies from the OECD proposed a job-loss rate of only 14% (Nedelkoska & Quintini, 2018). The authors added that an additional 32% of jobs run the risk of significant alteration due to automation but not complete loss. Unlike Arntz, M., et. al. (2017), the OECD authors omitted demographics, partly explaining their higher job-loss rate (9% vs. 14%). Despite this, the OECD figure remains considerably lower than the Oxford study's 47%. While the Frey & Osborne (2017) views a job as fixed and rigid across different scenarios, disregarding variables, Nedelkoska & Quintini (2018) assume other factors are at play, affecting a job's exposure to automation. However, the authors did not provide details on these variables, as noted by the Frey & Osborne (2017).

Related to these, we can anticipate more progress, or at the very least, we cannot expect less, given the existence of Moore's Law. Moore's Law is the observation that the number of transistors in an integrated circuit (IC) doubles approximately every two years. Rather than being a law of physics, it is an empirical relationship tied to improvements gained through experience in production (Moore, 1998). Named after Gordon Moore, the co-founder of Fairchild Semiconductor and Intel (and former CEO of the latter), Moore's Law was initially proposed in 1965, suggesting a doubling every year in the number of components per integrated circuit. He projected this growth rate to continue for at least another decade. By 1975, Moore revised the forecast to a doubling every two years, reflecting a (CAGR) of 41%. Despite Moore not relying on empirical evidence to predict the continuation of this historical trend, his forecast has held since 1975 and has come to be known as a law (Moore, 1975).



Source: Sevilla, et al. (2023)

Figure 18. *Computation used to train notable AI systems, total petaflop*

Figure 18 provides context for the trajectory of the underlying technology. As demonstrated by Sevilla et al. (2023), the exponential surge in computing power over the past decade has led to the current state. It is conceivable that the growth over the next 5-10 years could be even more pronounced. While it's evident that Moore's Law may not endure indefinitely, the remarkable progress witnessed in a relatively brief timeframe is noteworthy. However, some authorities argue that it is slowing down. Although it might be premature to declare that Moore's Law is definitively obsolete, there are indications that we have approached the physical limitations of silicon-based CPUs. In the absence of a practical alternative, engineers can no longer enhance the computing power of chips as rapidly or inexpensively as they did in the past (Tozzi, 2023).

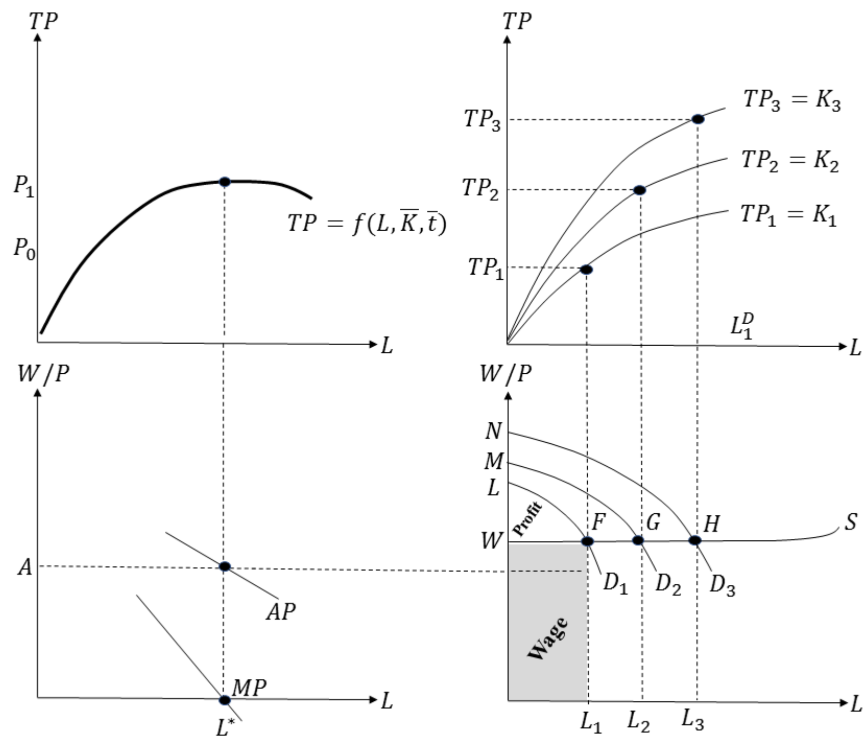
In connection with that, the future of manual jobs is undergoing significant changes with the integration of mobile robotics and machine learning technologies. Industrial robots, historically focused on routine manufacturing tasks, are evolving to handle non-routine manual jobs with enhanced sensors and manipulators. Examples include robots developed by General Electric for wind turbine maintenance and advanced surgical robots with increased maneuverability. The computerization of logistics is progressing as vehicles, like the driverless cars, equipped with on-board computers and advanced sensors, become potential robots.

Technological advancements, driven by big data from improved sensors, are overcoming past engineering challenges in robotics development. Autonomous vehicle navigation, aided by detailed three-dimensional maps and large datasets, is becoming feasible. This progress extends to resolving navigation challenges during changing seasons. The impact of these developments is significant on logistics jobs, where automation is imminent in agricultural vehicles, forklifts, cargo-handling vehicles, and autonomous robots deployed in hospitals. Enhanced sensors empower robots to produce goods with higher quality and reliability than human labor. Examples include Spanish food processor El Dulze using robotics for selective lettuce picking and robots like Baxter recognizing patterns in a variety of manual tasks at a relatively low cost (Frey & Osborne, 2017).

Technological advancements are driving a decline in robotics costs, making them more accessible. China is experiencing a surge in robot adoption due to rising wages, as seen in Foxconn's investment in robots for assembly (Wakefield, 2016). In this context, the landscape of production is undergoing a transformation. Several companies are transitioning their production methods to lights-out factories. A lights-out factory, also referred to as an automatic factory, is a facility where raw materials enter, and finished products exit with minimal or no human intervention (Walker, 1957). Global robot sales reached a record 166,000 units in 2011, and as costs decrease and capabilities expand, robots are expected to assume a broader range of manual tasks in manufacturing, packing, construction, maintenance, and agriculture. Additionally, robots are increasingly performing simple and complex service tasks in personal and household settings, indicating a gradual substitution of labor in low-wage service occupations traditionally shielded from computerization (IFR, 2012).

To analyze the impact of automation on the labor market, Schlogl & Sumner (2018) propose a categorization of the economy based on sectors: an automation-prone sector (APS), comprising jobs easily performed by machines, and an automation-resistant sector (ARS), encompassing jobs challenging for machines. The former includes simple manual routine tasks like lifting and drilling, while the latter involves creative work with face-to-face interaction.

For a clear understanding, let's delve into Lewis' “Economic Development with Unlimited Supplies of Labour” theory. According to the W. Arthur Lewis (1954), an underdeveloped economy is characterized by two distinct sectors: a traditional rural subsistence sector, which typically exhibits zero marginal labor productivity and is identified by Lewis as surplus labor. This surplus labor can be mobilized from the traditional agricultural sector without causing any decline in output. The other sector comprises a modern urban industrial sector with high productivity, gradually absorbing labor from the subsistence sector. The model primarily focuses on the process of labor transfer and the expansion of output and employment within the modern sector. While modern agriculture could be included, we will simplify by referring to it as the "industrial" sector.) Labor migration and employment growth in the modern sector are driven by increased output within that sector. The rate of this expansion is determined by the level of industrial investment and capital accumulation. Such investment is facilitated by the surplus of profits over wages in the modern sector, assuming reinvestment of all profits by capitalists. Additionally, Lewis proposed that the wage rate in the urban industrial sector remains stable, set as a fixed premium above the average subsistence wage in the traditional agricultural sector. At this consistent urban wage level, the supply of rural labor to the modern sector is viewed as perfectly elastic (Lewis, 1954).



Source: Adapted from (Todaro & Smith, 2012)

Figure 19. *Lewis's unlimited supplies of labor.*

In the bottom part of the Figure 19, the real wage level is measured on the vertical axis, and the quantity of labor used is measured on the horizontal axis. The D curves represent labor demand, while the S curve represents labor supply. Labor demand develops with capital accumulation and technological advances, reaching situations D_1, D_2 and D_3. These curves also indicate the marginal productivity of labor. In the industrial sector, if the capital usage is K_1, labor demand is D_1, the wage paid is W, and the employed labor is L_1. The total output created in the industry is the area $0LFL_1$. Of this, $0WFL_1$ represents the total wage paid to workers, and WLF represents the entrepreneur's profit. This profit will be reinvested, leading to a capital stock of K_2 and an employment level of L_2. The same process will repeat at the L_2 employment level, and the capitalist's profit will grow, rising from WLF to WMG. The labor supply curve is parallel to the horizontal axis up to point H. This is because increased labor employment at the current wage level is dependent on the increase in the marginal productivity of labor, which, as known, is linked to capital accumulation and technological advances in the industrial sector. The upward curvature of the labor supply curve after point H indicates that achieving more labor usage beyond L_3 is only possible with an increase in the wage level.

The figure shows that employing more labor than L_1can be achieved through increasing capital accumulation and usage in the industry. The distribution between profit and wage in the total output obtained through capital accumulation and usage depends on what is done with the profits. As these profits are reinvested to increase capital accumulation, more labor employment will be achieved. In this case, profits have grown, and capital accumulation has increased. According to the model, the labor supply is unlimited at wage level W, and after point H, increasing wages is necessary for further labor employment. This implies an upward curvature of the labor supply curve. The process continues until hidden unemployment in the agricultural sector is eliminated. Lewis referred to the growth achieved during this process as "self-sustaining growth."

Applying the Lewis model of economic development, Schlogl & Sumner (2018) emphasize that automation is viewed as generating "unlimited supplies of artificial labor" in the APS. The growing use of robots equates to labor force expansion in the APS, creating a new "robot reserve army" and limiting the bargaining power and wages of labor in that sector. Automation, if feasible technologically, legally, politically, and socially, gradually shifts the labor force from the APS to the ARS, leading to automation-driven structural change.

Automation itself acts as a supply shock, shifting the labor supply curve in the APS to the right, reducing the equilibrium wage in that sector (and potentially in the ARS). When the unit cost of automated production falls below the workers' reservation wage, a labor surplus emerges. This surplus can be absorbed by the ARS or, if not feasible, may result in technological unemployment, altering the functional distribution of income in favor of capital owners. Contrary to Lewis' model, there may not be a distinct "turning point" in this framework. The supply of "artificial labor" from automation is considered unlimited, not tied to demographic dynamics. Human labor in the APS could be entirely displaced by machines, leaving only the ARS, which evolves with technological innovation, giving rise to a new APS (Schlogl & Sumner, 2018).

