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Will Technological Developments Disrupt Income Distribution in the Near Future?

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Teknolojik Gelişmeler, Yakın Gelecekte Gelir Dağılımını Bozacak Mı?

Abstract

This study analyses the relationship between human factors, technological advancements, global shifts, labour structure, and income inequality across 21 selected upper-middle-income and high-income countries from 2008 to 2021. The study utilises variables such as high-tech exports, the human capital index, the misery index, the share of R&D expenditures in GDP, skilled and unskilled labour, patent counts, and the Global Innovation Index. The results from the one- and two-step GMM methods indicate that skilled and unskilled labour and the human capital index have significant positive effects on income distribution. In contrast, the misery index, high-tech exports, and patent counts are found to exacerbate income inequality. However, the global innovation index does not exhibit a significant effect in either analysis.

Keywords : Technological Development, Income Distribution, Gini, Skilled Workforce, Misery Index.

JEL Classification Codes : B22, E24, C40.

Öz

Bu çalışma, 2008-2021 döneminde seçilmiş 21 üst-orta gelirli ve yüksek gelirli ülkede insan faktörleri, teknolojik gelişmeler, küresel dönüşümler, emek yapısı ve gelir eşitsizliği arasındaki ilişkiyi incelemektedir. Tek ve iki aşamalı Sistem GMM yöntemleriyle elde edilen bulgular, nitelikli ve niteliksiz işgücünün yanı sıra beşerî sermaye endeksinin gelir dağılımı üzerinde anlamlı ve pozitif bir etkiye sahip olduğunu göstermektedir. Buna karşılık, sefalet endeksi, yüksek teknoloji ihracatı ve patent sayılarının gelir eşitsizliğini artırıcı yönde etkilediği tespit edilmiştir. Öte yandan, Küresel İnovasyon Endeksi'nin her iki analizde de gelir eşitsizliği üzerinde istatistiksel olarak anlamlı bir etkisi bulunmamaktadır.

Anahtar Sözcükler : Teknolojik Gelişme, Gelir Dağılımı, Gini Katsayısı, Vasıflı İşgücü, Sefalet Endeksi.

1. Introduction

Technological change has historically been a fundamental force shaping labour markets, often generating structural unemployment and widening income inequality by disrupting established production relations and altering the balance between labour and capital. From the early stages of industrialisation, labour-saving technologies increased productivity while simultaneously intensifying social stratification and economic insecurity among workers, contributing to collective resistance and class-based conflict (Thompson, 1966). A prominent early manifestation of these dynamics was the Swing Riots of 1830-1831 in England, during which agricultural labourers protested declining real wages, rising local tax burdens, and the rapid diffusion of mechanised threshing machines. These uprisings represented one of the earliest large-scale responses to technological displacement and deteriorating labour conditions, highlighting the distributive tensions embedded in early capitalist development (Hobsbawm & Rudé, 1969). More broadly, classical accounts of industrialisation document how mechanisation repeatedly generated labour resistance and uneven social outcomes, demonstrating that tensions between technological progress, employment security, and income distribution constitute a persistent structural feature of capitalist economies rather than a phenomenon unique to the contemporary era (Mantoux, 1928/2013).

Throughout history, as the effects of mechanisation deepened, social movements emerged in various areas. In 18th-century England, following the Industrial Revolution, workers who lost their jobs formed an anti-technological-advancement movement, organising multiple protests. This anti-technology group came to be known as "Luddites," and over time, this name became synonymous with opponents of technology. In Leeds, England, in 1791, workers voiced their grievances by publishing a letter in a local newspaper, complaining about the use of machines in their workplaces, deteriorating living conditions, and rising unemployment (Harrison, 1984: 71-72).

The Second Industrial Revolution emerged at the end of the 19th century and the beginning of the 20th century, and with the discovery of electricity, it transitioned to mass production through assembly lines. The commencement of mass production at Henry Ford's automobile factory is widely regarded as the onset of the Second Industrial Revolution. This event profoundly altered the course of the 20th century. In 1914, despite workers earning an average daily wage of 2-3 dollars, Henry Ford offered them a daily salary of 5 dollars to boost productivity, leading to long queues forming outside the factory from those eager to work at this wage level. Simultaneously, Henry Ford effectively utilised the emerging event to apply the efficient wage theory (Schwab, 2016: 16; Mankiw, 2010: 193).

The Industrial Revolution, often referred to as the Third Industrial Revolution, is characterised as an era of rapid advances in information technology that began after World War II and gained momentum from the 1970s onwards. The Third Industrial Revolution commenced with the production of transistors in 1947. It gained significant momentum in 1968, when machines were first programmed, marking the onset of this era; machine programming played a substantial role in its development. Key factors influencing the Third Industrial Revolution include computers, the internet, and digital products. In the 1960s, mainframe computers emerged, followed by personal computers in the 1970s and 1980s. Subsequently, with the widespread adoption of the internet in the 1990s, the Third Industrial Revolution became known as the digital revolution or computer revolution. In summary, the Third Industrial Revolution denotes the use of information technologies enabled by digitisation in production (Schwab, 2016: 16; Baines et al., 2009).

Although the term "thinking machines" was first used by British computer scientist and cryptologist Alan Turing in the 1950s, the first person to articulate the concept of "artificial intelligence" (AI) was the computer and cognitive scientist John McCarthy. Artificial intelligence (AI) can be viewed as a tool that assists humans in thinking holistically, analysing data, and improving decision-making by leveraging acquired knowledge. AI is a field that seeks to explain how robots and machines learn and respond in ways that resemble human behaviour. It is primarily designed to create intelligent machines that operate in ways that closely resemble human behaviour in tasks such as learning, speech recognition, problem solving, and planning. Therefore, artificial intelligence encompasses techniques based on machine learning, including the creation of models that combine data, algorithms, and numerous iterations to make predictions about unknowns using existing data, such as neural networks (West & Allen, 2018).

American artificial intelligence and robotics scientist and futurist Martin Ford, in his 2016 book "Rise of the Robots: Technology and the Threat of a Jobless Future," argued that artificial intelligence, robotics, and machine learning have significant and unsettling effects on income inequality, unemployment, and the job cycle. The first question that comes to mind is, "Does artificial intelligence and machine learning create a jobless future for humans?" According to Martin Ford, economists view the idea that machines will displace human workers in the near future and lead to long-term unemployment with skepticism, even disdain. The statement by American economist Milton Friedman further supports this skepticism: "When we look at history, we see that this concern has been baseless so far. Especially in 21st-century America, advancing technology has always propelled society forward" (Ford, 2015: 10).

