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MASTER THESIS

Pajamų nelygybės mažinimo akseleravimas dirbtinio intelekto pagalba: turto kaupimo skatinimas per valdžios paramą.	**Accelerating the Reduction of Income Inequality through AI: Promoting Asset-Based Wealth via Government Support**

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1. Introduction, relevance of the topic and the main aim of the Master's thesis

Income inequality is a pressing global issue, as substantiated by leading research and reports, including studies conducted by the World Bank, the International Monetary Fund (IMF), and leading academics such as Thomas Piketty in "Capital in the Twenty-First Century" that emphasize the need for innovative, multifaceted solutions to address its profound impacts on economic stability, social mobility, and overall well-being (Stiglitz, 2012) (Piketty, 2014). Empirical data indicates that income inequality has significant implications for economic growth, social cohesion, and political stability. For example, the World Inequality Database highlights that the share of wealth held by the top 1% has increased dramatically in most countries over the past few decades, exacerbating disparities. Research also shows that unequal income distribution can hinder poverty reduction efforts and limit access to essential services such as healthcare and education. Additionally, evidence from the Organisation for Economic Co-operation and Development (OECD) suggests that high levels of inequality undermine trust in institutions and reduce the social capital necessary for sustainable development. Policymakers and researchers continue to debate and test solutions, including progressive taxation, social welfare programs, and education reform, aimed at mitigating income disparities.

Income inequality has been a persistent challenge across the globe, with the wealth gap between the countries rich and the poor continuing to widen (The World Inequality Report 2022). In this context, the advent of artificial intelligence (AI) and related automation technologies presents both opportunities and risks in addressing this pressing issue. While AI has the potential to drive economic growth and create new job opportunities, it also threatens to displace a significant number of workers, particularly those engaged in routine and manual tasks (Acemoğlu & Restrepo, 2019).

Starting from the previously mentioned premises, the main aim of this Master thesis is to develop a comprehensive framework that demonstrates how AI can be strategically deployed to accelerate the reduction of income inequality, by promoting asset-based wealth creation through the following key interventions: skill development programs to equip individuals with the necessary capabilities to adapt to the changing labor market and leverage AI-powered opportunities; entrepreneurial education to foster a culture of innovation and wealth creation, especially among underserved communities; government policies and support mechanisms that create an enabling environment for skill development, entrepreneurship, and asset-based wealth creation; the systematic integration of these interventions with the strategic application of AI technologies to maximize the impact on reducing income inequality; the thesis will provide a detailed analysis of the synergies between these elements, as well as a mathematical model and a comprehensive project-based framework for implementation, with the aim of generating tangible and scalable solutions to address the pressing issue of income inequality.

2. Literature review

Recent studies have highlighted the potential for AI to exacerbate income inequality if not properly managed (Brynjolfsson & McAfee, 2015). The tendency of AI technologies to be labor-saving and resource-efficient, coupled with the winner-takes-all dynamics that advantage developed countries, poses a significant challenge for developing and emerging economies. At the same time, AI presents an opportunity to create new tasks and activities where labor can be productively employed, potentially mitigating the adverse effects on labor demand (Autor, 2015). To effectively leverage the benefits of AI and minimize its negative impacts, a comprehensive policy framework is needed—one that emphasizes human capital development, entrepreneurial education, high-value skills development, and strategic AI deployment ("Human Development Report 2020," 2020).

One promising avenue to address income inequality through AI is by focusing on asset-building strategies rather than merely addressing income disparities (Sherraden, 1990)(Sherraden 1991). Asset-based wealth creation—through entrepreneurship, skill acquisition, and investment—offers a more sustainable path toward economic equality. Ownership of assets such as property, businesses, and financial instruments tends to have a more lasting impact on reducing wealth inequality than temporary increases in wages or income substitution (Saez & Sucman, 2019). From an economic perspective, skills and competencies acquired through education and training can be treated as a form of intangible asset, commonly conceptualized as human capital, which generates long-term returns in the form of higher productivity, earnings, and economic resilience (Becker, 1964). By leveraging AI to enhance skill development and entrepreneurial capacities, individuals from lower-income groups can gain access to the tools needed for asset accumulation, thereby improving their long-term financial security. AI can also play a crucial role in democratizing access to these opportunities by helping governments create optimal support policies, making quality education, financial tools, and entrepreneurial resources more widely available, particularly to underserved communities or countries (Korinek & Stiglitz, 2017)

Skill development plays a critical role in helping individuals adapt to the changing labor market brought about by AI-driven automation (Goldin & Katz, 2007)(Autor et al., 2020). Workers equipped with advanced technical and cognitive skills are more likely to benefit from the opportunities created by AI, rather than being displaced by it (Autor et al., 2003). This not only helps maintain employment but also enables workers to participate in higher-paying, value-added sectors of the economy, thereby reducing income inequality. Entrepreneurial education is another vital component in this strategy. By fostering entrepreneurial skills at an early age, individuals can build the foundations for wealth creation and self-sufficiency, reducing their dependence on traditional employment and increasing their ability to accumulate assets (Fairlie, 2004)(Fairlie & Krashinsky, 2012). This can be particularly effective when paired with AI tools that aid in market analysis, business planning, and resource management, enabling aspiring entrepreneurs to succeed in increasingly competitive markets (Nambisan, 2017).

Government support is essential to ensure that the benefits of AI are equitably distributed (Rodrik, 2018). This includes not only financial support and subsidies for education and entrepreneurship but also the development of regulatory frameworks that prevent the concentration of AI-generated wealth in the hands of a few (Korinek & Stiglitz, 2017). Public policies must aim to create an enabling environment where skill development and entrepreneurship can thrive, ensuring that AI contributes to inclusive economic growth rather than deepening existing inequalities. In this regard, targeted government interventions can help lower-income groups overcome the barriers to asset accumulation, such as access to credit, capital, and education, thereby accelerating wealth creation and reducing inequality.

The discourse surrounding the intersection of AI and income inequality is increasingly pertinent for various stakeholders, particularly policymakers practitioners and academics. This research work describes and proofs the dual nature of AI's impact on income, assets, and especially opportunity distribution, highlighting both its potential benefits and drawbacks.

This work especially contributes to policy analysis by demonstrating that the impact of AI on income inequality is not automatic but depends on how AI adoption is embedded within public policy frameworks. It provides empirical evidence that asset-based wealth creation, social expenditure, and AI governance capacity are key policy channels through which technological change can be aligned with more equitable income distribution. By integrating cross-country econometric analysis with an institutional case study, the thesis offers policymakers a structured, evidence-based framework for designing and evaluating AI, education, and entrepreneurship policies aimed at reducing inequality.

For policymakers, AI represents a powerful instrument in the ongoing struggle against income inequality. The strategic implementation of AI technologies can facilitate economic growth and enhance productivity, which may contribute to wealth generation across different socio-economic strata. However, empirical studies indicate that AI investments are often correlated with increased income inequality. For instance, research encompassing a panel of 86 countries from 2010 to 2019 reveals that higher AI investments disproportionately benefit the top income decile while diminishing the income shares of lower deciles, suggesting that without appropriate regulatory frameworks, AI could exacerbate existing disparities (Artificial Intelligence, Services Globalisation and Income Inequality, 2023).

Moreover, the dual nature of AI's impact necessitates a nuanced approach from policymakers. On one hand, AI can drive innovation and create high-skill job opportunities; on the other hand, it may lead to structural shifts in labor markets that favor capital over labor, thereby widening wage gaps. Thus, effective policy interventions must be designed to mitigate these adverse effects while harnessing the positive potentials of AI.

From a practitioner's perspective, the integration of AI into business practices is not only useful but also essential for maintaining competitive advantage in an increasingly automated economy. Organizations that leverage AI effectively can optimize operations, enhance customer experiences, and ultimately drive profitability. However, this technological shift raises critical questions about workforce displacement and the need for upskilling initiatives.

Academically, the exploration of AI's implications for income inequality is particularly significant due to its novelty and evolving nature. The intersection of technology and socio-economic dynamics offers fertile ground for research that can inform both theoretical frameworks and practical applications. Recent studies have begun to unravel the complex relationships between AI adoption, labor market changes, and income distribution patterns, underscoring the importance of interdisciplinary approaches to understanding these phenomena.

In this master's thesis, income inequality is examined through the lens of inequality of opportunity by focusing on cross-country and over-time differences in income dispersion that are shaped by structural and institutional conditions rather than individual effort. Empirically, this is operationalised using country-level panel data by comparing market and disposable Gini indices and by analysing how variations in AI patents, AI readiness, education and skill formation, social expenditure, wealth, and globalization are associated with changes in disposable income inequality within countries. This approach interprets reductions in post-redistribution inequality as reflecting the extent to which unequal opportunities generated by market processes are mitigated through policy, technological capacity, and asset-building mechanisms, consistent with a macro-level conception of inequality of opportunity.