The critical questions then revolve around identifying the industries and tasks in the ARS and APS and assessing whether the demand for the ARS is sufficient for full employment at decent wages. The ARS is not necessarily confined to emerging post-industrial sectors but may include areas like modern agriculture. The service sector, known for non-routine work involving social interactions, contributes significantly to the ARS. There could be a dilemma if a productivity boost in the APS generates surplus labor, but the ARS cannot fully absorb it, leading to premature deindustrialization. This "Lewis 2.0" dynamic might result in workers moving to the service sector due to a lack of demand for unskilled labor in manufacturing. It is conceivable that the industrial sector, like today's extractive and agricultural sectors, might absorb a relatively small number of workers, while highly productive manufacturing clusters handle the demand for physical goods, and most human labor demand remains in the service sector.

After categorizing jobs, it is imperative to classify labor and talking about wages as well. According to Acemoglu & Autor (2010) a pertinent starting point for this discussion is the examination of the wage premium attributed to 'skills' in the labor market. A broad yet useful approach involves considering a labor market with two distinct worker types: "skilled" and "unskilled," where the former is identified with college graduates, and the latter with high school graduates. Under these assumptions, the college premium, indicating the relative wage of college versus high-school educated workers, serves as a comprehensive measure of the market's valuation of skills. Goldin & Katz (2007) highlight that the college premium reached its highest level in 2005 since 1915, the earliest year for which representative data is available. Moreover, subsequent data reveals a continued increase in the premium. Despite the past three decades witnessing fluctuations, the college premium has not consistently followed an upward trend. Notable data indicates a decline between 1971 and 1978, and a substantial compression during the 1940s, as documented by Goldin & Margo (1992) and Goldin & Katz (2007). The college premium exhibited an inflection point at the end of the 1970s, initially declining and then reversing course.

Source: Acemoglu & Autor (2010)

Figure 20. *College/High-school graduate Log Weekly Wage Ratio*

Figure 20 is from Acemoglu & Autor (2010). Illustrates the adjusted logarithmic wage difference between college and high school graduates in the US workforce from 1963 to 2008, considering full-time, full-year employment. This adjustment maintains consistent relative employment proportions among demographic categories like gender, education, and potential experience across the years under examination. Several significant trends are discernible from Figure 20. Firstly, after a steady increase spanning three decades, the wage gap between college and high school graduates peaked at 68 points in 2008, representing the highest point within the analyzed period. This 68-point gap indicates that, on average, the earnings of college graduates in 2008 exceeded those of high school graduates by 97%. In a broader historical context, Goldin & Katz (2007) argue that the wage gap in 2005 was the widest since 1915, the earliest year for which comprehensive data is available. The graph demonstrates a continuous upward trajectory thereafter.

Secondly, despite the overall upward trend observed over the past three decades, the wage gap has not consistently widened. Figure 20 indicates a noticeable decrease in the gap between 1971 and 1978. Goldin & Katz (2008) also highlight a significant narrowing of the gap during the 1940s. Another observation from the graph is that there was a turning point in the wage gap towards the end of the 1970s. It declined throughout that decade before reversing direction at its conclusion. Understanding this shift is essential for grasping the intricacies of supply and demand dynamics in determining inter-group wage disparities. The college premium, as a comprehensive measure of the market price of skills, is influenced by various factors, including the relative supply of skills. In this study, the supply of college graduate workers has increased, leading to an uptick in the real wages of college graduate workers. Consequently, the demand for high skills has increased more than the supply of high-skilled workers or the demand for low-skilled workers. This suggests a rising income inequality among different skill levels (Acemoglu & Autor, 2010).

Acemoglu & Autor (2010) also note that the wage disparity between college and non-college educated workers, serving as a broad indicator of skill valuation in the labor market, is subject to influences from various factors, among which is the relative abundance of skilled workers.

From the period following World War II until the late 1970s, there was a consistent rise in the proportion of college-educated individuals entering the workforce, with each successive generation exhibiting higher levels of educational attainment. However, post-1982, the pace of this increase in the proportion of college-educated workers slowed down. This deceleration was primarily attributed to a notable decrease in the proportion of young male college graduates entering the workforce, starting in 1975, followed by a less pronounced decline among females in the 1980s. It's noteworthy that this decline in the proportion of experienced male and female college graduates did not manifest until about two decades later.

The deceleration of the relative supply of college graduates in the 1980s, as analyzed by Card & Lemieux (2001), can be attributed to several factors. The conclusion of the Vietnam War, which artificially inflated college enrollment, resulted in a significant decrease in college attendance rates post-war, particularly among males. Consequently, there was a subsequent decline in college completion rates approximately five years later. The decline in relative earnings for college graduates during the 1970s likely dissuaded high school graduates from pursuing higher education, a point supported by Richard Freeman's argument (1976) suggesting that an oversupply of college-educated workers in the 1970s yielded negative social returns. Moreover, the sizable baby boomer cohorts in the 1960s and 1970s, though more educated, were also more populous, leading to a rapid rise in the average educational level of the workforce. However, cohorts born post-1964 were smaller, resulting in a less significant increase in the overall educational level. Lastly, the male college completion rate failed to revert to its pre-1975 trajectory, even following the recovery in the female college completion rate post-1980.

Despite potential concerns about measured real wage declines for less-educated workers, accounting for rising non-wage benefits did not substantially alter the conclusion that real compensation for low-skilled workers fell in the 1980s, as indicated by Pierce's thorough analysis of representative wage and fringe benefits data in 2001 (Pierce, 2001).

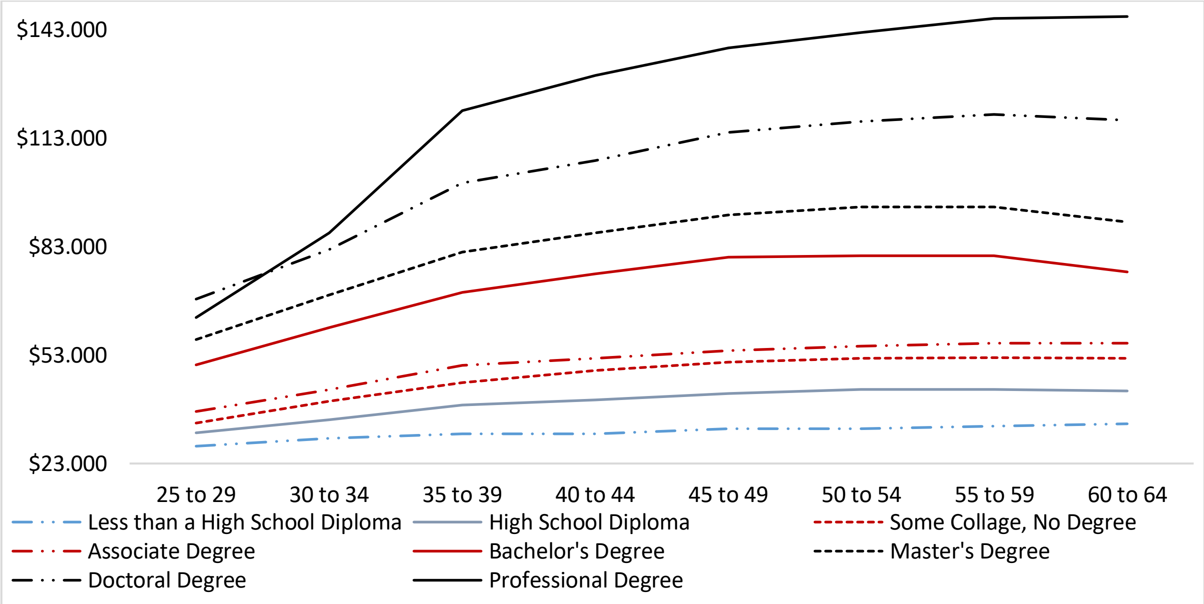
Table 1. *Task diversification*

Type	Sectoral	Occupational	Skill	Collar
Substitution	Automation Prone (APS)	Routine (Manual)	Low Skill	Blue Collar
		Non-Routine (Manual)	Low/Middle Skill	Blue/White Collar
		Routine (Cognitive)	Middle Skill	Blue/White Collar
Complementary	Automation Resistant (ARS)	Non-Routine (Cognitive/Abstract)	High Skill	White Collar

Source: The Author

Frey & Osborne (2017) approach the subject from a different perspective. Despite the historical predominance of the capitalization effect, our ability to discover ways to economize on labor might outpace our ability to find new applications for labor, as highlighted by (1930). Human labor has traditionally prevailed due to its capacity to adapt and acquire new skills through education (Goldin & Katz, 2009). However, as computerization extends into more cognitive domains, this adaptability is becoming increasingly challenging (Brynjolfsson & McAfee, 2011).

Several empirical studies highlight significant concerns. For example, Beaudry et al. (2013) observe a decline in the demand for skilled labor over recent years, despite the ongoing increase in the number of individuals with higher education. They demonstrate how highly-skilled workers have transitioned into occupations traditionally held by less-skilled workers. This displacement has further marginalized low-skilled workers, potentially leading some to exit the labor market altogether. Such circumstances prompt inquiries into the adaptability of human labor, facilitated by education, to keep pace with technological advancements, and the potential extent of technological-driven job loss. The acceleration of technological progress is expected to result in higher job turnover, potentially raising the natural rate of unemployment (Davis & Haltiwanger, 1992). While the current studies focus solely on investigating the adverse effects of technology, it nonetheless offers valuable insights into the necessary expansion of employment opportunities required to mitigate the looming threat to jobs in the coming years.



Source: (Ma & Pender, 2023)

Figure 21. *Median Earnings (in 2020 Dollars), by Age and Education Level, (2016−2020)*

The period from 2016 to 2020 witnessed significant shifts in the job market, reflecting the impact of automation on skill requirements and subsequent income disparities. Analyzing the data shown at Figure 21 reveals intricate relationships between educational attainment, skill acquisition, and income levels across different age groups in US. The steepest income path is observed among individuals with advanced degrees. Professional degree holders earned $13,100 (26%) more than those with bachelor’s degrees for 25- to 29-year-olds, increasing to $70,600 (93%) for 60- to 64-year-olds. This highlights the premium placed on advanced skills and expertise in an era where automation increasingly shapes the workforce. Also Figure 21 indicates that less skill means less wage increase.