However, the International Federation of Robotics (IFR) reported that global sales of industrial robots increased by nearly 60% from 2000 to 2012. In 2012, robot sales reached $28 billion worldwide. By a wide margin, China, the fastest-growing market in the robot industry, saw a 25% increase in robot usage between 2005 and 2012. In 2021, global robot production increased by 10% worldwide to reach 3 million units, and robot sales reached an international level of $50 billion (Ford, 2015: 21; IFR, 2021: 1).

The defining feature of this century, alongside the Fourth Industrial Revolution, is the belief that machines will replace workers. The assumption that "machines are tools that enhance worker productivity" regarding technological advancements warrants scrutiny. This is because machines are now becoming workers themselves. Another question that arises from the ongoing influence of technologies on our future is their impact on labour demand. While the increased efficiency brought about by new technologies is expected to raise overall income, the concern is how this increase in revenue will be distributed across skill levels of labour, particularly between low- and high-skilled labour (Özcan, 2019).

This study's main theme is to analyse whether technological developments lead to unemployment and how they affect income distribution. In this context, the study is divided into six sections. The first two sections examine the impact of industrialisation on the labour force, emerging technological theories, and the historical relationship among the labour force, wages, and income distribution. The third section categorises the literature into two parts. First, it discusses theories about technological developments. Second, it addresses the econometric model employed in this study and in related studies. The fourth and fifth sections cover econometric methodology and the results of applications. Finally, the analysis's findings and policy recommendations are presented.

2. Theoretical Framework

Simon Kuznets' 1955 book on inequality and distribution has provided clarity on the subject with a method and sources as transparent as possible. In his 1955 article titled "Economic Growth and Income Inequality," Simon Kuznets introduced what is now known as the Kuznets Inverted U Hypothesis, exploring the relationship between economic growth and income inequality. Kuznets posited that during the early stages of economic growth, income inequality would increase, but would later improve in subsequent years, forming an inverted U-shaped curve (Piketty, 2015: 19; Kuznets, 1955: 4). Later, technological advancements and low-cost borrowing also explained this relationship. In Western societies, economic and social development led to more equitable income distribution as large segments of the population demanded political changes. Initially, development increased income inequality, which, in turn, triggered social changes and the formation of democratic institutions that led to a more equitable income distribution. Kuznets' hypothesis applies to Western societies (Acemoglu & Robinson, 2002: 184).

Nobel laureate American economist Joseph Stiglitz articulated the idea that inequality hampers economic development in a 2013 New York Times article. He stated, "Inequalities stifle economic recovery, and historically, economic growth has been driven by consumer spending. But now the middle class, which used to support this, is weak." Robert Solow, who was awarded the Nobel Prize in Economics in 1987 for his work on the significance of technological advancements in long-term economic growth, also supports J. Stiglitz's viewpoint. Solow asserted that "as income inequality increases, the gap in income distribution widens." He emphasised the importance of consumer demand, stating that "consumer demand is the fundamental factor that fuels innovation and the economy, but in this case, the middle- class workers and middle-class incomes that sustain the continuity of demand are disappearing" (Ford, 2015: 203-204).

Over the past sixty years, our values, norms, and language have undergone significant changes. Yet, one enduring concern remains: the fear of machines. In 1956, Nobel laureate Herbert Simon predicted, “Machines will be capable, within twenty years, of performing any task that a human can do.” This foresight suggested that emerging technologies would eventually render many jobs obsolete, extending beyond traditional blue-collar positions in manufacturing. Today, we are surrounded by computers in various settings—homes, offices, banks, and even while ordering food at drive-in restaurants. Despite this, we seldom reflect on the potential job losses linked to these technological advancements. Whereas Professor Simon's fears centred on computers, our current anxiety is more profound: artificial intelligence (AI). AI encompasses the ability of machines to analyse vast amounts of data to make predictions and act in complex, unstructured environments (Ernst et al., 2019).

The literature contains numerous studies examining the impact of technological advancements, such as artificial intelligence, machine learning, and robotics, on income distribution. One of these is the (SBTC) theory, proposed by Katz and Murphy (1992) in the U.S. The theory emphasises how increasing demand for highly skilled labour has contributed to rising wage inequality, favouring university-educated workers. This trend has been observed not only in the U.S. but also in countries such as Japan and South Korea, albeit to varying degrees (Wood, 1998; Acemoglu, 2002). Purnastuti et al. (2013) suggest that differences in the intensity of SBTC’s impact on wage disparities may stem from variations in the entry rates of skilled labour into the workforce. Additionally, factors such as inequality levels, minimum wages, industry wages, and other economic investments also influence wage dynamics alongside SBTC (Card & Lemieux, 2001; Autor et al., 2008). The SBTC approach functions as an invisible regulator in the labour market, increasing the skill premium as technological knowledge expands (Acemoglu & Autor, 2011; Grossman & Helpman, 2018). However, because this approach is difficult to measure directly, indirect indicators such as R&D investments are necessary for analysis. Several researchers have demonstrated that increased R&D expenditures correlate with a widening wage gap in favour of workers with higher academic qualifications (Machin & Van Reenen, 1998; Michaelsen, 2011; Violante, 2008; Nogueira & Madaleno, 2023b).

The effects of technological advancements and mechanisation on income distribution, labour markets, employment, wages, and macroeconomic variables remain a subject of ongoing debate. Some argue that automation, exemplified by computer numerical control machinery, industrial robots, and artificial intelligence, may herald widespread job loss. Conversely, others suggest that current automation, akin to previous technological waves, will ultimately boost labour demand, thereby increasing employment and wages. Automation pertains to the development and adoption of new technologies that enable the substitution of capital for labour across various tasks. This process adversely affects the composition of production tasks for labour through a displacement effect, whereby capital assumes roles previously performed by labour. Historically, early innovations during the Industrial Revolution, which automated tasks previously carried out by artisans, and the mechanisation of agriculture, led to significant worker displacement. Today, we observe a similar trend: as industrial robots and other automated machinery displace production jobs, specialised software and artificial intelligence increasingly replace tasks performed by white-collar workers (Acemoglu & Restrepo, 2019).