Inequality is a multifaceted concept encompassing disparities in the distribution of resources, opportunities, rights, or outcomes among individuals or groups within a society. These disparities can manifest among various dimensions across economic, social and political, and are shaped by structural, historical, and systemic factors (Piketty, 2014; Wilkinson & Pickett, 2009).

Inequality manifests in multiple interrelated forms, each influencing and reinforcing the others across social, economic, and political dimensions. A central issue is economic inequality, which concerns disparities in income, wealth, and access to financial resources. This type of inequality is frequently quantified using measures such as the Gini coefficient and has been extensively discussed in foundational works by Sen and Atkinson (Sen, 1997; Atkinson, 2015). Closely connected is social inequality, which refers to the uneven distribution of opportunities and life outcomes, including access to education, healthcare, housing, and employment. Social inequality is often shaped by institutional and cultural factors such as race, gender, or ethnicity, creating persistent structural disadvantages for certain population groups (Hurst et al., 2017; Broome & Sen, 1993; Chong & Grastein, 2007). Another critical dimension is political inequality, which denotes imbalances in individuals' or groups' capacity to participate in and influence political decision-making processes. This form of inequality may be observed in differential voting rates, unequal representation in legislative bodies, or unequal access to policymaking arenas (Bartels, 2008). Political marginalisation often reinforces economic and social disparities, creating a feedback loop that sustains systemic disadvantage. Educational inequality represents disparities in the quality, accessibility, and affordability of education across different regions and population groups. Influenced by geography, socioeconomic status, and national policy frameworks, such inequality affects not only individual outcomes but also intergenerational mobility and national productivity. Studies such as Blanden et al. and the OECD's Education at a Glance report (Blanden et al., 2022; "Education at a Glance 2018," 2018) highlight the persistent gaps in educational access and achievement across developed and developing contexts. Finally, income inequality—a core concern of this thesis—describes the uneven distribution of earnings and accumulated wealth among individuals and social groups. While sometimes used interchangeably with economic inequality, income inequality specifically focuses on earnings from labor and capital, and how these are shaped by education levels, labor market structures, taxation policies, and capital ownership. Income Inequality refers to the uneven distribution of income and wealth across different segments of society, where certain individuals or groups earn significantly more than others. This disparity can be influenced by factors such as education, access to capital, and the labor market, leading to unequal economic opportunities (Piketty, 2014; Atkinson, 2015).

The concept of opportunity equality is intrinsically linked to income equality, as the equal availability of opportunities plays a crucial role in determining individuals' ability to access resources, secure well-paying jobs, and ultimately achieve financial stability. When opportunities are not distributed equitably across different social or economic groups, disparities in income are likely to persist or even widen. This relationship highlights the importance of ensuring equal access to education, healthcare, and employment opportunities, which are fundamental in shaping individuals' economic outcomes (Roemer, 1998).

Inequality arises from a combination of structural, historical, and policy-driven factors such as regional disparities: prosperous regions continue to grow faster because they attract investment, talent, and business, while struggling regions become more economically deprived due to a lack of these resources (Rodríguez‑Pose, 2012; Krugman, 1991), According to John Rawls in a book „A Theory of Justice" (1971), structural barriers are systemic constraints embedded in social institutions that limit individuals' access to opportunities and resources based on arbitrary factors like race, class, or gender. These barriers conflict with the principles of justice Rawls proposes, particularly the principle of fair equality of opportunity, which asserts that all individuals should have equal chances to pursue their goals regardless of their social starting point. Structural barriers perpetuate inequality by unfairly privileging some groups while marginalizing others, thereby violating Rawls' difference principle, which holds that social and economic inequalities are justifiable only if they benefit the least advantaged. For Rawls, eliminating such barriers is essential to create a society that aligns with the principles of justice as fairness. By addressing structural inequalities, institutions can provide a foundation where individuals have genuinely equal opportunities to succeed based on their talents and efforts rather than systemic disadvantages (Rawls, 1971). Income inequality is sustained and reproduced through a range of interrelated structural mechanisms that operate across social, institutional, and historical dimensions. One of the most persistent drivers of inequality is discrimination embedded in social and institutional practices. Systematic biases based on characteristics such as race, gender, or ethnicity shape individuals' access to education, employment, and social mobility, thereby perpetuating unequal treatment and reinforcing income disparities over time (Pager & Shepherd, 2008). These forms of discrimination often interact with institutional structures, creating cumulative disadvantages that are difficult to overcome through individual effort alone. Closely related to discriminatory processes are inequalities in access to education and healthcare. Variations in the quality, availability, and coverage of educational and health institutions significantly influence individuals' capacity to develop human capital and participate productively in the economy. When access to these foundational services is uneven across regions or social groups, disparities in skills, health outcomes, and earning potential tend to widen, contributing to persistent income inequality (Fleurbaey, 2008). Global economic forces further shape inequality dynamics. Processes of globalization and market liberalization have transformed labor markets, capital flows, and production structures across countries. While these processes have generated aggregate economic gains, empirical evidence indicates that they have also contributed to widening income and wealth gaps in many regions, particularly in contexts where institutional protections and redistributive mechanisms are weak (Milanović, 2016). Finally, historical and institutional legacies play a crucial role in shaping contemporary patterns of inequality. Long-standing systems such as colonial rule, segregation, or exclusionary political institutions have left enduring imprints on economic structures, access to resources, and social hierarchies. These historical arrangements continue to influence present-day inequality by constraining opportunities and reinforcing power asymmetries, even long after formal institutional reforms have taken place (Acemoglu & Robinson, 2001).

Quantifying inequality is critical for analyzing its extent and impacts. Common metrics include Gini Coefficient: A measure of income or wealth inequality ranging from 0 (perfect equality) to 1 (maximum inequality), Palma Ratio: A ratio comparing the income share of the top 10% to the bottom 40%, providing an alternative to Gini for policy discussions, Human Development Index (HDI): a statistical composite index of life expectancy, education (mean years of schooling completed and expected years of schooling upon entering the education system), and per capita income indicators, which is used to rank countries into four tiers of human development.

The consequences of inequality are profound, affecting both individuals and societal systems. Inequality affects economic Growth: high inequality is associated with lower economic mobility and growth potential, as it restricts access to opportunities and resources (Aghion et al, 1999; Panizza, 2002; Dominicis et al., 2008; Stiglitz, 2012), social Cohesion: Disparities in wealth and opportunities can fuel social unrest and political instability(Wilkinson & Pickett, 2009), intergenerational Equity: Inequality perpetuates cycles of poverty and limits upward mobility for future generations (Corak, 2013; Martinet et al, 2022; Chetty et al., 2014).

3. Theoretical framework

This master's thesis is grounded in a multidisciplinary theoretical foundation that draws from a range of classical and contemporary economic theories (i.e. automation theory, human capital theory, Schumpeterian theory of innovation, asset-based welfare theory) to conceptualize how AI can be strategically applied to reduce income inequality through mechanisms of asset-based wealth creation. Rather than viewing AI as a purely technological phenomenon, the thesis situates it within a broader socio-economic context, exploring how its deployment interacts with labor markets, innovation systems, human capital, and institutional structures.

At the center of the analytical framework is the task-based automation theory, as developed by Acemoglu and Restrepo (Acemoglu & Restrepo, 2019), which offers a nuanced understanding of the ways in which AI transforms employment. According to this theory, AI technologies are capable of automating specific, routine, or codifiable tasks, thereby displacing certain categories of labor. However, this process is not purely substitutive. It is also generative, as AI facilitates the emergence of new tasks and occupations—particularly those requiring advanced cognitive, creative, or interpersonal skills. The net effect on income inequality depends on the relative strength of what the authors term the productivity effect (increased output), the displacement effect (job loss), and the reinstatement effect (task creation). Understanding this triadic dynamic is essential for evaluating AI's potential as both a disruptor and an equalizer in the labor market.

Complementing this perspective is human capital theory, first articulated by Becker (Becker, 1964), which posits that investments in education and skill acquisition enhance an individual's productivity, earnings, and employability. Within the context of AI, human capital becomes even more critical. As AI reshapes the skill demands of the labor market, access to quality education and retraining opportunities becomes a prerequisite for inclusive participation in the new economy. AI-enhanced learning platforms, such as adaptive digital education tools and virtual training environments, can reduce traditional barriers to skill development—particularly for marginalized populations.