Therefore, this data illustrates a dynamic interplay between skill acquisition, automation, and income inequality. Higher educational attainment correlates with increased earning potential, emphasizing the evolving skill demands of an automated job market. As individuals, educational institutions, and policymakers navigate these changes, understanding the intricate relationships between skill development, automation, and income becomes imperative for fostering economic resilience and equal opportunities in the workforce. As we have discussed, individuals with lower skill levels should acquire additional skills to protect themselves from being displaced by those with higher skills, who may end up taking lower-skilled jobs.

Documenting the decline in employment within routine-intensive occupations—those primarily consisting of tasks following well-defined procedures that can readily be executed by sophisticated algorithms. In their study, Frey & Osborne (2017) underscore the ongoing decrease in manufacturing employment and the disappearance of routine jobs, supported by studies from Charles et al. (2013) and Jaimovich & Siu (2012). The prevailing narrative suggests that this decline significantly contributes to the current low employment rates.

The core tasks of manufacturing occupations, involving well-defined and repetitive procedures, lend themselves easily to codification in computer software, facilitating automation (Acemoglu & Autor, 2011). Additionally, Autor & Dorn (2013) document a structural shift in the labor market, where workers are reallocating their labor supply from middle-income manufacturing to low-income service occupations. This shift is attributed to the lower susceptibility of manual tasks in service occupations to computerization, as they demand a higher degree of flexibility and physical adaptability (Goos &Manning, 2007). Nevertheless, as previously discussed, the service sector will inevitably undergo significant transformations. AI, particularly robotics, is playing a pivotal role in reshaping various domains within the service sector, spanning from economic systems to education, as well as life sciences and healthcare (Machado, et al., 2024)

Concurrently, with the decline in computing costs, problem-solving abilities become relatively more valuable, contributing to significant job expansion in occupations focused on cognitive tasks, where skilled labor holds a comparative advantage. This phenomenon correlates with a consistent rise in the rewards for education (Katz & Murphy, 1992). The term "Lousy and Lovely Jobs" from the publication by Goos & Manning (2007) succinctly captures the essence of the ongoing polarization in the labor market, characterized by the growth of high-paying cognitive roles and low-paying manual jobs, alongside the decline of middle-wage routine positions. The pace of technological advancement continues to accelerate, with increasingly sophisticated software technologies reshaping labor markets and displacing workers. A noteworthy aspect highlighted in their research is that computerization now extends beyond routine manufacturing tasks.

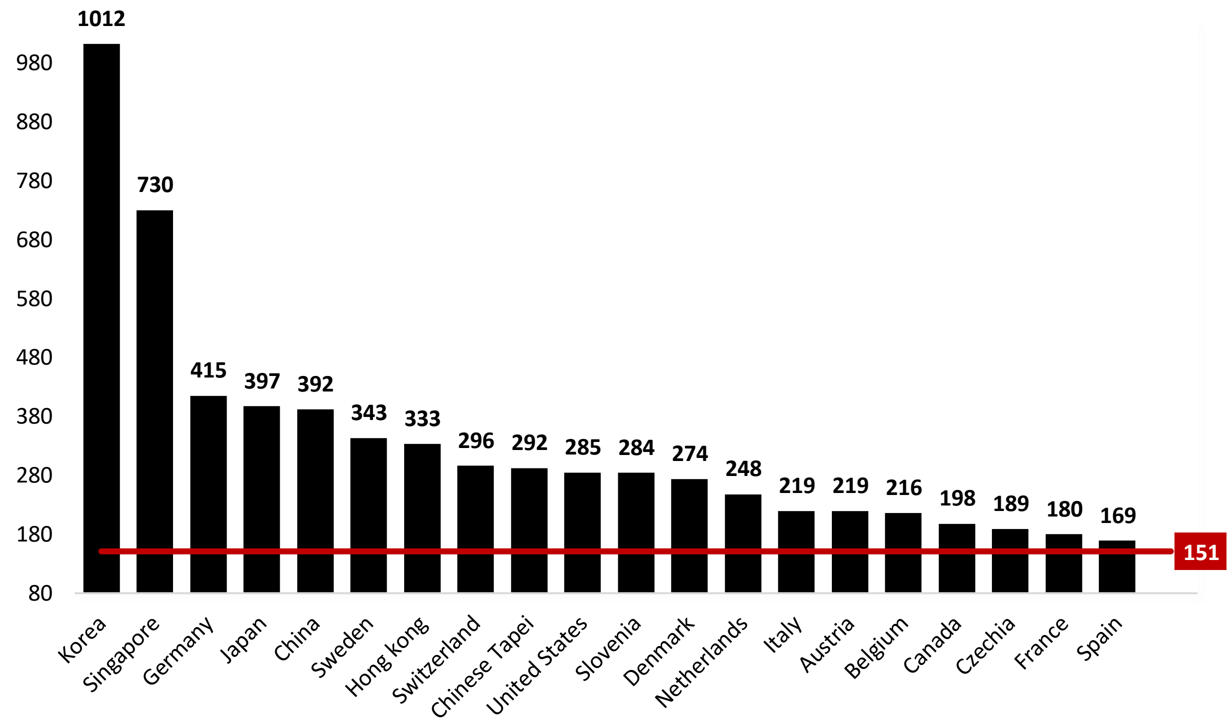
According to Gray (2013), the introduction of electrification (or automation) resulted in a "hollowing out" of the labor force, marked by an increase in clerical and manual tasks compared to dexterity-related tasks. This trend aligns with the contemporary polarization observed in the U.S. labor force due to computerization. Occupations emphasizing dexterity, mainly comprising skilled blue-collar jobs, saw a decline in demand relative to workers specializing in manual tasks (low-skill) and white-collar clerical tasks. The findings indicate that electrification led to a shift in skilled blue-collar work, with the average manufacturing employee in 1880 evolving from a craftsman to an operative (a significantly less-skilled worker) by 1940. The impact of electrification on the dexterity/manual task ratio is substantial. Comparing the observed decline between 1900 and 1920 to a counterfactual scenario without further electrification beyond the 1900 level, the change would have been an increase of 33%, contrasting with the actual decline of over 350%. These results suggest that other factors, such as demographic shifts, increased educational attainment, and immigration, had an offsetting effect on task distribution in U.S. manufacturing. Without these factors, the hollowing out of skill types would have been more pronounced. Even within the production sector, which constituted 81% of manufacturing employment by 1940, there are signs of increased relative demand for managerial tasks post-electrification. This aligns with historical literature and implies a "hollowing out" phenomenon within the factory floor personnel. The robustness of these findings is confirmed by including control variables such as capital per worker and educational attainment. The consistency of the hollowing out result across different specifications, including controls and a 1900–1920 baseline sample, supports the validity of the conclusions, especially during the period of rapid electricity adoption in the 1900s and 1910s. Brynjolfsson & McAfee (2011) emphasize that David Autor and David Dorn provide an intriguing variation to the “Skill-biased technical change” narrative. They observe a U-shaped relationship between skills and wages. Over the last decade, demand has declined the most for individuals in the middle of the skill distribution. While the highest-skilled workers have prospered, it is noteworthy that those with the lowest skills have experienced less decline compared to those with average skills. This reflects a polarization in labor demand.

The literature originates from the observation that despite a notable increase in the proportion of college-educated workers, the return on skills—illustrated by the wage ratio between college graduates and high school graduates—has consistently risen. This indicates a concurrent elevation in the demand for skills, relative to the surge in skill supply. Expanding on Tinbergen's foundational research (1974), the relative demand for skills is associated with technology, particularly the bias of technical advancements towards specific skills. This viewpoint emphasizes that the return on skills (including college education) depends on a competition between the expansion of skill supply and the skill-biased nature of technological progress, assuming that technological advancements inherently enhance the demand for 'skilled' workers.

These concepts are effectively implemented through the model that We have mentioned previously developed by Acemoglu & Autor (2010), which incorporates two skill categories involved in different occupations or in the production of goods. The model assumes that technology acts as a factor that enhances productivity, complementing either high- or low-skilled workers, thereby capturing changes biased towards certain skills. A 'task' is defined as a unit of work activity that generates output (goods and services), while 'skill' refers to a worker's abilities across various tasks. Workers utilize their skills to perform tasks in exchange for wages, and the application of skills to tasks results in output. The differentiation between skills and tasks becomes crucial when workers with a particular skill level can undertake a variety of tasks, adjusting to changes in the labor market and technology. Recent advancements in technology, as outlined by Autor, Levy, & Murnane (2003) , have enabled information and communication technologies to either directly execute or facilitate the outsourcing of core job tasks previously carried out by middle-skilled workers, leading to a significant alteration in the returns to skills and the allocation of tasks.

Moreover, when technology is regarded as external, it often assumes that technical advancements inherently favor certain skills. However, evidence indicates that the bias towards specific skills in technical progress varies over time and across different nations. Recent technological advancements and trends in offshoring and outsourcing have notably led to the direct substitution of workers in particular occupations and tasks. This trend could potentially worsen income inequality based on geographical location. However, as technology continues to automate jobs, the viability of offshoring and outsourcing decreases. Consequently, reliance on these strategies may diminish, potentially resulting in a rise in global income inequality.

Acemoglu and Autor present a model featuring three skill categories—low, high, and medium. Each worker possesses one of these skills, and the model, resembling Ricardian trade models, considers comparative advantages. Firms (or workers) opt for the optimal distribution of skills to tasks based on the prices of various tasks and the wages associated with different skill levels in the market. Crucially, the model accommodates new technologies that may directly displace workers in specific tasks, treating skills, technologies, and trade or offshoring as competing inputs for task completion, contingent on cost and comparative advantage.



Source: International Federation of Robotics (IFR), 2023

Figure 22. *Number of Industrial Robots per 10,000 employees*

In Figure 22, the usage of industrial robots per 10,000 workers is depicted. The world achieved a new milestone in 2022, with 3.9 million operational robots, driven by a substantial increase in industrial robot installations. The countries leading in robot density are The Republic of Korea (1,012 robots per 10,000 employees), Singapore (730 units), and Germany (415 units) while World average 151.