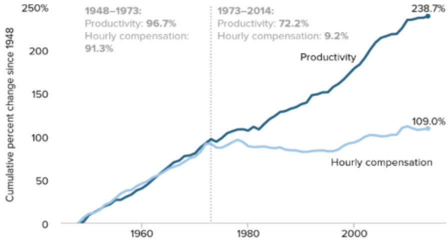
Technological advancements have increased demand for skilled labour, resulting in a sustained rise in skilled workers' wages. As Acemoglu (2002) noted, this phenomenon can be attributed to the faster growth in demand for skilled labour compared to its supply. The development of technologies used in the labour market and the improvement in workers' educational levels have enhanced productivity, leading to a persistent increase in demand for highly skilled labour (Violante, 2008; Acemoglu & Autor, 2011; Murphy & Topel, 2016). Meanwhile, increasing robotisation displaces medium-skilled workers in favour of higher-skilled workers, leading to unemployment and exacerbating labour-market polarisation. As a result, the labour market becomes increasingly polarised, with highly skilled workers at one end and low-skilled workers at the other, causing job opportunities for medium-skilled workers to gradually decline (Nogeira & Madaleno, 2023).

In addition to the destructive effects that long-term unemployment and labour shortages can have on societies and individuals, there will also be an economic cost. Increasing wages will lead to a collapse in the economic cycle that feeds between production and rising consumer spending. Inequality is not only growing in income levels but also in consumption nowadays. Currently, the top 5% of households are responsible for nearly 40% of total expenditures. The fundamental mechanism that places purchasing power in consumers' hands is employment and earnings. If this mechanism continues to erode, there may be insufficient consumers to sustain the growth of mass-market economies (Ford, 2015: 17).

3. The Evolution of Wages, Income, and Inequality from Historical to Modern Times

Despite the United States' sustained economic growth over the past decade, low-skilled workers have experienced stagnant average real wages since the 1970s. During the same period, wages for high-skilled workers with bachelor's or master's degrees have increased. Various signs indicate that we may be approaching the end of a favourable economic era. The relationship between increasing productivity and rising wages began to break down in the 1970s. As of 2013, despite a 107% increase in manufacturing workers' productivity, they earned 13% less in real terms than in 1973. The rise in wage inequality has been one of the most significant drivers of overall income inequality since the 1980s (De Santis, 2002: 725-746; Acemoglu & Autor, 2012: 426-463).

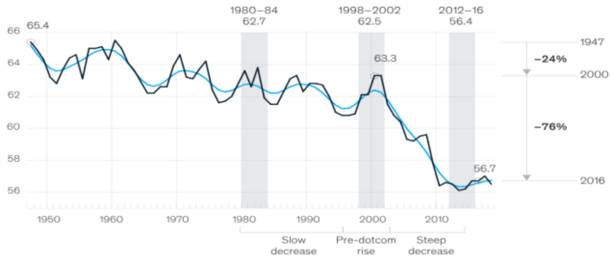
Figure: 1
Relationship between Blue-Collar Workers' Productivity and Real Hourly Wages (%) from 1948 to 2011



Source: Martin Ford (2015).

According to Figure 1, from 1948 to 1973, wage growth closely tracked productivity gains until the OPEC (Organisation of the Petroleum Exporting Countries) oil crisis. Rising prosperity was shared among all individuals contributing to the economy. However, since the mid-1970s, a clear divergence between productivity and wages has become evident. During this period, the returns from economic innovations were almost entirely directed to business owners and entrepreneurs, with workers not benefiting from these gains. Compared with 2000, productivity increased by nearly as much during 2009, comparable to the post-World War II golden era between 1947 and 1973.

Figure: 2
Share of Labour in U.S. National Income from 1947 to 2014 (%)

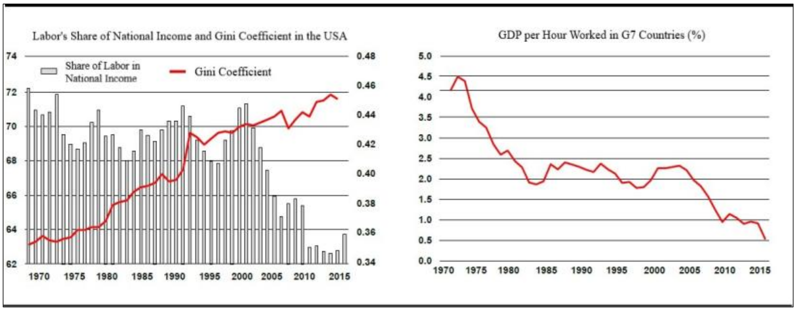


Source: McKinsey Global Institute (2019).

According to Figure 2, the share of labour in U.S. national income remained within a relatively narrow range as predicted by Bowley's Law in the post-war period, but from the mid-1970s onward, Bowley's Law lost validity. It can be observed that the share of labour in GDP sharply declined from this period onwards. This graph becomes even more striking when considering not only blue-collar workers but all labour-supplying employees. If we include the incomes of Wall Street executives, CEOs, movie stars, and athletes (whose incomes increase more than those of other blue-collar workers), or if we imagine that high-income employees are excluded from this graph, it is evident that the share of labour in national income would drop even more significantly.

As the years progressed, the share of labour in national income declined, while income inequality continued to increase. This situation is depicted in the graphs in Figure 3.

Figure: 3
Share of Labour in National Income and Gini Coefficient from 1970 to 2015 (%)



Source: Bureau of the Census, BEA, OECD, UniCredit Research. <https://www.unicreditresearch.eu/>.

According to Figure 3, since the 1970s, the share of labour in total income has steadily declined in the United States, whereas the Gini coefficient, which reflects income inequality, has risen persistently. Similarly, in G7 countries, the wage share of GDP (measured as GDP per hour worked) declined sharply between 1970 and 2015, indicating a reduction in labour’s contribution to national income. This trend can be attributed to industrialisation, technological progress, and mechanisation, all of which have contributed to the widening of wage disparities. Moreover, increasing wage inequality may exacerbate unemployment. This notion was explored in the fair wage theory proposed by George Akerlof and Janet Yellen (1990), which suggests that automation enhances the productivity and earnings of high-skilled workers while leaving low-skilled workers' wages relatively stagnant (Akerlof & Yellen, 1990: 255-283).