The framework also draws upon the Schumpeterian theory of innovation, which underscores the role of technological change in disrupting existing economic structures and redistributing wealth and opportunity. According to Schumpeterian logic, innovation fosters the entry of new firms, challenges incumbent monopolies, and creates pathways for upward mobility. More recent elaborations of this theory, such as those by Antonelli and Gehringer (Antonelli & Gehringer, 2017), suggest that AI-driven innovation—especially when adopted by new market entrants—can democratize access to economic participation. In this view, entrepreneurship functions as both a vector of innovation and a mechanism for more equitable wealth distribution.

Also central to the thesis is asset-based welfare theory, originally advanced by Sherraden (Sherraden, 1990), which argues that long-term economic security and reduced inequality are best achieved not merely through income transfers but through the promotion of asset accumulation. Assets—whether in the form of education, business ownership, housing, or savings—enable individuals to withstand economic shocks, invest in their future, and transfer wealth intergenerationally. AI, when used to expand access to entrepreneurial tools, digital finance, or education, can become a catalyst for inclusive asset building.

Lastly, the framework incorporates insights from the theory of government intervention in market failures, most notably articulated by Stiglitz (Stiglitz, 1987). This perspective highlights the importance of public policy in correcting systemic inequities, such as unequal access to finance, education, or technology. In the AI context, such interventions might include subsidized training programs, the provision of digital infrastructure, or regulation to ensure fair access to AI technologies. By actively addressing the structural barriers that limit access to wealth-building opportunities, government policies can enhance the redistributive potential of AI.

Together, these theoretical lenses provide a robust foundation for understanding how AI, when embedded within a broader framework of human capital development, entrepreneurial activation, and state intervention, can contribute to the reduction of income inequality through asset-based mechanisms. This integrated theoretical framework guides both the conceptual modeling and empirical strategy of the thesis. Theoretical foundations and their contributions to the analytical framework exhibited in annex 4.

4. The novelty of the Master's thesis, research gaps and research objectives, hypothesis

This master's thesis aims at making a significant contribution to the literature on income inequality by introducing a comprehensive and integrative framework that positions AI not merely as a disruptive force, but as a transformative instrument for inclusive wealth creation.

While existing studies have predominantly focused on the risks or limited benefits of AI in relation to inequality—particularly in terms of automation, labor market polarization, or productivity gains—this thesis shifts the analytical lens toward proactive solutions. It proposes a model in which AI is harnessed deliberately to support asset-based wealth accumulation, particularly among individuals and groups at the lower end of the income distribution.

At the core of this conceptual framework lies the conviction that long-term reductions in inequality require more than redistributive mechanisms or compensation for those displaced by technological change. Rather, the research argues that sustainable inequality mitigation must focus on empowering individuals to build economic assets. In this respect, the thesis integrates the transformative potential of AI with the strategic development of human capital, specifically through targeted skill-building and entrepreneurial education. These elements are framed not as secondary benefits, but as essential channels through which people—especially those from disadvantaged backgrounds—can adapt to changing labor market demands and create new income-generating opportunities.

Crucially, the research highlights the indispensable role of the state in facilitating such transitions. Rather than assuming that market forces alone will generate equitable outcomes, the thesis places government support at the center of its framework. It emphasizes the need for coordinated public investment in digital infrastructure, accessible education, and inclusive entrepreneurial ecosystems. In doing so, it provides an integrated approach that contrasts with much of the existing literature, which tends to analyze technological or policy-based interventions in isolation. The thesis thereby positions state intervention not as a reaction to inequality, but as a proactive enabler of equitable participation in the benefits of AI.

The thesis further distinguishes itself by offering a methodological approach and model that captures the interrelationships among AI adoption, skill development, entrepreneurial education, government support, and income inequality over time. This model is designed to be empirically testable and policy-relevant, allowing researchers and decision-makers to simulate the potential impacts of various interventions. By enabling the tracking of both level and acceleration effects in inequality dynamics, the model extends existing methodological tools and provides a conceptual foundation for further quantitative inquiry.

Moreover, the framework is designed with applicability across both developed and developing economies in mind. Recognizing that institutional capacities and socioeconomic contexts vary widely, the thesis ensures that its recommendations are adaptable and scalable. This broad relevance increases the potential policy utility of its findings and supports the development of internationally comparable strategies for reducing inequality in the era of digital transformation.

Lastly, the thesis offers not only theoretical insights but also a project-based roadmap for practical implementation. It outlines a structured set of actions—grounded in evidence and supported by measurable indicators—that could inform real-world policymaking. This applied dimension reflects a commitment to ensuring that academic research can contribute meaningfully to the design and evaluation of effective social and economic interventions.

The originality of this thesis lies in its dynamic and multidimensional approach to income inequality. By aligning the deployment of AI with investments in skill development, entrepreneurial education, and targeted government action, it moves beyond conventional analyses and proposes a strategic model that addresses both the symptoms and structural drivers of inequality. In doing so, it offers a scalable, inclusive, and future-oriented response to one of the most urgent challenges of the digital age.

Although a substantial body of empirical research has examined the relationship between income inequality and a wide range of socio-economic determinants, there remains a notable gap in understanding the role of AI in addressing income disparities through integrated and multi-dimensional mechanisms. Existing literature predominantly concentrates on conventional approaches to inequality reduction, including educational attainment, labor market regulation, fiscal redistribution, and social policy interventions. While these strategies are well documented, comparatively limited scholarly attention has been devoted to the capacity of AI to enhance equality of opportunity, facilitate targeted skill development, and support entrepreneurial activity, particularly within socio-economically disadvantaged populations. Consequently, the potential of AI as a complementary instrument for promoting income and broader economic equality remains insufficiently explored.

Recent advances in AI applications within educational contexts suggest significant potential for personalized learning and adaptive skill formation. However, current empirical studies tend to focus on general educational outcomes rather than explicitly examining how AI-driven educational tools can accelerate income inequality reduction through entrepreneurial education and labor market–relevant skills training. There is a need for systematic investigation into how AI-enabled personalization can improve access to high-quality entrepreneurial and vocational education for marginalized communities, thereby influencing long-term income outcomes.

Furthermore, the majority of research on entrepreneurial education emphasizes short-term indicators such as skill acquisition, business creation rates, or program participation, with limited longitudinal evidence on sustained income growth, wealth accumulation, and intergenerational mobility. Long-term empirical analyses across different socio-economic environments are necessary to assess whether entrepreneurial education, particularly when supported by AI-based tools, contributes to durable reductions in income inequality over time.

Public policy plays a critical role in shaping the diffusion and effectiveness of AI technologies. While AI is widely recognized as a driver of productivity and economic growth, there is a lack of comparative research on government policies that explicitly support AI integration in education and entrepreneurship as instruments for inequality reduction. Analyzing policy frameworks across countries and regions could provide evidence on which regulatory, financial, and institutional arrangements most effectively enable AI-driven skill development initiatives to address income disparities.

In addition, disparities in access to AI technologies and digital infrastructure represent an underexplored dimension of income inequality. Existing studies often overlook how unequal access to digital tools, data, and connectivity constrains participation in AI-supported education and entrepreneurship, particularly in low-income or rural communities. Empirical research is required to identify the socio-economic determinants of access to AI resources and to evaluate policy and institutional solutions aimed at reducing digital exclusion.

There is also limited comparative evaluation of AI-based initiatives designed to promote skills development and entrepreneurship. Current evidence is fragmented and rarely assesses the relative effectiveness of different AI applications across socio-economic groups. Comparative case studies could provide systematic insights into best practices, scalability, and contextual factors that influence program outcomes in terms of income inequality reduction.

Beyond structural and economic constraints, psychological and social factors influencing entrepreneurial behavior remain insufficiently addressed in the literature. Research has traditionally prioritized access to capital, education, and markets, while giving less attention to behavioral barriers such as risk aversion, lack of confidence, or fear of failure. AI-based assessment and support tools may offer new methods for identifying and mitigating such barriers, particularly among low-income individuals, but empirical validation of these approaches is still limited.

The labor market effects of AI also require careful examination. While AI adoption can generate new employment opportunities, it may simultaneously displace workers in lower-income or routine occupations. Existing studies often analyze job creation and job displacement separately, resulting in an incomplete understanding of AI's net impact on income inequality. Integrated analyses are needed to assess how these opposing dynamics interact and to identify policy strategies that maximize inclusive employment outcomes.