An intriguing case in this figure is China, given its vast population. The industrial robot usage in China stands out as the most dynamic when compared to other nations. In 2014, the robot density rate in China was 49 units per 10,000 workers, and the latest data from 2022 reveals an increase to 392 units, reflecting a remarkable growth of over 26% CAGR. These numbers underscore the significance of the situation, especially considering China's population of 1.4 billion. Asia as a continent has made substantial progress in robot usage, with Korea holding a leadership position since 2010. Korea's industrial robot usage per 10,000 workers has seen an average increase of 10% CAGR since 2010, which aligns well with the dominance of automotive and electronics sectors in the country. In addition, in 2014-2022 period the average of World's robot density's increase is more than CAGR %10 (IFR, 2023).

Moving to the West Block, increased automation is anticipated. Countries with sizable populations, such as Germany, Sweden, and Italy, are above average according to this data. In China, the concern about job replacement is not currently a high-priority issue for the government or its citizens. The country, known for its abundant labor force, has policies driven by challenges related to labor costs, labor shortages, and the ambition to lead a new wave of the Industrial Revolution and yet, this country has surpassed United States in robot density (IFR, 2022). Employers, facing labor force challenges, find robot adoption crucial (Cheng, Jia, & Li, 2019). According to this data, China, and hence the rest of the world, will soon face high robot density. In relation to that, significant income inequality can be interpreted as inevitable.

CHAPTER 3
POTENTIAL POLITIC RESPONSES

Every worker is also a consumer. From this perspective, supply surpluses and increased productivity, leading to cheaper products, do not necessarily augment the purchasing power of those who become unemployed due to automation. In the absence or reduction of wages, purchasing power cannot be achieved. This matter could potentially impact aggregate demand, consequently leading to a dilemma for firms wherein cheaper products may not find buyers. We embarked on a comprehensive examination of the impact of technological advancements on both the production process and income distribution. As we speak this before, we underscore a concerning trend: a discernible surge in technological unemployment appears imminent. This revelation prompts critical inquiries to surface naturally within the discourse, including ponderings on the feasibility of resolving this challenge and the strategies required to do so effectively. As we delve deeper into this multifaceted issue, the ongoing dialogue reveals the looming prospect of profound shifts in employment dynamics, primarily attributed to the accelerating pace of automation. These transformative changes are poised to reverberate across socio-political landscapes, ushering in a new era fraught with both opportunities and challenges.

Central to this paradigm shift are the intricate interplays of macroeconomic forces and labor market dynamics. These factors wield considerable influence over the quality, quantity, and distribution of employment opportunities available to citizens. Consequently, they exert tangible impacts on individuals' livelihoods, shaping not only their financial well-being but also their social standing and sense of identity. The intricate web of socioeconomic characteristics intricately woven into the fabric of society plays a pivotal role in shaping public perceptions and attitudes. Feelings of security, perceptions of relative deprivation, and aspirations for societal equity are deeply intertwined with these dynamics, wielding significant sway over political preferences and, by extension, shaping the trajectory of political outcomes.

In light of these insights, it becomes increasingly evident that addressing the challenges posed by technological advancement necessitates a multifaceted approach—one that acknowledges the complexities of the issue and embraces proactive measures aimed at fostering inclusive growth and equitable opportunities for all segments of society. Failure to navigate these waters adeptly risks exacerbating existing inequalities and widening fault lines within society. Thus, as we confront the dawn of this new technological era, it is imperative that we adopt a forward-thinking approach grounded in collaboration, innovation, and a steadfast commitment to promoting social justice and inclusive prosperity.

The enduring fascination with the significance of work and the phenomenon of unemployment as fundamental elements of political empowerment traces its roots back to early empirical investigations (Jahoda, et al., 1933), as well as the seminal works of classical social theorists such as Karl Marx (1867) and Max Weber (1922). With the advent of technological advancements shaping the landscape of labor markets, a pivotal area of scholarly inquiry revolves around the exploration of individuals marginalized by modernization, who emerge as potent political actors. As we mentioned before, this phenomenon is exemplified by the concept of 'technological anxiety' and the resistance it sparks against innovation (Mokyr et al., 2015).

The response of governments to technological shifts in the workplace is a subject of widespread debate among policy experts, academics, and journalists. A diverse array of potential policy measures exists, ranging from unemployment benefits, education, and retraining initiatives, to the implementation of a universal basic income, industrial policies, taxation adjustments, and regulatory frameworks. Bürgisser (2023) proposes a categorization of policies based on their intended objectives into three main types: (i) compensation policies, which aim to mitigate the adverse effects of technological change after the fact, particularly to address the risk of frictional unemployment; (ii) investment policies, which aim to proactively equip and enhance the skills of workers to navigate structural shifts in the workplace and align with the skill and task requirements of emerging technologies; and (iii) steering policies, which view technological change not merely as an external market force but actively seek to guide its pace and direction by influencing the employment, investment, and innovation decisions of businesses. While a research has begun to explore the relationship between technological change and social compensation and investment policies (Busemeyer et al., 2022), there remains a dearth of research on the active role of the state in steering technological change.

From a policy standpoint, the displacement resulting from technological advancements is not inherently problematic; rather, it's the potential for skill mismatches that poses challenges. Workers displaced by technology often find their skills rendered obsolete, while acquiring the skills in demand can be a costly endeavor (Restrepo, 2015). Within this frame of reference, Investment Policies are quite significant. In response, governments can intervene by proactively preparing individuals to cope with workplace structural changes or addressing skill gaps through investments in retraining and lifelong learning programs tailored to meet the evolving demands of new technologies. In recent decades, welfare states have transitioned from merely providing compensation to implementing more proactive, investment-oriented policies (Hemerijck, 2012). This evolution has seen welfare states adopt a new array of functions and policy instruments designed to mitigate emerging social risks stemming from structural shifts. Challenges in the job market resulting from low or outdated skill sets can be mitigated through active labor market policies and targeted educational initiatives emphasizing lifelong learning (Arlow, 2023).

Table 2. *Space of Public Policy Responses to Technological Change*

	Investment Policies	Steering Policies	Compensation Policies
Goal	Prioritize the proactive preparation and skill enhancement of workers to effectively navigate workplace structural shifts and meet the evolving demands of emerging technologies	Influence the trajectory and speed of technological advancements by guiding firms' decisions regarding employment, investment, and innovation, thereby directing the course of change	Mitigate the adverse impacts of technological advancements after they occur to address frictional unemployment effectively
Idea	Social investment and predistribution	Economic interventionism	Social insurance and redistribution
Target	Individual	Firm	Individual
Policies	• Education • Training • Active labor market policy • Early childhood education and care	• Capital tax deductions • Robot and digital tax Research & development • Employment protection • Work time (reduction) • Minimum wage • Collective bargaining • Work councils	• Passive labor market policy • Early retirement • Wage insurance • Job guarantee • Negative income tax • Universal basic income

Source: Adapted from (Bürgisser, 2023)

Workers facing technological changes may experience significant short- to mid-term challenges. While the long-term effects may stabilize or even increase overall employment levels, as evidenced by robust productivity effects (see Acemoglu & Restrepo, 2018), frictional unemployment and skill redundancy will pose substantial hurdles. As mentioned earlier, existing evidence suggests that a significant portion of occupational shifts from manufacturing to services occurs through reduced job opportunities. Additionally, an aspect not previously addressed is the phenomenon of early retirement (Dottori, 2021). Consequently, labor displacement due to technology often unfolds over a generation, with older workers leaving the workforce and fewer younger workers entering such roles. Nevertheless, actual displacements incur significant costs for affected workers, resulting in substantial income losses either through unemployment or low-wage employment. The emergence of artificial intelligence has the potential to exacerbate these adjustment costs, particularly if automation takes over routine and non-routine service tasks (Acemoglu, 2021), disproportionately affecting younger workers who may lack the option of early retirement.

Thus, frictional unemployment and skill redundancy emerge as two major challenges facing society today.

While technological advancements may yield societal benefits, the labor market vulnerabilities precipitated by technological change tend to disproportionately affect specific social groups, leading to considerable economic and political upheaval. These ramifications hold substantial importance and necessitate effective policy interventions to address them adequately. Prettner & Strulik (2020) delve into the complexities of addressing the challenges brought forth by automation, focusing on an overlapping generations model of the population and examining endogenous education decisions and the subsequent impacts of policy interventions. As the automation of low-skilled labor progresses, individuals may mitigate its adverse effects and reap its benefits by investing in skill enhancement. The authors demonstrate that the rise in the skill premium, driven by automation, incentivizes a growing proportion of the population to pursue higher education, typically in the form of college degrees. However, in societies characterized by heterogeneity, not all individuals possess the means or inclination to pursue higher education. Consequently, those constrained by limited abilities find themselves marginalized, exacerbating income and wealth inequalities across generations. In their analysis, Prettner & Strulik (2020) introduce redistributive policies, funded through either labor income taxes or levies on automation technologies (i.e., 'robot taxes'), aimed at ameliorating the widening inequality spurred by R&D-driven growth. However, they illustrate the intricate interplay between education and technological advancement, highlighting the challenges of enhancing the disposable income of low-skilled individuals while maintaining the endogeneity of both variables. While income redistribution strategies may initially seem attractive, their implementation can inadvertently hinder educational attainment and impede economic growth.

The potential consequences of such policies are far-reaching. Both robot taxes and progressive income taxes, designed to transfer wealth from skilled to unskilled workers, may diminish the incentives for higher education attainment, thereby expanding the pool of low-skilled labor and depressing wages in the short to medium term. Only in the long run, when educational levels stabilize, do redistributive measures unequivocally enhance the disposable income of low-skilled workers. Furthermore, the efficacy of education subsidies in stimulating economic growth hinges on their method of funding (Aghion, et al., 2009). Subsidies financed through robot taxation may inadvertently stifle innovation and dampen growth, whereas those funded by income taxes can foster educational attainment and spur economic development. Despite the apparent redistribution from the less skilled to the more skilled, these policies may not exacerbate post-tax inequality, as the higher supply of skilled labor induced by education subsidies mitigates pre-tax inequality. However, in the short to medium term, income inequality is most likely to increase among low-skilled workers compared to high-skilled workers. In essence, the intricate trade-offs inherent in formulating effective increases automation-induced inequality. Balancing the imperatives of education, technological innovation, and income redistribution poses formidable challenges, with far-reaching implications for socioeconomic dynamics and long-term prosperity (Atkinson, 2015, pp. 150-180).