The concept of labour-replacing technological progress gained prominence with Erik Brynjolfsson and Andrew McAfee's 2011 book "Race Against the Machine," which addressed another agent, the robot. Brynjolfsson and McAfee argued that technological advancements, commonly understood as automation, make some people more innovative, productive, and wealthier, while causing problems such as unemployment and wealth inequality for others (Brynjolfsson & McAfee, 2011).

As technological advancements continue to exacerbate income and consumption inequality worldwide, they will undermine the critical foundation of a prosperous life: broad-based market demand. Consumer markets not only sustain current economic activities but also stimulate innovation (Ford, 2015: 259). Because automating high-skilled labour is more challenging than automating low-skilled labour, high-skilled workers can mitigate the adverse effects of technological change and turn the situation in their favour by enhancing their skills. However, some individuals may be motivated to pursue higher education if they anticipate gains in their abilities as a result of automation. Nevertheless, not everyone in a heterogeneous society is inclined or able to pursue higher education. Due to skill limitations, some individuals may fail to attain higher education degrees and lag behind others. In this way, research and development (R&D)-driven growth can lead to rising income and wealth inequality from one generation to the next, and to increased involuntary unemployment among low-skilled individuals. In situations where both technology and education are intrinsic, improving the disposable income of low-skilled individuals can be more challenging than improving that of high-skilled workers. To reduce unemployment and address the situation faced by low-skilled labour, policy recommendations such as eliminating income taxes on labour and implementing a robot tax have been suggested (Prettner & Strulik, 2020: 250).

Income redistribution policies aimed at addressing inequality, such as progressive income taxation or taxes on capital inputs, are often justified by concerns over declining labour incomes. However, when educational choices and technological progress are endogenously determined within a general equilibrium framework, such policies may generate unintended medium-term consequences. In particular, higher taxes on income or capital reduce incentives to invest in education, innovation, and productive activities, thereby reducing economic growth and aggregate welfare. As the expected returns to education decline, more individuals choose to remain low-skilled, increasing the supply of low-skilled labour and exerting downward pressure on real wages. Under these conditions, redistribution can raise the disposable income of low-skilled workers only in economies where educational attainment remains largely stagnant (Gasteiger & Prettner, 2020).

Progressive taxation and redistribution policies play a crucial role in combating growing inequality. The situation in which technological advancements are biased against unskilled labour, combined with the "winner-takes-all" principle and increasing monopoly power, has exacerbated income and wealth inequality worldwide. This has underscored the importance of progressive taxation. However, numerous countries have implemented tax cuts. For instance, in the United States, the highest-income groups pay a smaller share of their earnings in taxes than the broader population (Saez & Zucman, 2019).

The most dangerous scenario concerning technological advancement, machine learning, and robotics is the possibility that the world could simultaneously face multiple challenges. When the effects of technological unemployment and climate change exacerbate one another, the benefits of technological innovation can be realised if used appropriately. This requires identifying the impacts on employment and income distribution accurately and taking measures to address potential problems. Humanity's most challenging struggle today is finding our way through complex and seemingly insurmountable issues to leave a future of widespread prosperity and security for the next generations (Ford, 2015: 316).

4. Literature Review

The effects of technological advancements on income distribution are widely discussed in the literature. While technological progress has improved living standards and increased overall prosperity, concerns have grown regarding its implications for income distribution and the future of the labour force. In particular, the continuous evolution of technology raises important questions about how its effects differ across skilled and unskilled labour markets. The literature on the impact of technological advancements on income inequality and labour segmentation includes numerous key studies. For example, Blackburn and Bloom (1987) examined the early effects of technological change on income inequality in the U.S., highlighting how technology tends to favour skilled over unskilled workers. Berman, Bound, and Griliches (1994) showed that technological progress increased the demand for skilled labour in manufacturing, thus contributing to wage inequality.

Bresnahan and Trajtenberg (1995) analysed the role of general-purpose technologies, such as computers, in boosting productivity while also disrupting labour markets and income distribution. Similarly, Autor, Katz, and Krueger (1998) demonstrated that computerisation raised wage inequality by increasing productivity predominantly for high-skilled workers.

Card and DiNardo (2002) questioned the skill-biased technological change (SBTC) hypothesis, noting that wage inequality patterns do not always align with technological shifts. In contrast, Autor, Katz, and Kearney (2006) provided evidence that SBTC has led to labour market polarisation in the U.S., increasing demand for both high- and low-skilled jobs at the expense of middle-skilled positions. Goldin and Katz (2008) explored the historical relationship between technological progress and educational attainment in shaping U.S. income distribution. Van Reenen (2011) offered updated insights into how both technology and trade contributed to wage inequality in the 21st century.

Brynjolfsson and McAfee (2020) argued that digital technologies are transforming economies, with automation displacing middle-skill jobs and amplifying income disparities. Similarly, Piketty (2014) discussed how long-term capital accumulation and technological change fuel inequality. Fitzgerald et al. (2014) analysed how digital transformation and industry restructuring influence income distribution. Murphy and Topel (2016) examined labour market shifts, emphasising how technology favours skilled workers and exacerbates income gaps.

Brynjolfsson and McAfee (2017) further investigated how artificial intelligence (AI) raises demand for high-skilled labour while threatening low-skilled employment, potentially deepening inequality. Acemoglu and Restrepo (2017) provide empirical evidence that robot adoption in the U.S. labour market substitutes for low-skilled labour, thereby increasing income inequality.

Korinek and Stiglitz (2017) explored the implications of AI and labour-replacing technologies on factor prices and policy interventions. Graetz and Michaels (2018) examined how robot adoption affects income distribution, arguing that while productivity rises, low-skilled jobs are threatened. Stiglitz (2018) discussed the macroeconomic and policy implications of labour-substituting technologies. Ernst et al. (2019) showed that automation exacerbates inequality, particularly in countries with weak labour protections, and emphasised the role of social safety nets.

Bessen (2019) analysed how AI impacts job demand and the resulting income inequality. He emphasised that while demand may rise in some sectors, others may vanish entirely, widening the inequality gap. Levy and Murnane (2013) examined how robotics and automation disproportionately affect low-skilled workers.