Measuring the success of programs aimed at promoting asset-based wealth through skills development and entrepreneurship presents an additional challenge. There is no consensus on standardized indicators for evaluating long-term impacts on income inequality. Developing comprehensive measurement frameworks that combine quantitative income data with qualitative indicators of economic resilience and opportunity could improve the empirical assessment of such initiatives.

Finally, much of the current research is geographically concentrated, limiting the ability to generalize findings across institutional contexts. Cross-national comparative studies are necessary to evaluate how different policy environments influence the effectiveness of AI-supported education and entrepreneurship initiatives. In this context, the role of non-governmental organizations (NGOs) also remains under-researched, despite their growing involvement in implementing AI-driven educational and entrepreneurial programs. Empirical investigation into NGO-led initiatives could provide additional evidence on their contribution to asset-based wealth formation and income inequality reduction.

The central problem addressed in this Master's thesis is formulated as a research question concerning the extent to which AI can be systematically employed to accelerate the reduction of income inequality. In particular, the study seeks to examine how AI-driven solutions, when combined with asset-based wealth creation strategies, skill development, and entrepreneurial education, and supported by appropriate government policies, can contribute to more equitable income distribution outcomes.

To address this problem, the first research objective is to identify and define the potential of AI in facilitating the reduction of income inequality through mechanisms such as asset-based wealth accumulation, targeted skill development, and entrepreneurship-oriented education, with specific attention to the enabling role of public policy. This objective focuses on establishing a conceptual and empirical foundation for understanding AI as a tool for inclusive economic development.

The second research objective is to analyze an integrated framework that combines AI-powered interventions with skill development initiatives, entrepreneurial education programs, and government support mechanisms. This framework aims to assess how coordinated implementation across these domains can promote sustainable wealth creation and contribute to long-term reductions in income inequality.

The third research objective is to develop evidence-based policy recommendations and a project-oriented implementation plan for governments and relevant stakeholders. This objective seeks to translate analytical findings into actionable strategies that enable the effective and responsible deployment of AI technologies in addressing income inequality.

Finally, the fourth research objective is to evaluate the impact of the proposed interventions on income inequality outcomes. This evaluation aims to assess the effectiveness of AI-supported policies and programs using appropriate qualitative and quantitative indicators, thereby providing empirical insights into their potential contribution to reducing income disparities.

This Master's thesis is guided by a central empirical hypothesis concerning the role of AI in addressing income inequality. The main hypothesis posits that AI-driven interventions—specifically those applied to skill development programs, entrepreneurial education, and government support systems—contribute significantly to the acceleration of income inequality reduction by facilitating asset-based wealth creation among low-income individuals. This hypothesis is grounded in the assumption that AI can enhance the efficiency, targeting, and scalability of existing economic and educational interventions, thereby improving long-term income and wealth outcomes.

In contrast, the null hypothesis asserts that AI-driven interventions do not produce a statistically or economically significant effect on reducing income inequality or on promoting asset-based wealth accumulation among low-income populations. Under this assumption, the integration of AI into skill development, entrepreneurship, and public support mechanisms does not yield outcomes that differ meaningfully from traditional, non-AI-based approaches.

Building on these hypotheses, the research is structured around a central research question that seeks to determine how AI, in combination with skill development initiatives, entrepreneurial education, and government support, can be strategically deployed to accelerate income inequality reduction through asset-based wealth creation. Additionally, the research aims to examine how such interventions can be systematically measured and evaluated across different national and institutional contexts. This includes the identification of appropriate indicators, methodological approaches, and comparative frameworks necessary for assessing the effectiveness and cross-country applicability of AI-supported strategies in reducing income disparities.

5. Methodology

5.1 Data and variables

The empirical backbone of this investigation rests upon a meticulously curated unbalanced panel dataset, serving as the essential quantitative foundation for testing the central hypotheses. This analytical framework spans a critical five-year period, 2018–2022, and encompasses a diverse set of 22 countries, yielding N=110 country-year observations, which could lead to potential limitation while evaluating causal relationships. The selection of nations was a deliberate strategic choice, moving beyond simple availability to focus on those with a pronounced role in the global dynamics under study. The sample purposefully integrates advanced economies (e.g., the United States, Germany, France, Canada, the United Kingdom, and Sweden), recognized for their leadership in AI adoption, alongside strategically chosen large emerging economies (e.g., China, Brazil, Indonesia, and Poland), which often contend with more acute structural income inequality. The final dataset thus captures a rich variation in both technological maturity and socio-economic policy landscapes. The analysis is executed at the country level (NUTS 0), a decision driven by the nature of the data, which is consistently aggregated at the national level by international statistical organizations. While a desire for granular completeness is ideal, the panel is necessarily unbalanced—a pragmatic acknowledgement of the inherent variations in data reporting and publication cycles across different institutions and indicators. This methodological approach is justified by its commitment to maximizing data retention, thereby preserving the explanatory power of the model across the most comprehensive sample possible.

The dependent variable in this thesis is income inequality, measured using the Gini index for both market income and disposable income. Market Gini reflects inequality generated by pre-tax and pre-transfer income distributions, while disposable Gini captures inequality after taxes and transfers, thereby incorporating the redistributive role of public policy. Both indicators are obtained from the Standardized World Income Inequality Database (SWIID), which provides harmonized and internationally comparable inequality estimates across countries and time. SWIID is widely used in cross-country inequality research due to its transparent methodology and its ability to ensure comparability despite differences in national income concepts and survey designs. Using both market and disposable Gini indices allows this study to distinguish between inequality generated by market processes and inequality outcomes after institutional intervention.

The empirical analysis incorporates a set of independent and mediating variables that capture technological capacity, human capital formation, institutional support, and asset accumulation. All variables are measured at the country-year level and are selected based on theoretical relevance, empirical robustness, and data availability within the 2018–2022 panel.

Artificial Intelligence Adoption (AI). Artificial Intelligence doption is proxied using internationally comparable indicators of AI patents, government AI readiness, drawing primarily on AI-related patent counts (number of patents in 3 patent categories: IPC_class, G06N, G06F, G06K) and the Oxford Insights Government AI Readiness Index. These indicators reflect a country's ability to develop, deploy, and govern AI technologies and capture variation in institutional preparedness, technological infrastructure, and innovation ecosystems.

Although Quantum Artificial Intelligence (Quantum AI) is a theoretically established field with significant potential, it refers to the integration of AI techniques with quantum computing technologies. Unlike classical AI, which relies on binary logic and conventional computing architectures, quantum computing exploits quantum-mechanical properties such as superposition and entanglement. While these properties may, in theory, enable more efficient solutions to complex optimization and simulation problems, Quantum AI is not included in this Master's thesis due to its experimental stage of development, the absence of observable and comparable empirical indicators, and its lack of measurable economic and distributional impact within the studied time period.

Skill development (S). Skill development is measured using indicators related to population-level competencies relevant to technologically intensive environments. In the panel, this is operationalized through education- and training-related indicators that capture the quality of skill formation and preparedness for digital and AI-driven labor markets. These measures reflect the capacity of the workforce to adapt to technological change.

Entrepreneurial education and training (E). Entrepreneurial education and training is proxied using the Global Entrepreneurship Monitor (GEM) National Expert Survey indicator on basic school entrepreneurial education and training. This variable captures the extent to which national education systems support entrepreneurial capabilities, innovation, and opportunity recognition, which are essential for translating technological change into productive economic activity.

Government support (G). Government supportis measured using aggregate social expenditure as a percentage of GDP, compiled from the OECD Social Expenditure Database (SOCX) and complementary IMF sources. This variable reflects public investment in social protection, labor market policies, education, health, and related programs that shape the distributional consequences of technological and economic change.

Wealth (W). Wealth is measured using adjusted net wealth per adult, expressed in constant 2022 US dollars, based on data from the Credit Suisse / UBS Global Wealth Databook. This indicator captures asset-based economic resources rather than income flows and allows inequality dynamics to be interpreted from a structural, long-term perspective. Wealth is treated as a key mediating variable through which AI, skills, education, and government support may influence income inequality.

Each of these variables is selected for its empirical robustness, cross-national comparability, and theoretical relevance to the conceptual model presented in this thesis.

To reduce omitted variable bias and isolate the associations of interest, the model includes a standard set of macroeconomic control variables commonly used in the inequality literature.

GDP per capita (GDP). Real GDP per capita (constant 2015 US dollars), obtained from the World Bank World Development Indicators, is included to control for differences in economic development levels across countries. Prior research suggests a potentially non-linear relationship between income levels and inequality (e.g., the Kuznets hypothesis). Accordingly, GDP per capita captures broad income effects that are not directly related to AI or institutional variables.