The phenomenon of increasing inequality has been posited to potentially exacerbate unemployment rates (Prettner & Strulik, 2020). To delve into this notion, Akerlof & Yellen's (1988) fair wage theory should be examined. The essence of their argument lies in the impact of automation, which amplifies the productivity and income of high-skilled workers while leaving the productivity of low-skilled workers unaffected. Under the assumption that low-skilled workers are compensated neoclassical wages based on their marginal productivity in conditions of full employment, the escalating disparity in income distribution may be perceived as unjust by low-skilled workers, potentially leading to reduced work effort. In response, firms may opt to involve low-skilled workers in the productivity gains from automation and adjust their workforce accordingly, thereby precipitating involuntary unemployment among this demographic. However, it's crucial to note that this mechanism does not inherently entail a direct correlation between automation and unemployment. This seemingly counterintuitive outcome can be attributed to the simultaneous increase in the skill premium induced by automation, which, in turn, incentivizes higher levels of education. Consequently, the supply of low-skilled labor diminishes alongside a rise in the demand for skilled labor, resulting in an ambiguous effect on unemployment. It is only when the level of education remains stagnant that the combined impact of automation and concerns regarding fair wages unequivocally predicts a surge in unemployment.

In literature, various studies have delved into the implications of automation within the broader context of long-term development. Notably, the works of Hémous & Olsen (2016) & Acemoglu & Restrepo (2018) bear close relevance to the contributions of Prettner & Strulik (2020). These investigations center on R&D-driven innovations and their relationship with inequality in the trajectory of economic progress. While these studies adopt a simplified model of household dynamics, omitting educational decisions and assuming skills as predetermined for the infinitely living (representative) individual, the production aspect is depicted with greater complexity. Specifically, Hémous & Olsen (2016) posit the production of final goods through a variety of intermediate inputs, while Acemoglu & Restrepo (2018) consider a diverse range of tasks contributing to production. Both models incorporate labor and the potential substitution of (low-skilled) labor with machines. R&D activities generate new varieties of goods initially in non-automated form, prompting firms to invest in automation technologies for intermediate goods production. Consequently, R&D-driven innovations, and even automation, may augment wages for low-skilled workers by stimulating further R&D endeavors. Both theories primarily scrutinize the production side of the economy and explore conditions under which (low-skilled) labor could benefit from automation, warranting a simplified portrayal of household dynamics. However, these contributions do not delve into the dynamics of the race between education and technology or the effects of redistribution policies.

In contrast to the assumptions made by Hémous & Olsen (2016) and Acemoglu & Restrepo (2018) regarding R&D's role in creating new intermediate inputs or tasks initially devoid of automation, Prettner & Strulik (2020) conceptualize R&D as a mechanism for generating patents related to automation capital. This perspective finds support in the research conducted by Mann and Püttmann (2017), who analyzed US patents granted between 1976 and 2014, identifying innovations in automation. Their findings reveal a significant increase in the share of automation patents relative to total patents over the observation period, reinforcing the notion of R&D's pivotal role in driving automation advancements.

However, Baldwin (2019) aptly advises against advocating solely for "more education" in a general sense. They argue that insufficient attention is often given to nurturing uniquely human capabilities, with individuals frequently being trained in skills that machines have already mastered or are on the verge of mastering. Therefore, the focus should not solely be on the quantity of education but also on ensuring that the skills taught will remain valuable and resistant to automation for a longer period. In this regard, it becomes imperative not only to adopt a new mindset that regards lifelong learning and fluid transitions in and out of education as the new norm but also to orient training and education towards digital skills and non-cognitive abilities such as communication, planning, and teamwork, which are anticipated to be in higher demand (Gonzalez Vazquez et al., 2019).

Another category of investment policies, known as active labor market policies, is increasingly prevalent in Europe and might be categorized under the Education heading, but it is more comprehensive and different in a sense. These encompass a range of activation measures, including upskilling programs, employment assistance, job creation initiatives, and workfare-oriented incentive schemes (Bonoli, 2013). Emphasizing upskilling, lifelong learning, and retraining initiatives geared toward human capital investment holds promise for enhancing the skills and employability of displaced workers.

Ideally, the effective implementation of such training measures would not only alleviate pressure on social security and unemployment insurance programs but also address wage disparities, especially among lower-income earners. Scandinavian nations, known for their extensive adoption of active labor market policies, are better positioned in this regard compared to other advanced capitalist democracies (Morel et al., 2011). Conversely, while Continental European countries have started to expand their active labor market policies, Anglo-Saxon and Southern European nations still lag behind (Bürgisser, 2022). Of particular concern is the limited focus on enabling policies that prioritize skills development, which typically receive minimal funding within total expenditures on active labor market policies across most countries. Hence, there is significant potential to redistribute resources towards enhancing skills development efforts to address the evolving training requirements of the current and future workforce.

In crafting effective policies to assist workers in adapting to technological shifts through investments in education and retraining, as well as mitigating adverse effects through compensation, governments possess the ability to influence the pace and direction of technological change. Studies from environmental and labor economics suggest that technological advancements are not solely driven by market forces but are significantly influenced by public policies and economic incentives (Hémous & Olsen, 2021). For instance, environmental steering policies like carbon taxes penalize environmentally harmful practices and innovations by raising costs. Similarly, governments can employ policies to either hasten, decelerate, or redirect the course of technological progress. This presents an opportunity for governments to play a pivotal role in shaping policies that steer technological development toward more equitable outcomes and alleviate economic hardships.

In spite of considerable discourse in recent years, empirical investigations explicitly delving into the effects of tax steering policies on the trajectory and velocity of technological advancement, particularly in the realms of automation and artificial intelligence, remain scarce. Bratta et al. (2020) undertake a study examining the impact of Italy's tax depreciation allowances for digital technologies on technological investments and employment levels at the firm level. This initiative was part of Italy's Industry 4.0 plan, entailing a hyper-depreciation scheme for smart tangible assets essential for firms' digital transformation. Leveraging a comprehensive dataset encompassing all Italian companies, the study employs a difference-in-differences methodology coupled with propensity score matching to discern the influence of digital investments on firm-level employment from 2017 to 2019. Results indicate a marked surge in investments in digital technologies attributable to the depreciation allowances, alongside positive employment outcomes for investing firms. While the study focuses on a relatively brief intervention period and is situated within the specific context of

Italy, its findings align with the notion that labor displacement predominantly occurs among firms that do not adopt such measures. Similarly, Garrett et al. (2020) conducted research on the effects of depreciation allowances for capital investment on regional labor markets in the United States between 2002 and 2012. Their findings suggest that areas experiencing more substantial decreases in investment expenses witnessed modest and short-lived employment expansion but significant and enduring growth in capital investments. This implies that depreciation allowances have hastened the substitution of labor with capital.

It is imperative to recognize the influence of labor market institutions on firms' operational decisions. These institutions significantly impact firms' choices regarding innovation, investment, and employment practices. Employment protection legislation, for instance, influences firms' costs associated with hiring and firing. Similarly, increases in minimum wages can alter the incentive structure for firms considering automation. Furthermore, broader corporatist frameworks, including collective bargaining agreements and work councils, shape the dynamics between workers, unions, and employers, impacting trust levels and coordination in implementing new technologies (Seidl, 2022).

The role of labor market institutions in influencing technology adoption is increasingly acknowledged, with factors such as minimum wages, collective bargaining, work councils, and employment protection legislation playing pivotal roles (Acemoglu, 2010). Environments with robust labor market institutions, automation tends to progress more rapidly. This trend is attributed to two main perspectives.

Firstly, the relative cost dynamics between labor and capital are highlighted (Aaronson & Phelan, 2020). Studies indicate that higher wages, stemming from worker-friendly institutions, incentivize firms to adopt labor-substituting technologies while dissuading investments in labor-complementing ones (Lordan & Neumark, 2018). This is supported by research examining the adoption of industrial robots across OECD countries, which shows a strong link between worker-friendly institutions and robot adoption rates (Presidente, 2020).

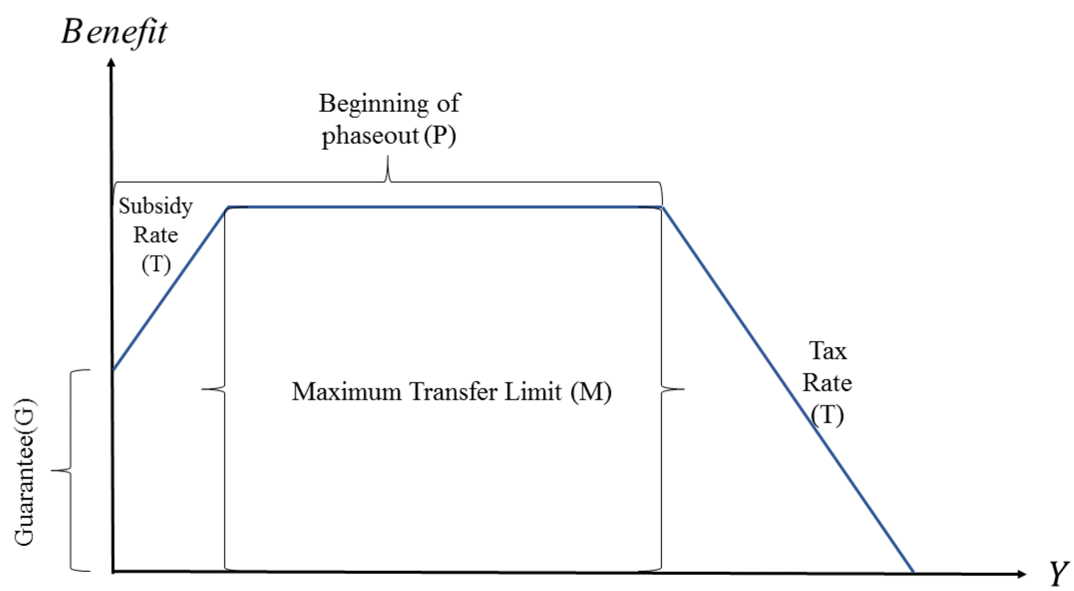
Conversely, minimum wage increases may drive automation as labor costs rise relative to technology, particularly affecting routine-intensive occupations (Downey, 2021).