Furman and Seamans (2019) explored how AI and machine learning reshape economic structures, increasing demand for high-skilled labour while displacing low-skilled workers. Kreiterling (2023) and Autor (2022) reviewed how economic perspectives on technology and inequality have evolved over four decades. Autor et al. (2020) discussed how SBTC has reduced the labour share of total income and contributed to the rise of "superstar" firms, thereby widening firm-level income inequality. Acemoglu and Restrepo (2020) provided further evidence that robots depress demand for low-skilled workers, thereby contributing to broader income gaps.

Brynjolfsson and McAfee (2020) analysed how SBTC has shaped labour markets and wage structures amid rapid technological change. Ferreira (2020) presented a case study showing how U.S. low-skilled workers have been disproportionately affected by technological progress. International perspectives also enrich the discussion.

Goldin and Katz (2020) explored how historical shifts in educational attainment interact with technological change to drive income inequality. Mindell, the author, and Reynolds (2023) discussed the future of labour under AI, emphasising shifts in skill-based labour and inequality.

Country-specific studies provide further insights. Wang et al. (2023) examined the long-term relationship between financial development, innovation, and urban-rural income inequality in China. Autor (2022) offered a comprehensive reflection on how paradigms in economic thought have evolved in the analysis of technology and inequality. Nogueira and Madaleno (2023a) focused on gender wage inequality driven by SBTC across OECD countries.

Acemoglu and Restrepo (2023) argued that automation has been a significant force behind wage dispersion since the 1980s, particularly harming workers in routine jobs. Lastly, Van Dijck, Poell, and De Waal (2023) investigated how platform-based business models (e.g., Uber, Airbnb) reshape labour markets, fostering new forms of precarious employment and inequality.

Few econometric model studies in the literature directly examine the relationship between the SBTC theory and income distribution. In general, issues related to income inequality and the labour force have been discussed in the context of technological developments. Prominent findings from these studies indicate that, while technological progress in developed countries does not directly affect income distribution, technological progress in developing countries does have a disruptive effect on income distribution. Other studies have found that technology does not affect income distribution. Some studies conducted using econometric modelling are as follows:

Perugini and Pompei (2009) examined the relationship between technological developments and income inequality across eight sectors in 14 European countries between 1995 and 2001. Their analysis, which used Feasible Generalised Least Squares (FGLS) and the Murphy-Topel correction method, revealed that income inequality follows an inverted U-shaped pattern alongside technological development.

Ciriaci et al. (2016) studied innovative and non-innovative companies in Spain from 2002 to 2009. Using simple regression analysis, they found that innovative companies contributed to employment and economic growth. In contrast, Frey and Osborne (2017) categorised 702 computer-assisted occupations in the U.S. as either skilled or unskilled, then examined the data using logistic regression. Their analysis revealed that approximately 47% of these occupations were at risk of being eliminated.

Kharlamova et al. (2018) examined how technological developments and labour productivity affected income inequality in EU countries from 2007 to 2017. The researchers defined two periods for their study: 2007-2010 and 2010-2017. They then performed clustering and regression analyses. Their results showed that the higher the level of development, the more positive the relationship between technological developments and income distribution. In countries with high income inequality, however, technological developments have both positive and negative effects. Santos et al. (2017) examined the relationship between technological development and income distribution in 41 countries from 1960 to 2003 using a panel data analysis. Their analysis revealed that technological developments increased inequality.

Antonelli and Scellato (2019) employed the two-stage least squares method to examine the relationship between technology choice, firm size, and wage structure among 6,205 Italian firms from 1996 to 2005. The analysis revealed that large companies prefer high-technology and skilled workers, whereas medium and small companies tend to opt for labour-intensive technologies. This situation disrupts income distribution by creating wage disparities across companies.

Carvalho and Guilmi (2020) used data obtained from a simulation-based, stock-flow-consistent agent model. This model employed agents such as households, firms, governments, and banks. The study examined the relationship between income inequality and indebtedness in the context of technology-induced unemployment.

Using the least-squares method, Lewandowski et al. (2022) conducted a regression analysis of survey data from 47 OECD countries on skill-based routine jobs. Their study revealed that the nature of a given job varies across countries depending on the level of technological advancement.

Li (2023) conducted a panel data analysis to determine whether digital transformation increased the labour share in China between 2010 and 2020. The study found that, while digital transformation did not completely replace labour, it increased productivity in some areas. Specifically, digital transformation in China did not lead to increased unemployment but rather contributed positively to income distribution.

Xiao et al. (2024) analysed the relationship between technological development and income inequality in 51 developed and developing countries from 1995 to 2020. They first applied the augmented and average group (CCEMG) estimator to their panel data analysis, then used the augmented average group (AMG) estimator to corroborate their results. Their study revealed that technological development increases income inequality in developed countries.

5. Methodology

The Generalised Method of Moments (GMM) was first introduced by Hansen (1982) as a flexible estimation technique that does not require strong distributional assumptions, making it particularly useful for econometric models with endogeneity issues. Soon after its introduction, Anderson and Hsiao (1982) applied this method to panel data, demonstrating its potential for addressing dynamic panel data models in which traditional estimation techniques, such as Ordinary Least Squares (OLS) or Fixed Effects estimators, can yield biased results.

Building on these initial developments, Arellano and Bond (1991) refined the method by introducing a first-difference GMM estimator, which effectively controls for unobserved heterogeneity and endogeneity in dynamic panel models. This approach became widely used in empirical economics, especially in growth and productivity studies. Further refinements were made by Arellano and Bover (1995) and Blundell and Bond (1998), who developed a system GMM estimator that enhances efficiency by incorporating both level and differenced equations in the estimation process. This advancement significantly improved the reliability of GMM estimators, particularly in small-sample settings and when explanatory variables are persistent.

Over time, these methodological advancements led to the creation of what is now recognised as the dynamic GMM model, a commonly used tool in panel data econometrics. Arellano (2016) later provided a detailed discussion on the development of GMM techniques, highlighting their significance in modern empirical research. Today, dynamic GMM estimators are widely employed in areas such as finance, labour economics, and macroeconomic modelling, where addressing endogeneity, autocorrelation, and omitted variable bias is essential for producing reliable results.