Trade openness (TO). Trade openness is measured as the sum of exports and imports as a percentage of GDP. This variable controls for a country's exposure to international trade, which can influence inequality through labor market competition, sectoral specialization, and capital mobility. Given that AI diffusion and globalization often occur simultaneously, including trade openness helps disentangle the effects of AI from broader global economic integration.

Globalisation Index (GI). The KOF Globalisation Index is included as a composite measure capturing economic, social, and political dimensions of globalization. This index controls for the multifaceted ways in which cross-border integration, information flows, and international institutional alignment may affect inequality. The expected direction of its association with inequality is theoretically ambiguous and therefore treated empirically.

Here are variables' measurements:

(IIE) Gini disp

- Underlying indicator: Gini index of disposable (post-tax, post-transfer) income.
- Definition: Gini index measures the extent to which the income distribution deviates from perfect equality. It is calculated as the area between the *Lorenz curve* of income and the line of perfect equality, expressed as a percentage of the maximum possible area.
- Scale / unit: Dimensionless **index, 0–100**, where 0 = perfect equality and 100 = maximal inequality.

(IIE) Gini mark

- Underlying indicator: Gini index of market (pre-tax, pre-transfer) income.
- Definition: Same Gini methodology as above, but computed on *market income* (before personal income taxes and cash transfers).
- Scale / unit: Dimensionless **index, 0–100**, same as disposable Gini.

(AI) Patent count

- Underlying indicator: Number of patent applications (or granted patents), by priority date and inventor residence.
- Definition: Number of Patents.
- Metric / unit: **No of patents**

(AI) The Oxford Insights Government AI Readiness Index (GAIRI)

- It is a composite, country-level index (0–100 scale) that measures how prepared national governments are to implement AI in the delivery of public services. According to Oxford Insights, the core question is: how ready is a given government to implement AI in the delivery of public services to their citizens?
- Metric / unit: **index score from 0 to 100**, higher values = greater government AI readiness.
- Country-year composite score between 0 and 100, obtained as the equally weighted average of 39 normalised indicators grouped into 10 dimensions and 3 pillars (Government, Technology Sector, Data & Infrastructure), capturing national government readiness to implement AI in public services.

(S) Government expenditure

- Underlying indicator: General government expenditure (% of GDP).
- Definition: Total current expenditure by government on education expressed as a percentage of GDP.
- Metric / unit: **Percentage of GDP.**

(E) Entrepreneurial education and training

- Underlying indicator: GEM National Expert Survey (NES) "Basic School Entrepreneurial Education and Training" index.
- Scale / unit: Likert scale 1-9 , where 1 = "highly insufficient" and 9 = "highly sufficient", as explicitly stated in **GEM** country reports.
- Metric type: Ordinal index; higher = better entrepreneurial education environment in basic schools.

(G) Governments' Social Expenditure (agreg. SOCX+IMF)

- Governments' expenditure across policy areas as: old-age, incapacity, health, family, ALMP (Active Labour Market Policies), unemployment, housing.
- Scale / unit: **Percentage of GDP.**

(W) Adjusted net wealth per adult

- Underlying indicator: Net wealth per adult, adjusted to 2022 US dollars, based on Credit Suisse / UBS Global Wealth Databook.
- Definition: Average net wealth (net assets) per adult: total value of financial and non-financial assets (e.g. housing, financial portfolios) minus debts and liabilities, divided by the number of adults.
- Scale / unit: **Constant 2022 USD per adult**.

(GDP) Real GDP

- Underlying indicator: World Bank WDI GDP (constant 2015 US$).
- Definition: Gross domestic product = total value added (or total income) generated by the production of goods and services within the country during a year, adjusted for inflation to 2015 prices.
- Scale / unit: Constant 2015 USD

(TO) Trade openness

- Underlying indicator: Trade (% of GDP), World Bank WDI code NE.TRD.GNFS.ZS ("Trade as share of GDP").
- Definition: *Sum of exports and imports of goods and services, divided by GDP*, expressed as a percentage.
- Scale / unit: **Percentage of GDP (%)**.

(GI) Globalization index

- Underlying indicator: KOF Globalisation Index (KOFGI).

- Definition: **Composite index** measuring economic, social and political dimensions of globalisation; overall index is average of de facto and de jure indices across these three dimensions.
- Scale / unit: **Index 1–100** (effectively 0–100), where higher values indicate more globalised economies.

X: Vector of control variables (GDP per capita, trade oppeness, globalization index)

i: country

t: year

Table 1

Conceptual Structure and Role of Variables in the Empirical Model

Variable	Label	Type	Role in Model	Main Data Source
Income Inequality	IIE	Dependent	Outcome variable (market & disposable Gini)	SWIID
AI Adoption	AI	Independent	Primary explanatory variable	Oxford Insights, OECD
Skill Development	S	Mediator	Transmits AI effects	Education/skills datasets
Entrepreneurial Education	E	Mediator	Enhances innovation capacity	GEM NES
Government Support	G	Moderator / Independent	Shapes institutional context	OECD SOCX
Wealth	W	Mediator	Captures asset-based accumulation	Credit Suisse / UBS
GDP per capita	GDP	Control	Development level control	World Bank WDI
Trade Openness	TO	Control / Moderator	Global integration control	World Bank WDI
Globalization	GI	Control / Moderator	Broad external influence	KOF Index

Source: Author's compilation based on the theoretical and methodological framework of the thesis.
Notes: Conceptual table only; measurement, units, and data sources are reported separately.

The interrelationship between AI, skill development, entrepreneurial education, government support, and wealth creation presents a complex and dynamic framework within which income inequality is either exacerbated or mitigated. Each of these components plays a distinct yet interrelated role in shaping economic outcomes, with their collective impact depending largely on how equitably they are deployed and accessed across populations.

Artificial intelligence serves as a transformative force in modern economies, capable of displacing routine and low-skill jobs through automation while simultaneously creating new employment opportunities that require advanced technical, cognitive, and creative capabilities. This duality underscores the critical role of skill development in determining who benefits from AI-induced changes. As AI technologies evolve, workers must adapt by acquiring competencies in fields such as data science, machine learning, and digital literacy. The extent to which societies are able to provide inclusive and accessible training programs will significantly influence whether AI becomes a driver of shared prosperity or a catalyst for deeper inequality. In scenarios where skill acquisition is uneven or inaccessible, low-skilled workers risk being excluded from emerging labor markets, thereby intensifying existing income disparities.

Beyond employment, AI also creates new avenues for entrepreneurship and innovation. The proliferation of AI-powered tools lowers barriers to entry in many sectors, allowing individuals to launch and scale businesses with unprecedented efficiency. However, the capacity to recognize and exploit these opportunities is contingent on adequate entrepreneurial education. Early exposure to entrepreneurial principles equips individuals with the mindset and tools to navigate the risks and rewards of business creation in the digital age. In contexts where entrepreneurial education is widely available, AI can serve as an equalizing force by democratizing wealth creation. Conversely, in the absence of such education, the gains from AI-driven innovation may become concentrated in the hands of a technologically literate elite, thereby worsening inequality.

Government intervention plays a central role in shaping the extent to which AI and associated opportunities are inclusive. Public policy can facilitate equitable access to AI-related benefits through a combination of regulation, financial support, and infrastructure development. This includes targeted subsidies for skills training, grants and tax incentives for startups, and investments in digital infrastructure in underserved regions. Moreover, governments can implement safeguards to ensure that the economic benefits of AI are not monopolized by large corporations or concentrated in specific geographical areas. Regulatory mechanisms, such as competition laws and progressive taxation, can help redistribute AI-generated gains and fund public programs that enhance human capital and social protection.

The relationship between AI and wealth creation is particularly salient in the context of asset-based welfare. AI technologies offer individuals and firms new tools to improve productivity, make data-driven investment decisions, and enhance operational efficiency. This can accelerate the accumulation of financial and non-financial assets among those who have access to these tools. Yet, this same dynamic poses a risk of deepening inequality if access to AI remains restricted to already-wealthy actors. When AI-driven financial platforms and investment tools are broadly accessible, they can enable a larger segment of the population to engage in asset accumulation, thereby contributing to a more equitable economic landscape.

Skill development and entrepreneurial activity further reinforce the potential for widespread wealth creation. Individuals equipped with the right skills are more likely to secure well-paying jobs in AI-related sectors or to innovate within them. When combined with entrepreneurial acumen, these skills allow individuals not only to earn income but to build and own productive assets. This transition from wage dependence to asset ownership marks a significant shift in the structure of inequality, as it enables more durable and intergenerational forms of economic security.