Secondly, the impact of corporatism, facilitated by strong unions and collective bargaining, is emphasized (Lloyd & Payne, 2019). Despite expectations that liberal market economies excel in radical innovation while coordinated ones focus on incremental innovation (Hall & Soskice, 2001), evidence suggests otherwise. Norway, with its institutionalized social partnership model, demonstrates more advanced workplace automation compared to the UK, despite the latter's strength in technological innovation (Dølvik & Steen, 2018). Strong unions are found to improve the prospects of routine workers, with regions characterized by higher union density experiencing lower displacement effects from robots (Dauth et al., 2021). Overall, the interplay between labor market institutions and technology adoption underscores the importance of policy frameworks in shaping the trajectory of technological change and its impact on the workforce (Acemoglu & Restrepo, 2018).

The increasing income-wealth distribution inequality created by the industrial revolutions, which has been growing so fast, has led people to seek solutions to this issue with the advent of the Fourth Industrial Revolution, Industry 4.0. One of the most comprehensive solutions discussed is the Universal Basic Income Hypothesis (Schwander and Vlandas, 2020). According to this hypothesis, governments would provide monthly assistance to all citizens, regardless of age, income level, automation-related unemployment, or any other criteria (Bidadanure, 2019). This assistance could be in-kind or in cash, but generally, cash assistance is emphasized.

Although the idea of Universal Basic Income (UBI) is relatively new, its logic is quite old. During the time of the French Revolution, the idea of individual retirement was proposed, which was considered magnificent but utopian at the time (Weisman, 1999). However, the German Chancellor Bismarck turned this idea into policy and implemented it, making the individual retirement system a part of daily life (Sigerist, 1943). Additionally, the famous economist Milton Friedman, the founder of monetarist economics, popularized the idea of a

Negative Income Tax (Friedman, 2013). According to Friedman, the progressive tax rate should be revised, a base income should be determined, and incomes above that should be taxed at a progressive rate. Those below the base income should be negative tax payers, meaning the government should provide cash assistance to these individuals and raise their income to the base income level.



Source: Adepted from (Hoynes & Rothstein, 2019)

Figure 23. *UBI model*

Figure 23 depicts a standard transfer program characterized by several nontrivial parameters (G, S, M, and T are non-zero, and P is finite). In this illustration, a family devoid of earnings is entitled to a benefit G. As earnings increase, the benefit rises at a subsidy rate S until it reaches the maximum benefit M. Following this, there is a flat segment where the benefit remains constant at M, succeeded by a phase-out segment for incomes surpassing P at a rate of T. While no single program in the United States adheres precisely to this schedule, Dube (2018) has proposed a similar one.

Nevertheless, the fundamental characteristics of most existing programs in the United States, encompassing traditional cash welfare, in-work tax benefits, retirement schemes, and child allowances, can be encompassed by adjusting these six parameters. This framework, which can also accommodate both NITs and UBIs, elucidates the unique aspects of UBI that differentiate it from the conventional social safety nets prevalent in developed countries (Hoynes & Rothstein, 2019).

There is ongoing discourse regarding the potential of UBI, akin to the concept of negative income tax, to incentivize unemployment. However, an analysis has shed light on this matter, suggesting that the inclination towards unemployment may not be as pronounced as previously assumed. According to this research, upon the implementation of UBI, the increase in unemployment stands at 7% for men and 17% for women (Greenwell, 2022). With the foreseeable automation of various job sectors in the coming years, it would be inaccurate to deem this rise as substantial given the prospective unemployment that may ensue. Notably, due to the substantial allocation of income towards essential expenditures such as healthcare and mandatory consumption, the opportunity cost associated with poverty is notably high (Dalton, et al., 2017). The focus on subsistence concerns among those deemed economically disadvantaged detracts from their productivity potential, rendering them less effective contributors to the workforce. Within this framework, it is envisaged that individuals experiencing a relative reduction in subsistence challenges through UBI will harness their newfound leisure time, courtesy of Industry 4.0's fully automated production, to engage more productively in fields such as art and science. Moreover, they will have the opportunity to equip themselves with the requisite skills demanded by the emerging job opportunities facilitated by Industry 4.0.

UBI is also anticipated to engender certain social challenges. The analysis which is mentioned that women are more than twice as likely as men to choose unemployment can be attributed to their desire to revert to traditional "motherhood" roles after securing financial independence. This phenomenon may be regarded as a relinquishment of the cumulative rights achieved through the struggle for feminism, even though it may not be directly linked to Universal Basic Income, it is one of the opposing views held towards those who opt for this path. Another issue is the migrant problem. In the event of Universal Basic Income being translated into policy, given that its initial implementation cannot be global in scale, it is anticipated that there will be mass migration movements from countries that do not implement this policy (Parijs & Vanderborght, 2010).

A comprehensive implementation of a program incorporating UBI features would incur significant costs. Based on 2022 figures from Bureau of Labor Statistics and Federal Reserve Economic Data, providing a universal payment of $14,580 annually to every US resident aged 18 and above would amount to approximately $3.8 trillion per year. This sum represents about 62% [4]of the total federal expenditures for 2022, encompassing both on- and off-budget items. Excluding individuals over 65 would marginally reduce this expense by around one-fifth. Realizing such a UBI scheme without reducing funding for other initiatives would necessitate nearly doubling federal tax revenues. Even by eliminating all existing transfer programs, constituting roughly half of federal expenditures, the cost reduction would only be marginal. Consequently, many UBI proposals and trials in developed nations deviate from the canonical program's conditions, either by reducing payment amounts below subsistence levels or by imposing eligibility restrictions based on income or family characteristics.

In contrast, a specific trial conducted by the Finnish social insurance agency Kela between January 2017 and December 2018 sheds light on practical implications. Kela distributed a monthly payment of €560 to two thousand unemployed individuals, with no strings attached. Participants, aged between twenty-five and fifty-eight initially, had to be receiving the lowest level of unemployment insurance to be eligible for the trial. Those who remained unemployed throughout the two-year period or found employment by January 2, 2017, would continue to receive the monthly payment. While behavioral data on the two thousand participants is still being reviewed and has not yet been published, preliminary findings

[4] This calculation is an updated version of (Henderson, 2019).

indicate that most participants ended up working similar amounts compared to the control group (O'Donnell, 2019).

The Finnish initiative represented the first national randomized control trial where an advanced industrialized country integrated an unconditional basic income, although it was partial rather than universal, into its social safety net. While basic income experiments have been conducted in the developing world to improve aid targeting and effectiveness, historical parallels to Finland's experiment can be found in North America during the late twentieth century. Between 1968 and 1982, the United States conducted four experiments with a Negative Income Tax (NIT), while the Canadian province of Manitoba experimented with basic income in the 1970s (Munnell, 1986; Hum & Simpson, 1979). In the U.S., some of these experiments garnered considerable success, with President Nixon even proposing a de facto negative income tax through his Family Assistance Plan. However, due to political opposition, Nixon withdrew the proposal. Despite pockets of success, these North American experiments encountered similar challenges in design and ideology as the Finnish experiment. By 1985, all the experiments had ceased, reflecting a broader shift in political and economic sentiment towards reduced spending on social safety nets. Finland's two-year experiment aimed to mainstream basic income but ultimately faced a fate akin to its predecessors (Wispelaere, 2019). Before Finland, Switzerland considered to try Unconditional Basic Income idea in 2016. However, this idea was rejected by voters (Liu, 2020).

Emerging research in labor economics highlights constraints in the market's ability to allocate resources efficiently towards technologies with substantial productivity gains (Bürgisser, 2023). The prevailing incentive structure often favors the development of labor-substituting technologies over more productive alternatives, resulting in the creation of "so-so technologies" and suboptimal artificial intelligence applications (Acemoglu & Restrepo, 2019). Consequently, there is a growing call for a reassessment of existing incentive frameworks and proactive government intervention to promote labor-augmenting technologies. Taxation emerges as a viable policy tool to incentivize firms towards adopting technologies that enhance labor productivity. By adjusting tax rates on labor and capital, governments can influence relative pricing and reduce distortions in technology adoption. However, implementing a specific robot tax poses practical challenges, as defining what constitutes a robot and managing automation driven by artificial intelligence remains complex. Furthermore, while robots may displace certain tasks, they also complement human labor, yielding overall positive effects on employment and productivity. Taxing robots indiscriminately risks stifling innovation and impeding economic advancement (Susskind, 2020).

One potentially influential policy for steering economic dynamics is the implementation of a robot tax. This concept can be viewed as both a supplementary financial mechanism to existing policies and as a standalone policy aimed at discouraging reliance on what Acemoglu & Restrepo (2019) have termed "so-so technologies". Under this framework, companies could be required to pay a tax on each robot employed, equivalent to the salary of a displaced human worker. Another approach could involve levying higher corporate tax rates on companies utilizing robots in their workforce, considering the likely profit augmentation resulting from the heightened efficiency of robotic labor (Silkin, 2018). Bill Gates has advocated for a strategy to moderate the pace of automation, suggesting the implementation of a robot tax. He envisions that the revenue generated from such a tax could be allocated to enhancing education, including reducing class sizes, supporting the elderly, and assisting individuals with disabilities—all roles that rely on human empathy. Addressing concerns about inhibiting innovation, Gates contends that technological progress should not come at the detriment of marginalized groups. He emphasizes the importance of governmental intervention in rectifying inequality, particularly considering the anticipated economic benefits stemming from technological advancements. Furthermore, he underscores that levying taxes on robots could serve as a deterrent to tax evasion tactics employed by major multinational corporations, often involving the transfer of taxable profits to offshore tax havens. A robot tax, similar to a salary, would be computed based on a theoretical amount payable from revenue, ensuring that it is paid within the tax jurisdiction where the robot operates. This approach mitigates the risk of taxable profits being siphoned away from the jurisdiction (James, 2017).

The implementation of a robot tax has the potential to decelerate the pace of job displacement caused by automation, thus prolonging individuals' retention in the workforce. Transitioning skills from one industry or job type to another requires time and investment, both in terms of individual training and government-supported programs. By slowing down the adoption of robots, workers are afforded the opportunity to undergo retraining and acquire new skills (Silkin, 2018). Governments might also explore methods to alleviate the tax burdens associated with employing individuals, opting instead to incentivize investments in human capital. Initiatives such as the retraining support program introduced in Liverpool exemplify efforts to encourage such investments in individuals (Hinds, 2019).