Dynamic panel data analysis shows that the causal relationships between economic conditions and facts are dynamic and evolve (Topolewski, 2021: 5). Furthermore, as noted by Tatoğlu (2020), dynamic models fall into the category of autoregressive lag models, where past values of the dependent variable act as predictors. Additionally, prior values of the independent variable(s) can also be included in the model as explanatory factors. In the relevant study, the panel model is set up as an autoregressive lagged model, with the structure of the model shown in Equations 1-4.

$$y_{it} = \alpha y_{i,t-1} + x'_{it}\beta + u_{it} \tag{1}$$

$$u_{it} = \mu_i + v_{it} \tag{2}$$

$$E[\mu_i] = E[v_{it}] = E[\mu_i v_{it}] = 0 \tag{3}$$

$$\mu_i \sim IID\left(0, \sigma_\mu^2\right) \text{ and } v_{it} \sim IID(0, \sigma_v^2) \tag{4}$$

The subscript i in Equations 1-4 represents units, while the subscript t represents time. x'_{it}, in Equation 1, represents the Kx1-dimensional independent variable vector. The expression $y_{i,t-1}$in the same equation symbolises the one-period lagged value of the dependent variable included in the model. It is predicted that the error term v_{it}in the model follows a one-way error component model. Since the variables yy_{it} and $y_{i,t-1}$ in Equation 1 are functions of the unit effect, the lagged value of the dependent variable $y_{i,t-1}$is correlated with the error term u_{it}. In this context, the OLS estimator in Equation 1 cannot yield unbiased and consistent estimates (Baltagi, 2021: 187).

To address the endogeneity that arises when lagged dependent variables are used as independent variables, instrumental variable estimators are employed. In this context, various transformations are applied to control for endogeneity in the GMM model. One such method is the Difference GMM (Differenced GMM), which is obtained by subtracting the previous period's values from the current period's values (Roodman, 2009). If the error terms of the difference model have constant variance and no autocorrelation, the Anderson and Hsiao estimator can be used (Baltagi, 2021: 135-136). However, because the error terms in the first-difference model are typically negatively autocorrelated, it is more appropriate to use the GMM estimator proposed by Arellano and Bond (1991). In the GMM approach, the first-difference model is first transformed using the instrumental-variables matrix, and generalised least squares are then used to estimate the transformed model. Due to these transformations, the first difference model is referred to as the "two-stage instrumental variable estimator" (Tatoğlu, 2020).

The dynamic model is presented in the following equation (5):

$$y_{it} = \delta y_{i,t-1} + u_{it} \qquad i = 1, \dots, N; \qquad t = 1, \dots, T \tag{5}$$

Since the error term u_{it} is defined as $u_{it} = \mu_i + v_{it}$ in Equation 2, the unit effect must be eliminated, and the first difference must be taken in order to obtain δ as a consistent estimator. This transformation is shown in Equation 6.

$$y_{it} - y_{i,t-1} = \delta(y_{i,t-1} - y_{i,t-2}) + (v_{it} - v_{i,t-1}) \tag{6}$$

$(v_{it} - v_{i,t-1})$ in Equation 6 represents the MA(1) unit root process. For t=3, Equation 5 is expressed as follows:

$$y_{i3} - y_{i,2} = \delta(y_{i,2} - y_{i,1}) + (v_{i3} - v_{i,2})$$

Unless v_{it} in Equation 5 shows serial correlation, the instrumental variable $y_{i,1}$ in Equation 6 is highly correlated with $(y_{i,2} - y_{i,1})$ and uncorrelated with $(v_{i3} - v_{i,2})$. When t is evaluated for t=4 in Equation 5, in addition to $y_{i,1}$, the variable $y_{i,2}$ is also used as a valid instrumental variable. Arellano and Bond (1991) stated that although the instrumental variables method yields consistent estimates, omitting some instruments reduces efficiency. Therefore, techniques that utilise all instrumental variables are recommended. When the error terms have constant variance, one-stage GMM estimators are recommended; when they have variable variance, two-stage GMM estimators are recommended (Baltagi, 2021: 189).

To address the challenges caused by first-differencing in small T or unbalanced panel data, Arellano and Bover (1995) and Blundell and Bond (1998) introduced the System GMM approach. Because the first-difference transformation entails data and information loss (Roodman, 2009), the forward orthogonal deviation transformation has been proposed as an alternative. In this method, the mean of all available future observations is subtracted from the current-period values, thereby preventing data loss (Tatoğlu, 2020: 138). This forms the basis of the System GMM approach to efficient instrumental-variable estimation. The System GMM estimator yields more efficient results than the first-difference GMM estimator. Furthermore, it enables analysis of models that account for autocorrelation, heteroscedasticity, and endogeneity. This approach requires a minimum of T=3 time periods and N>T observations, ensuring efficient estimates under these conditions (Thorpe & Leitao, 2012: 126).

The system GMM method served as the empirical approach in the research for analysing dynamic panel data. This method demonstrates robustness against issues such as autocorrelation, heteroskedasticity, and endogeneity, delivering consistent results. Among the estimators for dynamic analysis, the two-stage System GMM is the most widely used. This estimator alleviates problems arising from collinearity among independent variables, increases degrees of freedom, incorporates more observations into the analysis, and ensures greater homogeneity across observations (Drukker, 2008). In light of these attributes, it surpasses the Difference GMM.

6. Data and Econometric Model

This study examines the impact of the share of research and development activities in GDP, the globalisation index, high-technology exports, the human capital index, and the Misery Index on income distribution in 21 upper-middle- and high-income countries from 2008 to 2021. To address the study's dynamic structure and potential endogeneity, reliable and valid results were obtained by employing one-step and two-step system Generalised Method of Moments (GMM) estimators. The equation model utilised in the analysis is as follows: Equation 6:

$$Gini_{it} = \beta_0 + \beta_1 Gini_{i,t-1} + \beta_2 lnR\&D_{i,t} + \beta_3 lnGII_{i,t} + \beta_4 lnHTE_{i,t} + \beta_5 HCI_{i,t} + \beta_6 lnMI_{i,t} \beta_7 USKL_{i,t} + \beta_8 lnSKL_{i,t} + \beta_9 lnPAT_{i,t} + u_{i,t} \quad (7)$$

$$i = 1 \ldots.. N, t = 1 \ldots. T$$

Table 1 presents the variables and their descriptions used in the one-step and two-step Generalised Method of Moments estimates.