Government support remains a pivotal determinant in this ecosystem. Effective public policy can ensure that AI development aligns with societal goals, mitigating the risks of exclusion and displacement. This may involve progressive regulation of AI technologies, inclusive taxation and redistribution systems, or the implementation of social safety nets such as universal basic income or retraining programs for displaced workers. Such measures can serve to redistribute both the risks and the rewards of technological advancement, fostering a more inclusive economic trajectory.

In sum, the relationship between AI and inequality is not linear or deterministic. Rather, it is mediated by multiple factors, including the availability of skills training, the accessibility of entrepreneurial education, the design of public policy, and the distribution of digital infrastructure. When these elements are aligned, AI can serve as a powerful force for inclusive growth, enabling broader participation in wealth creation and reducing income disparities. However, in the absence of strategic intervention, the same technological forces can amplify existing inequalities and entrench structural disadvantages. The framework developed in this thesis thus emphasizes the importance of integrated, multi-level strategies that combine technological innovation with human capital development and inclusive public policy to ensure that the benefits of AI are equitably distributed.

5.2. Research design and model Specification

This research follows a **mixed-methods** design, combining a broad cross-country quantitative analysis with qualitative case study. The rationale is to leverage the strengths of each approach – generalizability from the quantitative panel data and contextual richness from qualitative evidence – to address the complex question of how AI can accelerate reductions in income inequality. In particular, an explanatory sequential mixed-methods strategy is employed (quantitative analysis conducted first, followed by qualitative case studies) as described in "*Designing and Conducting Mixed Methods Research*" by Creswell & Plano Clark, 2018).

The quantitative component identifies macro-level relationships between AI, skills, entrepreneurship education, government support, and income inequality across countries.

The qualitative component through case studies then explores how and why those relationships manifest in specific national contexts, helping to interpret the statistical findings. This design allows the study to gain a more complete picture than could be achieved by a standalone quantitative or qualitative approach, as recommended in contemporary mixed-methods research.

5.2.1. Quantitative methods

The model through different econometric techniques aims to simulate how AI-driven interventions affect income inequality by increasing asset-based wealth (human capital, entrepreneurial assets). The system of differential equations is used to represent the growth and interaction of these variables, with inequality measured via a proxy like the Gini coefficient. The core idea is that AI amplifies skill development (S), entrepreneurial activity (E), and government-backed wealth redistribution, government support (G), which collectively build individual wealth (W) and reduce inequality (IIE).

Assumptions:

- The logistic growth assumption is rooted in technology diffusion theory, particularly the S-curve model (Rogers, 2003). Technologies typically spread slowly at first, accelerate during mid-stage adoption, and then plateau as saturation is approached.
- Based on human capital theory (Becker, 1964) and recent work on digital skills development in response to technological change. AI-enabled education tools are shown to facilitate scalable and adaptive skill formation.
- Entrepreneurial assets (E) depend on skills and AI tools, with a success rate tied to education: this aligns with entrepreneurial human capital theory and resource-based views that link entrepreneurial success to prior skills, knowledge, and digital tool accessibility (Davidsson & Honig, 2003; Shane, 2003).
- Drawn from theories of fiscal capacity and political economy, which suggest that government policy responsiveness is linked to economic returns but moderated by institutional and political constraints (Stiglitz, 1987; Acemoglu & Robinson, 2001).

- Wealth (W) aggregates S, E, and G, and reduces inequality (IIE) as it becomes more evenly distributed: This assumption draws from asset-based welfare theory and inclusive growth frameworks, which posit that wealth built through education, entrepreneurship, and public policy reduces long-term inequality (Sherraden, 1990; Piketty, 2014).
- Based on the definition of inequality as measured by dispersion indicators such as the Gini index. As wealth distribution becomes more equal, statistical measures of inequality decline (Atkinson, 2015; Solt, 2020).

An expanded reduced-form model incorporating these relationships is formulated:

$$IIE_{it} = \beta_0 + \beta_1 AI(patents)_{it} + \beta_2 AI(readiness)_{it} + \beta_3 S_{it} + \beta_4 E_{it} + \beta_5 G_{it} + \beta_6 W_{it} + \beta_7 X_{it} + \mu_{it} \quad \{1\}$$

$$\beta_0 = E\left(IIE_{it}/AI_{it} = 0, S_{it} = 0, E_{it} = 0, G_{it} = 0, W_{it} = 0, X_{it} = 0\right) \{2\}$$

Each subsequent βetas represents the ceteris paribus (all else equal) effect of one explanatory variable on the dependent variable IIE_{it}:

Table 2

Interpretation of Estimated Coefficients (Marginal Effects)

Coefficient (marginal effects)	Interpretation and formula
β1	β1=∂IIEit/∂AIit effect of AI adoption {3}
β2	β2=∂IIEit/∂Sit effect of skill development {4}
β3	β3=∂IIEit/∂Eit effect of entrepreneurial education {5}
β4	β4=∂IIEit/∂Git effect of government support {6}
β5	β5=∂IIEit/∂Wit effect of wealth accumulation {7}
β6	β6=∂IIEit/∂Xit effect of control variables (GDP per capita, trade openness, globalization) {8}

Source: Author's compilation based on the econometric model specification.
Notes: Subscripts *i* and *t* refer to country and year, respectively.

The expected empirical relationships examined in this study are based on established findings in the literature on income inequality, skill formation, and public policy. First, AI is expected to be associated with a reduction in income inequality when its development and implementation are guided by inclusive governance frameworks. Under such conditions, AI adoption is anticipated to enhance access to education, labor market opportunities, and productive assets, thereby contributing to more equitable income distribution. Second, investments in skill development, entrepreneurial activity, and government support mechanisms are expected to exhibit a negative relationship with income inequality. Empirical evidence suggests that human capital accumulation, support for entrepreneurship, and public interventions aimed at wealth creation facilitate income growth among lower-income groups and promote asset accumulation, which in turn contributes to a narrowing of income disparities. Finally, the direction and magnitude of these effects are expected to vary depending on a set of control variables. Factor such as levels of economic development may moderate the impact of AI-driven interventions, resulting in heterogeneous outcomes across countries and socio-economic contexts.

5.2.2. Qualitative methods

The qualitative component of this Master's thesis is designed to complement the quantitative panel econometric analysis by providing an in-depth institutional and policy-based examination of a single national case. In line with the mixed-methods research design outlined in the methodology chapter, the qualitative approach adopts a single-country case study, focusing exclusively on Norway. This design choice reflects the objective of deepening the understanding of causal mechanisms identified in the quantitative analysis rather than maximizing cross-country variation.

Norway is selected as the qualitative case due to its distinctive combination of characteristics identified in the empirical analysis, including relatively low disposable income inequality, high levels of public social expenditure, strong institutional capacity, advanced digital infrastructure, and a high degree of government readiness for AI implementation. These features make Norway a theoretically relevant and empirically informative case for examining how AI-related policies, skill development systems, and entrepreneurial education interact within a coordinated welfare-state framework to influence income inequality outcomes.

The qualitative analysis relies exclusively on secondary data sources, ensuring methodological consistency and reproducibility. The primary materials include official Norwegian government policy documents, national AI strategies, education and skills development frameworks, entrepreneurship support programs, and social welfare policy reports.

A structured qualitative content analysis is applied to these materials. The analysis follows an analytical framework derived directly from the theoretical foundations of the thesis, including human capital theory, asset-based welfare theory, innovation economics, and theories of government intervention. Policy documents are examined to identify AI integration into public service delivery, education and training systems, and entrepreneurship support mechanisms, as well as how these interventions are aligned with broader redistribution and social protection policies.

The qualitative case study focuses on four interrelated dimensions. First, it examines Norway's national approach to AI governance and public-sector AI deployment, with particular attention to inclusiveness, regulatory oversight, and institutional coordination. Second, it analyzes skill development policies and lifelong learning systems, assessing how digital and AI-related competencies are incorporated into formal education and adult training frameworks. Third, it evaluates entrepreneurial education and support structures, including the role of public agencies in facilitating technology-driven entrepreneurship and asset accumulation. Fourth, it assesses the interaction between these AI-related interventions and Norway's redistributive welfare state, focusing on how social expenditure and public investment mitigate potential inequality-enhancing effects of technological change.

The purpose of the qualitative analysis is not to establish causal inference in a statistical sense but to provide contextualized explanatory evidence that clarifies how and why the relationships identified in the quantitative analysis manifest in a specific institutional setting. The Norway case allows for the identification of enabling conditions, policy complementarities, and institutional safeguards that shape the distributional consequences of AI adoption.