There are doubts regarding the transformative impact of automation on employment, contrary to Gates' predictions, which raises concerns about the feasibility of a robot tax. One major issue is the ambiguity surrounding the definition of a robot. The current definition is so expansive that it could encompass nearly all technology, given that autonomous features are prevalent in many everyday devices, such as vending machines. Venture capitalist Mark Hershberg questions whether every piece of machinery, like tractors, should be subject to taxation under this broad definition (Dunlop, 2017). This broad scope poses challenges in determining when a job is genuinely replaced by a robot.

Furthermore, the introduction of automation varies among countries, leading to questions about the appropriate level at which to establish legislation and definitions—whether at the national, regional (such as the EU or US), or state level. Without uniform adoption of a robot tax and consistent definitions across borders, there is a risk that robotics companies will relocate their operations to jurisdictions without such taxes or with definitions that align more favorably with their interests. This phenomenon, known as capital outflow, could have severe consequences for emerging economies (Vishnevsky & Chekina, 2018). As discussed earlier, emerging countries are increasingly utilizing industrial robots, and capital inflows—whether through foreign direct investment (FDI) or foreign portfolio investment (FPI)—are crucial for their development. Without these inflows and considering the potential domestic capital outflow due to unfavorable tax policies, emerging countries may struggle to catch up with the developing world. Consequently, this could result in lower employment levels, which is not in harmony with the idea of a robot tax.

Robots excel at completing repetitive tasks quickly and efficiently, resulting in reduced waste, lower production costs, and increased profits. However, implementing a robot tax might be perceived as actively discouraging a beneficial aspect of society through taxation. Ryan Avent argues against taxing a specific type of capital that enhances productivity, suggesting instead the adoption of a general wealth tax or a tax on land (Davenport, 2019). Nonetheless, when comparing the productivity of robots to that of humans, it's worth noting that we already have a form of taxation related to human labor: employer's National Insurance Contributions, which deduct wages at the source. In this context, a robot tax could be viewed as a direct substitute for this existing mechanism. Moreover, there are ongoing debates regarding whether companies are deterred from investing in new technologies due to the apprehension of facing exorbitant robot taxes, potentially leading to a slowdown in technological development within the sector. A UK government report published in 2019 argued that to foster innovation in the country, there should be a greater emphasis on increasing the adoption of robotics and automation, rather than limiting it. The report recommended that the government implement tax incentives aimed at stimulating investment in emerging technologies, including robotics. Interestingly, the report highlighted Japan's implementation of a tax credit scheme designed to directly incentivize investments in robotics. Furthermore, the report pointed out that economic growth in affluent nations has stagnated over the past century, suggesting a dwindling pool of innovative opportunities. This, coupled with declining business investments, underscores the importance of setting robot technology taxes at a level that does not discourage businesses from making investments (UK Government Report, 2021).

Due to these issues, potential alternative solutions are currently under debate. In the event of job losses due to automation, businesses stand to gain higher capital returns and profits. Rather than implementing targeted taxes on individual robots, nations could explore alternative methods of generating revenue from corporations. This could involve increasing taxation on corporate profits and capital gains, or imposing higher value-added tax rates on the purchase of robot systems. One proposal, put forth by Bloomberg columnist Noah Smith, suggests establishing a sovereign wealth fund. Alternatively, the government could acquire shares in companies, thereby receiving dividends that could be redistributed across society. Another approach could involve replacing the existing corporate tax structure with a mandate for all companies to allocate a portion of their shares to the government (Smith, 2017).

Several countries have implemented policies akin to the concept of a robot tax. For instance, on August 6, 2017, South Korea became the first country to introduce such a measure. South Korea has swiftly embraced the integration of robots into its workforce, particularly within the manufacturing sector, where robot-generated semiconductors play a significant role. Another motivating factor for South Korea's rapid adoption of automation is its 17-year high unemployment rate, with approximately 1.7 million individuals currently unemployed (Silkin, 2018). However, the tax implemented in South Korea doesn't precisely resemble the individual robot tax envisioned by Gates. Instead, South Korea is amending its corporate tax regulations to discourage capital investments in technology. In essence, it's not truly a robot tax but rather an acknowledgment of South Korea's rapid automation progress, which poses the imminent threat of widespread unemployment (Bottone, 2018)

Furthermore, Bill de Blasio, the Mayor of New York and a candidate in the 2020 presidential election, has proposed an automation policy aimed at safeguarding the 36 million jobs that could become obsolete due to technological advancements by 2030 (Perry, 2019). The revenue generated from a robot tax under his proposal would be allocated towards creating new employment opportunities in sectors such as green energy, healthcare, and education. This initiative seeks to address tax loopholes where companies deduct investments in automation from their taxes, despite the knowledge that such investments will lead to job displacement. De Blasio's proposed reforms surpass the ambitions of many other politicians in the United States. However, critics argue that his robot tax proposal could compel companies to pay out five years' worth of wages for every displaced worker, potentially driving innovation away from the country. Additionally, some skeptics question the necessity of de Blasio's tax plan. A German think tank has indicated that the risk of job loss in the United States decreases significantly, from 38% to 9%, when considering workplace heterogeneity—suggesting that instead of jobs being eliminated, workers will transition into new roles (Arntz, et al., 2017).

Steering policies can also concentrate on influencing the locus of technological innovation by enhancing and directing government investment into specific areas of research and development. As posited by Mazzucato (2011), proactive government intervention is essential for prioritizing innovation-led growth. Drawing insights from historical technological advancements, she contends that the state has frequently played a pivotal role in fostering groundbreaking discoveries that later paved the way for private sector development. However, recent trends in the United States reflect a more laissez-faire approach, with limited governmental commitment to innovation. Presently, a handful of large corporations dominate investment in artificial intelligence research, raising concerns that innovation may veer towards suboptimal technology choices (Acemoglu, 2021). Hence, governments must allocate greater resources to specialized research and development endeavors to effectively shape and guide the trajectory of new technologies.

Another steering policy may be evaluated, as governments have the option to offer subsidized loans and tax incentives aimed at facilitating workers' acquisition of their workplaces (Klock, et al., 1998). Often, additional assistance is required for plant upgrades and employee training, alongside provisions for ongoing support from the previous owner, such as committing to purchasing a specified output for a mutually agreed duration. While buyout arrangements can assume diverse management structures, studies suggest that outcomes are generally more favorable when workers actively participate in selecting management teams and hold positions on boards of directors. This engagement tends to enhance the likelihood of achieving requisite productivity improvements while ensuring equitable distribution of resultant gains. (Jones & Pliskin, 1991)

CONCLUSION

The first industrial revolution stands as a watershed moment in history, where technological innovations revolutionized production processes on an unprecedented scale. Examining these advancements through the lens of the first industrial revolution yields valuable insights into their profound impact on income distribution. Despite initial apprehensions voiced by Luddites regarding the displacement of labor by machines, the anticipated shift in income distribution favoring workers has not materialized. Even as highly skilled workers adapt to the evolving technological landscape, the returns on capital have dramatically outpaced those of labor. Current data that we discussed reveals a stagnation in both labor's share of production and wages relative to capital gains. This discrepancy underscores the monopoly profits generated by industrial technological advancements, facilitated by new patents and licenses, or the efficiency gains achieved by reducing costs. Consequently, the trend reinforces the increase in returns on capital, contributing to widening income disparities.

Until recently, unemployment rates have remained relatively stable, owing largely to technological advancements. While task and occupation losses have occurred, compensatory measures in the form of new job creation have mitigated the adverse effects on employment. This trend has engendered a prevailing sense of optimism among scholars regarding the neutralizing effect of technological developments on job displacement. However, emerging research suggests that this trend may be approaching an inflection point. The accelerating pace of Industry 4.0, characterized by advancements in Artificial Intelligence, Machine Learning, and Automation, portends a paradigm shift in labor markets. Studies indicate a looming risk associated with the automation of jobs, with the potential to exacerbate income inequality. As unemployment rates rise, the chasm between the employed and the unemployed may widen to unprecedented levels, amplifying existing disparities in income distribution.

The prospect of technological advancement reshaping the labor landscape underscores the urgency for proactive policy interventions to mitigate the adverse effects on income distribution. Policymakers face the imperative of addressing the challenges presented by Industry 4.0, striving to balance the promotion of technological innovation with the crucial goal of ensuring equitable income distribution. In this context, investment in education and skill enhancement programs emerges as a crucial policy response, equipping workers with the tools to navigate the evolving labor market. Furthermore, steering policies that guide firms' decisions on employment, investment, and innovation can shape the trajectory of technological advancement, ensuring that its benefits are equitably distributed. Additionally, compensation policies aimed at mitigating the adverse impacts of technological displacement on workers are imperative, fostering social cohesion and resilience in the face of economic upheaval.

In conclusion, while technological advancements hold the promise of enhancing productivity and driving economic growth, their impact on income distribution remains a subject of intense scrutiny. The accelerating pace of Industry 4.0 necessitates a concerted effort to address the challenges posed by automation and artificial intelligence, ensuring that the benefits of technological progress are shared equitably across society. Failure to do so risks exacerbating income disparities and undermining social cohesion, underscoring the imperative for proactive policy interventions to shape a future of inclusive and sustainable growth.

Each worker is also a consumer. From this perspective, supply surpluses and increased productivity, which lead to cheaper products, do not necessarily translate into augmented purchasing power for those who become unemployed due to automation. In the absence or reduction of wages, purchasing power cannot be attained. This situation could potentially impact aggregate demand, posing a dilemma for firms where cheaper products may not find buyers. Policy responses to these issues are subject to ongoing debate and are categorized in three sections: Investment, Steering, and Compensation Policies.

Investment Policies prioritize proactive preparation and skill enhancement of workers to navigate workplace structural shifts effectively. Steering Policies influence the trajectory and speed of technological advancements through regulations such as employment protection, minimum wage, and tax regimes like robot taxes. Compensation policies aim to mitigate the adverse impacts of technological advancements after they occur, addressing frictional unemployment effectively through solutions like job guarantees, Universal Basic Income (UBI), and Negative Income Tax. Each policy has its trade-offs, and the potential consequences are far-reaching.

For instance, both robot taxes and progressive income taxes, designed to transfer wealth from skilled to unskilled workers, may diminish incentives for higher education attainment, expanding the pool of low-skilled labor and depressing wages in the short to medium term. Education subsidies funded through robot taxation may stifle innovation and dampen growth, whereas those funded by income taxes can foster educational attainment and spur economic development. Despite the apparent redistribution from less skilled to more skilled workers, these policies may not exacerbate post-tax inequality. However, in the short to medium term, income inequality is likely to increase among low-skilled workers compared to high-skilled workers.