Table: 1
Description of Variables Used in the Model

Code of Series	Variable Type	Name of Series	Source of the Series	Description of the Series
Gini	Dependent variable	Gini coefficient	World Bank Standardised World Income Inequality Database (SWIID)	%
LR&D	Independent variable	R&D Expenditures on GDP	World Bank	%
LGII	Independent variable	Global Innovation Index	Mendeley Data	%
LHT	Independent variable	High Technology Exports	World Bank	%
HCI	Control variable	Human Capital Index	United Nations Development Program (UNDP)	%
USKL	Control variable	Unskilled Labor*	World Bank	%
LSKL	Control variable	Skilled Workforce**	World Bank	%
LPAT	Control variable	Number of Patents Resident	World Bank	Number
LMI	Control variable	Misery Index	World Bank	%

** The unskilled labour force consists of people between the ages of 15 and 64 with primary education.*
*** The skilled labour force comprises persons aged 15-64 with higher education.*

This study examines how technological developments affect the labour force and the extent to which they influence income distribution, using the GMM method based on SBTC theory. In this context, skilled and unskilled labour, factors influencing technological progress, and socio-economic factors affecting income distribution are analysed. To robustly evaluate income distribution with the Gini coefficient as the dependent variable, our model incorporates four contemporary control variables grounded in recent empirical literature. The Human Capital Index (HCI), which reflects population-level education and health, enhances productivity and reduces inequality; regions with lower HCI consistently exhibit higher Gini coefficients (World Bank, 2024). Unskilled labour and skilled workforce shares are included to capture labour-market polarisation driven by technological change: automation and digitalisation disproportionately benefit skilled workers and displace unskilled workers, thereby widening wage gaps (Perera-Tallo et al., 2024; Gilfoyle, 2023). As a proxy for innovation capacity, the number of resident patents quantifies domestic technological output. Empirical evidence suggests that although innovation can boost high-skilled employment, it tends to favour capital and skilled labour, thereby widening income disparities (Abbas et al., 2024). Lastly, the Misery Index, which combines inflation and unemployment, measures macroeconomic distress. Recent studies confirm that higher levels of this index are associated with increased inequality, as economic hardship disproportionately affects low-income households (Osuma & Nzimande, 2025). Together, these variables enable a comprehensive assessment of how human capital development, labour market composition, innovation, and macroeconomic pressures mediate the impact of technological change on income distribution.

Table 2 presents the minimum, mean, maximum, kurtosis, and skewness values for both the dependent and independent variables.

Table: 2
Descriptive Statistics for Upper-Middle and High-Income Countries

Variable	Obs.	Mean	SD	Min	Max	Skew	Kurt.
Gini	291	0.3733402	0.0989457	25	69	1.170723	4.038992
LR&D	291	0.3674059	0.8013432	-2.525729	1.316408	-1.246189	4.576965
LGI	291	4.287936	0.2479744	3.234749	4.562263	-.8996689	3.06693
LHT	291	2.974051	1.574333	0.0861777	6.848334	.3738461	2.356235
HCI	291	0.8584192	0.0887898	0.654	0.961	-.7320914	2.139515
LMI	291	2.176431	0.8844166	-3.912023	4.166665	-2.056991	13.6182
LPAT	290	8.664732	2.054298	5.955837	14.17084	1.09365	3.124377
USKL	291	103.4864	5.653309	82.21154	123.7547	1.100025	4.924272
LSKL	291	4.127978	0.4293876	2.808318	4.784845	-1.233669	4.053628

Mean: Average, SD: Standard deviation, Min: Minimum, Max: Maximum, Skew: Skewness, Kurt: Kurtosis.

In Table 2, the number of observations used in the analysis is 291. Based on this data, USKL exhibited the highest standard deviation, while Gini had the lowest. The skewness coefficient showed that LR&D, LGI, HCI, and LMI are left-skewed, whereas Gini, LHT, LPAT, and USKL are right-skewed. The positive kurtosis coefficients for all variables suggest that the distributions are concentrated at the centre and exhibit sharp peaks rather than being normally distributed.

7. Analysis Results

The analysis focuses on middle- to high-income countries and presents the findings from the Generalised Method of Moments (GMM) estimator, using both single- and two-stage systems, in Table 3.

Table: 3
One-Stage System GMM and Two-Stage System GMM Analysis Results

One-Stage System GMM			Two-Stage System GMM	
Variables	**Coefficient**	**P>z**	**Coefficient**	**P>z**
Gini L1.	0.7175824	0.000	0.7866366	0.000
LR&D	-0.0897766	0.014	-0.0762944	0.001
LGI	-0.0657204	0.127	-0.0189779	0.657
LHT	-0.0415433	0.010	-0.028814	0.040
HCI	1.67775	0.005	1.23239	0.001
LMI	0.0260696	0.034	0.0113593	0.471
LPAT	0.0412402	0.016	0.0297915	0.025
USKL	-0.0042935	0.014	-0.0040301	0.021
LSKL	-0.2089431	0.032	-0.1542552	0.007
Number of observations: 262				
Number of Groups: 21 Number of Vehicle Variables: 19				
Wald (x^2) = 48867.54 Prob> chi2 = 0.0000			Wald (x^2) = 24917.11 Prob> chi2 = 0.0000	
AR (1) z =-3.17 Pr > z = 0.002 AR (2)z = 1.16 Pr> z = 0.244			AR (1) z =-3.21 Pr> z = 0.001 AR (2) z = 1.60 Pr> z = 0.110	
Sargan test chi2(10) = 7.35 Prob> chi2 = 0.692			Chi2(10) = 7.35 Prob> chi2 = 0.692	
Hansen Test			Chi2(10)=10.96Prob>chi2=0.278	