The findings from the qualitative case study are subsequently integrated with the quantitative results to enhance interpretative validity and policy relevance. This integration supports the development of evidence-based policy recommendations and informs the project-based implementation framework presented in the later chapters of the thesis, ensuring that proposed interventions are grounded in empirically observed institutional practices.

6. Research results

6.1. Quantitative research results

The quantitative analysis is designed to rigorously test the impact of AI adoption on income inequality and the modifying role of the specified variables, while addressing the econometric challenges of panel data (such as non-stationarity, heterogeneity, and endogeneity). All estimations are conducted using the R statistical software, with specialized packages for panel analysis. The approach involves several stages: preliminary diagnostic tests (for cross-section dependence, unit roots), panel cointegration analysis to check for a long-run equilibrium relationship, model estimation using a suitable panel error-correction model (specifically, the Cross-Sectional Augmented ARDL), robustness tests using alternative indicators, causality tests.

The following panel data econometric techniques are performed:

6.1.1. Descriptive statistics and exploratory analysis

The dataset comprises 110 country–year observations covering the period 2018–2022 for 22 countries: Argentina, Austria, Brazil, Canada, China, Costa Rica, Denmark, Egypt, France, Georgia, Germany, Indonesia, Ireland, Moldova, Norway, Poland, Singapore, Sweden, Türkiye, the United Kingdom, the United States, and Uruguay. The countries included in the dataset were selected based on analytical relevance and data availability. The sample consists of countries for which internationally comparable data exist for key variables central to the research framework, including income inequality, macroeconomic indicators, asset-based wealth, and measures of artificial intelligence capacity. Limiting the sample to countries with sufficient data coverage ensures internal consistency and reduces measurement error arising from heterogeneous reporting standards. At the same time, the selected countries display substantial variation in economic development, institutional arrangements, income distribution, and approaches to technology governance. This cross-country heterogeneity is methodologically important, as it allows the analysis to identify conditional and mediated relationships between AI capacity and income inequality rather than assuming uniform effects. The resulting unbalanced panel reflects standard practice in cross-country panel studies, prioritizing analytical breadth and institutional diversity while accommodating differences in data availability across indicators and years.

All variables are measured at the national level, and the panel is unbalanced due to differences in data availability across indicators and years. An examination of missingness reveals that all inequality measures and macroeconomic variables are fully observed, whereas some institutional and policy-related indicators—specifically AI readiness, entrepreneurial education, and social expenditure—are available only for a subset of country–year observations. This pattern reflects the reliance of these indicators on survey-based or institution-specific reporting rather than continuous administrative data.

An examination of missing data reveals a clear distinction between core outcome and macroeconomic variables, which are fully observed, and policy- or survey-based indicators, which exhibit partial coverage. No missing observations are present for income inequality measures (market and disposable Gini indices), AI patent counts, wealth per adult, GDP, trade openness, or the globalization index. In contrast, the AI readiness index exhibits 44 missing observations (40 percent of the panel), entrepreneurial education 43 missing observations (39.09 percent), social expenditure 25 missing observations (22.73 percent), and government expenditure on education 5 missing observations (4.55 percent). Consequently, all inequality and macroeconomic indicators are complete, while selected institutional and policy variables are observed only for subsets of country–year combinations.

Table 3

Summary of Data Coverage and Missingness

Variable group	Missing observations	Share missing
Income inequality (Gini disp., Gini mark)	0	0.00%
AI patents	0	0.00%
Wealth, GDP, trade openness, globalization	0	0.00%
AI readiness index	44	40.00%
Entrepreneurial education	43	39.09%
Social expenditure	25	22.73%
Government expenditure (% GDP)	5	4.55%

Source: Author's calculations based on SWIID, OECD, Oxford Insights, GEM, World Bank, and KOF databases.
Notes: The panel is unbalanced; missingness reflects data availability across countries and years.

Across the full panel, income inequality exhibits clear and systematic patterns. Disposable income inequality averages 34.88 on a 0–100 scale, while market income inequality is consistently higher, with a mean of 48.46. For every country–year observation, the market Gini exceeds the disposable Gini, underscoring the role of taxes and transfers in reducing inequality (see Annex 1). Variation across observations is moderate, but the range of values indicates substantial cross-country differences in both pre- and post-redistribution income distributions. Indicators of artificial intelligence activity display pronounced heterogeneity. AI patent counts are highly skewed, with most observations characterized by very low values and a small number of country–years accounting for the majority of patenting activity. By contrast, the government AI readiness index, available for a subset of observations, is more evenly distributed and concentrated in the middle-to-upper range of the scale, suggesting relatively high but uneven institutional preparedness for AI across countries. Public expenditure variables further highlight cross-country diversity. Government spending on education averages 4.88 percent of GDP, while social expenditure is substantially higher and more dispersed, with an average of 20.90 percent of GDP. Entrepreneurial education levels are generally moderate, with values clustered in the lower-to-middle range of the scale, indicating limited variation but relatively modest overall intensity. Economic size and wealth indicators show especially large disparities. Adjusted net wealth per adult varies widely across countries, as does real GDP, reflecting substantial differences in economic scale and asset accumulation. Measures of openness and global integration also vary considerably, with trade openness spanning a wide range and the globalization index indicating generally high but heterogeneous levels of international integration.

Country-level averages reveal marked contrasts within the sample. Brazil records the highest average income inequality, while Norway exhibits the lowest disposable income inequality. The United States stands out with the highest average levels of AI readiness, AI patenting, GDP, and wealth per adult, whereas countries such as Moldova, Costa Rica, and Argentina are positioned toward the lower end of several distributions. Differences in public expenditure are also evident, with Sweden exhibiting the highest average education spending and France the highest social expenditure share.

Table 4

Cross-Sectional Extremes Based on Country Means

Dimension	Lowest mean	Highest mean
Disposable Gini	Norway (26.42)	Brazil (46.48)
Market Gini	Argentina (39.80)	Brazil (59.80)
AI readiness	Moldova (41.83)	United States (86.45)
AI patents	Costa Rica (0.00)	United States (9 396.18)
Social expenditure	Singapore (7.13 %)	France (32.12 %)
Wealth per adult	Argentina (10 714 USD)	United States (552 892 USD)
Globalization index	Indonesia (61.83)	United Kingdom (87.93)
Trade openness	United States (25.78 %)	Singapore (328.91 %)

Source: Author's calculations based on SWIID, OECD, Oxford Insights, Credit Suisse/UBS, World Bank, and KOF Globalisation Index.

Notes: Values represent country-level means over the 2018–2022 period.

Panel means over time show limited variation in income inequality. Disposable Gini fluctuates narrowly between 34.70 and 34.98, and market Gini between 48.25 and 48.55, indicating high persistence in inequality measures. In contrast, AI patent activity increases markedly between 2018 and 2021, before a slight decline in 2022, remaining well above initial levels. AI readiness, observed from 2020 onward, rises between 2020 and 2021 and remains above the 2020 level in 2022.

Table 5

Yearly Descriptive Statistics (2018–2022)

Variable	Statistics	2018	2019	2020	2021	2022
Gini Disposable	Mean	34.98	34.88	34.7	34.89	34.95
	SD	6.68	6.67	6.57	6.4	6.36
Gini Market	Mean	48.5	48.45	48.55	48.54	48.25
	SD	4.41	4.42	4.6	4.59	4.42
AI Patent Units	Mean	262.89	429.7	588.09	677.94	638.94
	SD	1035.16	1688.39	2280.22	2584.13	2367.22
Gov. AI Readiness	Mean	—	—	63.28	66.45	65.73
	SD	—	—	14.81	13.7	13.01

Source: Author's calculations based on SWIID, OECD, and Oxford Insights.
Notes: Government AI readiness data are available from 2020 onward; values are unreported for earlier years due to data unavailability.

Public and social expenditure both increase between 2018 and 2020 and then decline toward 2022. Entrepreneurial education peaks around 2019–2020 and is lower in subsequent years. Average wealth per adult rises steadily from 2018 to 2021 and declines in 2022, while GDP recovers after a dip in 2020. Trade openness decreases temporarily in 2020 and exceeds pre-2020 levels by 2022. The globalization index remains highly stable throughout the period.