In essence, the intricate trade-offs inherent in formulating effective policy responses to increase automation-induced inequality pose formidable challenges, with far-reaching implications for socioeconomic dynamics and long-term prosperity. There are ongoing debates regarding whether companies are deterred from investing in new technologies due to the apprehension of facing exorbitant robot taxes, potentially leading to a slowdown in technological development within the sector.

UBI is another policy option with its own set of trade-offs. UBI may increase voluntary unemployment. According to research that we mentioned, upon the implementation of UBI, the increase in unemployment stands at 7% for men and 17% for women. Given the foreseeable automation of various job sectors in the coming years, it would be inaccurate to deem this rise as substantial given the prospective unemployment that may ensue. Additionally, the implementation of UBI may lead to mass migration movements from countries that do not adopt this policy. Financing UBI is also a significant challenge as it is a costly program.

From a policy standpoint, the displacement resulting from technological advancements is not inherently problematic; rather, it's the potential for skill mismatches that poses challenges. Workers displaced by technology often find their skills rendered obsolete, while acquiring the skills in demand can be a costly endeavor. Within this frame of reference, Investment Policies play a crucial role. Governments can intervene by proactively preparing individuals to cope with workplace structural changes or addressing skill gaps through investments in retraining and lifelong learning programs tailored to meet the evolving demands of new technologies. In recent decades, welfare states have transitioned from merely providing compensation to implementing more proactive, investment-oriented policies. This evolution has seen welfare states adopt a new array of functions and policy instruments designed to mitigate emerging social risks stemming from structural shifts. Challenges in the job market resulting from low or outdated skill sets can be mitigated through active labor market policies and targeted educational initiatives emphasizing lifelong learning. Currently, investment policies seem to be one of the most effective policy responses.

In summary, we explored the impact of technological advancements on income and wealth distribution. Our review of the literature indicates that previous technological advancements in various industries were perceived as less influential on the labor market. However, the rapid pace of current technological change necessitates a reevaluation of these effects.

Future researchers may obtain different results by utilizing models with updated data, reflecting the most recent trends and innovations. It is crucial to consider the dynamic nature of technological progress and its broader economic implications. Replicating existing studies with varied samples, including different geographical locations, economic sectors, and demographic groups, can provide a more comprehensive understanding of these impacts. We recommend that future research should also examine the interplay between technology and other factors such as education, policy interventions, and global economic shifts. This holistic approach will offer deeper insights into how technological advancements shape income and wealth distribution in diverse contexts.

In conclusion, our findings underscore the importance of continuous and diversified research in this field. By extending the scope of study to include different variables and updated data, future research will significantly contribute to the development of effective strategies for addressing income and wealth disparities in the face of ongoing technological change.

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APPENDIX1. ETHICS BOARD WAIVER FORM

	HACETTEPE ÜNİVERSİTESİ **SOSYAL BİLİMLER ENSTİTÜSÜ**	Doküman Kodu *Form No.*	FRM-YL-09
		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-YL-09 **Yüksek Lisans Tezi Etik Kurul Muafiyeti Formu** *Ethics Board Form for Master's Thesis*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih: 25/06/2024

Tez Başlığı (Türkçe): Teknolojik Gelişmelerin Gelir ve Servet Dağılımına Etkileri

Yukarıda başlığı verilen tez çalışmam:

1. İnsan ve hayvan üzerinde deney niteliği taşımamaktadır.
2. Biyolojik materyal (kan, idrar vb. biyolojik sıvılar ve numuneler) kullanılmasını gerektirmemektedir.
3. Beden bütünlüğüne veya ruh sağlığına müdahale içermemektedir.
4. Anket, ölçek (test), mülakat, odak grup çalışması, gözlem, deney, görüşme gibi teknikler kullanılarak katılımcılardan veri toplanmasını gerektiren nitel ya da nicel yaklaşımlarla yürütülen araştırma niteliğinde değildir.
5. Diğer kişi ve kurumlardan temin edilen veri kullanımını (kitap, belge vs.) gerektirmektedir. Ancak bu kullanım, diğer kişi ve kurumların izin verdiği ölçüde Kişisel Bilgilerin Korunması Kanuna riayet edilerek gerçekleştirilecektir.

Hacettepe Üniversitesi Etik Kurullarının Yönergelerini inceledim ve bunlara göre çalışmamın yürütülebilmesi için herhangi bir Etik Kuruldan izin alınmasına gerek olmadığını; aksi durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

Serhat EZEN

Öğrenci Bilgileri		
	Ad-Soyad	Serhat EZEN
	Öğrenci No	N21134694
	Enstitü Anabilim Dalı	IKTISAT
	Programı	İNGİLİZCE İKTİSAT – Yüksek Lisans

DANIŞMAN ONAYI

UYGUNDUR.
Doç. Dr. Onur YENI

* Tez **Almanca** veya **Fransızca** yazılıyor ise bu kısımda tez başlığı **Tez Yazım Dilinde** yazılmalıdır.

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-YL-09
		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-YL-09 **Yüksek Lisans Tezi Etik Kurul Muafiyeti Formu** *Ethics Board Form for Master's Thesis*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 25/06/2024

ThesisTitle (In English): Impacts of Technologıcal Advancements on Income and Wealth Dıstrıbutıon

My thesis work with the title given above:

1. Does not perform experimentation on people or animals.
2. Does not necessitate the use of biological material (blood, urine, biological fluids and samples, etc.).
3. Does not involve any interference of the body's integrity.
4. Is not a research conducted with qualitative or quantitative approaches that require data collection from the participants by using techniques such as survey, scale (test), interview, focus group work, observation, experiment, interview.
5. Requires the use of data (books, documents, etc.) obtained from other people and institutions. However, this use will be carried out in accordance with the Personal Information Protection Law to the extent permitted by other persons and institutions.

I hereby declare that I reviewed the Directives of Ethics Boards of Hacettepe University and in regard to these directives it is not necessary to obtain permission from any Ethics Board in order to carry out my thesis study; I accept all legal responsibilities that may arise in any infrigement of the directives and that the information I have given above is correct.

I respectfully submit this for approval.

Serhat EZEN

Student Information		
	Name-Surname	Serhat EZEN
	Student Number	N21134694
	Department	ECONOMICS
	Programme	ECONOMICS - M.A

SUPERVISOR'S APPROVAL

APPROVED
Associate Professor Dr. Onur YENI

APPENDIX2. ORIGINALITY REPORT

	HACETTEPE ÜNİVERSİTESİ **SOSYAL BİLİMLER ENSTİTÜSÜ**	Doküman Kodu *Form No.*	FRM-YL-15
		Yayım Tarihi *Date of Pub.*	04.12.2023
	FRM-YL-15 **Yüksek Lisans Tezi Orijinallik Raporu** *Master's Thesis Dissertation Originality Report*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih: 25/06/2024

Tez Başlığı: Teknolojik Gelişmelerin Gelir ve Servet Dağılımına Etkileri

Yukarıda başlığı verilen tezimin a) Kapak sayfası, b) Giriş, c) Ana bölümler ve d) Sonuç kısımlarından oluşan toplam 107 sayfalık kısmına ilişkin, 24/06/2014 tarihinde şahsım/tez danışmanım tarafından Turnitin adlı intihal tespit programından aşağıda işaretlenmiş filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 13'tür.

Uygulanan filtrelemeler*:

1. ☐ Kabul/Onay ve Bildirim sayfaları hariç
2. ☒ Kaynakça hariç
3. ☐ Alıntılar hariç
4. ☒ Alıntılar dâhil
5. ☒ 5 kelimeden daha az örtüşme içeren metin kısımları hariç

Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orijinallik Raporu Alınması ve Kullanılması Uygulama Esasları'nı inceledim ve bu Uygulama Esasları'nda belirtilen azami benzerlik oranlarına göre tezimin herhangi bir intihal içermediğini; aksinin tespit edileceği muhtemel durumlarda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

Serhat EZEN

Öğrenci Bilgileri		
	Ad-Soyad	Serhat EZEN
	Öğrenci No	N21134694
	Enstitü Anabilim Dalı	İKTİSAT
	Programı	İNGİLİZCE İKTİSAT – Yüksek Lisans

DANIŞMAN ONAYI

UYGUNDUR.
Doç. Dr. Onur YENI

* Tez **Almanca** veya **Fransızca** yazılıyor ise bu kısımda tez başlığı **Tez Yazım Dilinde** yazılmalıdır.
**Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orjinallik Raporu Alınması ve Kullanılması Uygulama Esasları İkinci bölüm madde (4)/3'te de belirtildiği üzere: Kaynakça hariç, Alıntılar hariç/dahil, 5 kelimeden daha az örtüşme içeren metin kısımları hariç (Limit match size to 5 words) filtreleme yapılmalıdır.

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-YL-15
		Yayım Tarihi *Date of Pub.*	04.12.2023
	FRM-YL-15 **Yüksek Lisans Tezi Orijinallik Raporu** *Master's Thesis Dissertation Originality Report*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

TO HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 25/06/2024

Thesis Title (In English): Impacts of Technological Advancements on Income & Wealth Distribution

According to the originality report obtained by myself/my thesis advisor by using the Turnitin plagiarism detection software and by applying the filtering options checked below on 24/06/2024 for the total of 107 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled above, the similarity index of my thesis is 13%.

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I hereby declare that I have carefully read Hacettepe University Graduate School of Social Sciences Guidelines for Obtaining and Using Thesis Originality Reports that according to the maximum similarity index values specified in the Guidelines, my thesis does not include any form of plagiarism; that in any future detection of possible infringement of the regulations I accept all legal responsibility; and that all the information I have provided is correct to the best of my knowledge.

Kindly submitted for the necessary actions.

Serhat EZEN

Student Information		
	Name-Surname	Serhat EZEN
	Student Number	N21134694
	Department	ECONOMICS
	Programme	ECONOMICS – M.A

SUPERVISOR'S APPROVAL

APPROVED
Associate Professor Dr. Onur YENİ

**As mentioned in the second part [article (4)/3]of the Thesis Dissertation Originality Report's Codes of Practice of Hacettepe University Graduate School of Social Sciences, filtering should be done as following: excluding refence, quotation excluded/included, Match size up to 5 words excluded.