The results presented in Table 3 show the effects of the lagged income inequality coefficient on various economic and social indicators. According to the findings from the one- and two-step system GMM analyses, a Wald test statistic p-value < 0.05 indicates that the model is statistically significant. First, the AR(1) autocorrelation test shows the presence of first-order autocorrelation, while the AR(2) test results indicate no second-order autocorrelation. This suggests that only first-order autocorrelation should be considered in the model. The Sargan test results, which assess the instruments' validity, indicate that the p-value exceeds 0.005, supporting their validity. According to the one-step system GMM estimation, the lagged value of the Gini coefficient (L1) significantly affects the current-period Gini coefficient. Accordingly, holding other variables constant, a one-unit increase in the lagged Gini coefficient is associated with a 0.71-point increase in income inequality in the current period. The analysis findings show that the share of R&D expenditures in GDP (LR&D), high-tech exports (LHT), human capital index (HCI), the number of patents held by residents (LPAT), skilled labour (LSKL), and unskilled labour (USKL) have a statistically significant impact on the income inequality coefficient. However, the global innovation index (LGI) doesn't have a statistically significant effect, as its p-value exceeds 0.05. According to the model's coefficient interpretation, holding other variables constant, a 1% increase in the share of R&D expenditures in GDP reduces the Gini coefficient by approximately 0.009 points. A 1% increase in high-tech exports reduces the Gini coefficient by 0.0041 points. A one-point increase in the human capital index increases the Gini coefficient by 1.67 points. A 1% increase in the misery index increases the Gini coefficient by 0.0026 points. A 1% increase in the number of patents raises the Gini coefficient by 0.004 points. A 1% increase in skilled labour decreases the Gini coefficient by 0.002 points. Although unskilled labour is statistically significant, it does not significantly impact the Gini coefficient.

According to the two-step system GMM estimation, the lagged value of the Gini coefficient (L1) has a significant effect on the Gini coefficient. Thus, a one-unit increase in the lagged Gini coefficient increases the current period's Gini coefficient by 0.78 points. The analysis findings show that the share of R&D expenditures in GDP (LR&D), high-tech exports (LHT), human capital index (HCI), the number of patents held by residents (LPAT), skilled labour (LSKL), and unskilled labour (USKL) have a statistically significant impact on income inequality. However, the global innovation index (LGI) and the misery index (LMI) do not have statistically significant effects, as their p-values exceed 0.05. Based on the coefficient interpretation, holding other variables constant, a 1% increase in the share of R&D expenditures in GDP reduces the Gini coefficient by approximately 0.008 points. A 1% increase in high-tech exports reduces the Gini coefficient by around 0.003 points. A one-point increase in the human capital index raises the Gini coefficient by 1.23 points. A 1% increase in the number of patents increases the Gini coefficient by 0.001 points. Each 1% increase in skilled labour decreases the Gini coefficient by 0.001 points. These results suggest that significant economic indicators, such as innovation and technology exports, which are often discussed in the economic literature, have adverse effects on income inequality.

8. Conclusion

Advances in artificial intelligence, robotics, and machine learning have rapidly transcended national borders, thereby influencing the global economy in two distinct ways. First, technological advancements not only enhance national income and economic competitiveness but also play a balancing role in increasing human capital and in the distribution of per capita income. Second, these advancements have heightened the risk of supply-side issues, unemployment, and inflationary pressures in national economies. In particular, concerns about job availability for workers and employers' demand for skilled labour have escalated in labour markets. This study employs a one-step and a two-step GMM model to assess the impact of technological advancements, fundamental human capital indices, and skilled labour on income inequality. The findings indicate that high-tech exports, the share of R&D expenditures in GDP, and variables related to skilled and unskilled labour reduce income inequality. At the same time, the human capital index and patent counts increase. The misery index is significant only in the one-step GMM model, whereas the global innovation index has no significant effect in either model.

In light of these findings, the implementation of inclusive labour market policies is essential to mitigate the potential inequality effects of technological advancements. Expanding vocational training and reskilling programs for low-skilled workers would enhance both labour market flexibility and the balance of income distribution. To further strengthen the inequality-reducing impacts of high-tech exports and R&D expenditures, tax incentives and financial support should be directed toward small and medium-sized enterprises operating in these sectors. Furthermore, to limit the inequality-enhancing effects of patents, a balanced legal framework should be established, one that safeguards intellectual property rights without hindering competition while promoting wider access to innovative activities through mechanisms such as patent pools and licensing agreements.

Although technological advancements are generally expected to increase income inequality by raising the demand for skilled labour, this study presents a contrasting finding. The results indicate that when both skilled and unskilled labour increase simultaneously, income inequality tends to decline. This suggests that an inclusive expansion of the labour market, enabling the participation of individuals with varying skill levels, may contribute to a more balanced income distribution. These results highlight the importance of social and economic policies in preventing the disparities that technological advancements may create, particularly in middle- and high-income countries. Notably, the findings align with measures undertaken by high-income countries to mitigate income disparities, as reported in the IMF's The Future of Jobs Report 2023 (Di Battista et al., 2023). When considering developing and developed countries on a broader scale, some measures that could minimize income inequality arising from technological advancements include providing training to unskilled labor to integrate them into the skilled workforce, securing the rights of unskilled workers through legal regulations, reviewing minimum wage policies, collaborating with employers through unions to ensure fair income distribution, implementing progressive tax policies to support the development of unskilled workers by taxing high-income companies at higher rates, offering opportunities to prevent skilled labor from emigrating to other countries, and improving work conditions compatible with technology to enhance productivity. Another important finding is that an increase in the human capital index is associated with greater income inequality. Generally, a negative relationship is expected between human capital and income inequality. However, two factors can alter this relationship. First, according to Lee and Lee (2018) and Hanushek and Woessmann (2023), education is a fundamental component of human capital. In this context, even if the duration of schooling is the same across countries, the quality of education provided may differ. This does not reduce income inequality among countries. Another critical factor is the level of schooling, as noted by Castelló-Climent and Doménech (2021). Increased schooling at the primary level does not significantly affect income inequality. However, higher education, where skilled-level competencies are acquired, can reduce income inequality. Lastly, the positive relationship between patent counts and income inequality suggests that companies acquiring patents may monopolise production processes, thereby contributing to income disparities. One way to prevent monopolisation is to establish a legal framework that protects both other producers and the original producer. In summary, while increasing the share of R&D expenditures in GDP and high-tech exports can help reduce income inequality, unchecked growth in patent numbers and monopolistic tendencies may exacerbate income disparities. Therefore, implementing social and economic policies that accompany technological advancements is essential for mitigating income inequality in middle- and high-income countries.

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