Table 6

Mean Values of Variables (2018–2022)

Year	Public Exp. (S)	Social Exp. (G)	Entrep. Edu.	Wealth per Adult	Real GDP (Trillions)	Trade Openness	Globaliz. Index
2018	4.87%	19.80%	3.31	$179,326.00	$2.37	85.80%	76.91
2019	4.93%	19.94%	3.9	$188,393.00	$2.45	87.34%	76.98
2020	5.10%	23.52%	3.88	$202,222.00	$2.40	82.42%	76.42
2021	4.84%	21.25%	2.98	$222,717.00	$2.57	86.63%	76.64
2022	4.68%	19.98%	3.09	$189,774.00	$2.65	95.51%	76.87

Source: Author's calculations based on OECD, IMF, GEM, Credit Suisse/UBS, World Bank, and KOF databases.
Notes: All values represent unweighted country-year means; monetary variables are expressed in constant prices as specified in the methodology.

Taken together, the descriptive statistics highlight substantial cross-country heterogeneity and strong persistence over time, particularly for inequality outcomes, providing essential context for the subsequent econometric analysis.

6.1.2 Correlations calculations

Subsequently bivariate associations among the key variables were examined. Correlation analysis serves as an exploratory step that complements descriptive statistics by identifying the direction and strength of linear relationships between pairs of variables prior to multivariate estimation. While correlation analysis does not imply causality, it provides important information on empirical regularities, potential multicollinearity, and consistency with the conceptual framework.

Pairwise Pearson correlation coefficients were computed for all variables, all available country–year observations for each variable pair, implying that the number of observations varies across correlations due to partial missingness in selected institutional indicators. This approach maximizes the use of observed data while preserving transparency regarding coverage differences.

The correlation results indicate systematic differences between market income inequality and disposable income inequality in their associations with other variables. Disposable income inequality exhibits a strong negative correlation with wealth per adult, suggesting that countries with higher average wealth levels tend to display lower post-redistribution inequality. A similarly strong negative correlation is observed between disposable inequality and the globalization index, indicating that more globally integrated countries in the sample tend to exhibit lower disposable income inequality.

Market income inequality, by contrast, shows weaker correlations with most explanatory variables. Its association with wealth is negative but less pronounced than for disposable inequality, while correlations with AI-related indicators are small in magnitude. These patterns are consistent with the conceptual distinction between inequality generated by market processes and inequality outcomes after redistribution.

Strong positive correlations emerge among AI adoption indicators, wealth, and globalization. AI patent counts and the AI readiness index are both positively correlated with wealth per adult, indicating that countries with greater technological capacity and innovation intensity tend to exhibit higher levels of asset accumulation. Globalization is also strongly positively correlated with wealth and AI indicators, suggesting that technological development and global integration are closely intertwined at the country level.

At the same time, correlations between AI indicators and income inequality are comparatively weak, particularly for market income inequality, suggesting that any relationship between AI adoption and inequality is unlikely to be direct and may operate through intermediate structural variables, such as wealth accumulation or institutional arrangements, rather than through immediate distributional effects.

Government expenditure on education and social expenditure are positively correlated, indicating that countries allocating higher levels of public resources to one domain of social policy also tend to prioritize investment in other forms of human capital and social protection. Social expenditure exhibits a negative correlation with disposable income inequality, whereas its correlation with market inequality is weaker. Entrepreneurial education shows moderate positive correlations with AI readiness and globalization, indicating that countries with more developed institutional and international environments tend to score higher on entrepreneurship-related educational measures.

However, entrepreneurial education and skill-related indicators exhibit limited correlation with short-run changes in inequality, consistent with their role as slow-moving structural variables rather than immediate determinants of income distribution.

GDP per capita is strongly positively correlated with wealth per adult and globalization, reflecting the close association between economic development, asset accumulation, and global integration. Trade openness is positively correlated with globalization and AI indicators but exhibits a more heterogeneous relationship with inequality measures. These correlations highlight the importance of including macroeconomic controls in the regression analysis to avoid confounding effects.

The correlation matrix below reveals relatively high pairwise correlations among wealth, GDP per capita, globalization, and AI indicators. This pattern signals a potential risk of multicollinearity in multivariate regressions and motivates the use of parsimonious model specifications and robustness checks in the econometric analysis.

To facilitate interpretation, the full set of pairwise correlations is presented in Annex 2. The heat map visually highlights clusters of strongly correlated variables, particularly among AI indicators, wealth, GDP per capita, and globalization. In contrast, correlations involving income inequality measures—especially market income inequality—are generally weaker and more dispersed.

The graphical representation underscores two key empirical regularities observed in the data: first, the close association between technological capacity, globalization, and wealth accumulation; and second, the comparatively weak direct association between AI indicators and inequality outcomes. These regularities inform the subsequent econometric strategy by emphasizing the importance of mediating and structural channels rather than direct short-run effects.

The correlation analysis documented Pearson correlation matrix, Annex 2 provides preliminary evidence of strong structural linkages among AI adoption, globalization, and wealth, alongside a robust negative association between wealth and disposable income inequality. At the same time, the absence of strong bivariate correlations between AI indicators and inequality suggests that simple direct relationships are unlikely to capture the complexity of the underlying mechanisms. These findings motivate the multivariate panel estimations that follow, which are designed to account for unobserved heterogeneity, dynamic adjustment, and common global factors.

Table 7

Pearson correlation matrix

Variables	(IIE) Gini disp	(IIE) Gini mark	(AI) Patent	(AI) Readiness	(S)	(E)	(G)	(W)	(GDP)	(TO)	(GI)
(IIE) Gini disp	1	-0.096	0.108	-0.487	-0.3978	-0.084	-0.495	-0.571	0.201	-0.305	-0.8
(IIE) Gini mark	-0.096	1	0.234	0.261	0.489	-0.262	0.418	0.288	0.267	-0.156	0.279
(AI) Patent	0.108	0.234	1	0.377	0.045	0.098	-0.02	0.458	0.8	-0.195	0.088
(AI) Readiness	-0.487	0.261	0.377	1	0.195	0.26	0.286	0.85	0.417	0.252	0.764
(S)	-0.397	0.489	0.045	0.195	1	0.052	0.613	0.325	-0.018	-0.215	0.4
(E)	-0.084	-0.262	0.098	0.26	0.052	1	-0.158	0.345	0.146	-0.052	0.11
(G)	-0.495	0.418	-0.02	0.286	0.613	-0.158	1	0.352	-0.098	-0.464	0.481
(W)	-0.571	0.288	0.458	0.85	0.325	0.345	0.352	1	0.322	0.286	0.835
(GDP)	0.201	0.267	0.8	0.417	-0.018	0.146	-0.098	0.322	1	-0.301	-0.033
(TO)	-0.305	-0.156	-0.195	0.252	-0.215	-0.052	-0.464	0.286	-0.301	1	0.403
(GI)	-0.8	0.279	0.088	0.764	0.4	0.11	0.481	0.835	-0.033	0.403	1

Source: Author's calculations based on the compiled 2018–2022 country-year panel dataset.
Notes: Pearson correlation coefficients are computed pairwise; the number of observations may vary across variable pairs due to missing data in selected indicators.

In summary Pearson correlation analysis reveals that while disposable income inequality has a strong negative correlation with wealth and globalization, market income inequality shows much weaker associations with most factors. Ultimately, the results indicate that the link between AI adoption and inequality is likely indirect, operating through structural variables like wealth accumulation rather than through immediate effects.

6.1.3 Ordinary Least Squares (OLS) Analysis

The Ordinary Least Squares (OLS) regression analysis is conducted as an initial structural step in the empirical strategy. Given the broader econometric sequence adopted in this thesis—ranging from descriptive statistics and panel diagnostics to cross-sectionally augmented dynamic models—OLS serves as a benchmark framework for understanding linear associations between AI, wealth, policy variables, and income inequality. Although OLS is not designed to fully address endogeneity, cross-sectional dependence, or dynamic adjustment, it provides a transparent starting point against which more advanced estimators can later be interpreted.

OLS estimates the parameters of a linear regression model by minimizing the sum of squared residuals between observed and predicted values. Under standard assumptions—linearity, zero conditional mean of the error term, no perfect multicollinearity, homoscedasticity, and independence—OLS estimators are unbiased and consistent. In this thesis, heteroskedasticity-robust (HC1) standard errors are used throughout to relax the homoscedasticity assumption and ensure valid inference in the presence of heteroskedastic residuals.

Given the panel structure of the dataset (22 countries observed over 2018–2022), three OLS-based approaches are considered: pooled OLS, one-way country fixed-effects OLS (FE-OLS), and two-way fixed-effects OLS.

The data exhibit strong and persistent cross-country heterogeneity in income inequality, wealth per adult, AI capacity, globalization, and institutional characteristics. These features are plausibly correlated with the regressors of interest, rendering pooled OLS and random-effects approaches inappropriate due to likely omitted-variable bias. By employing a one-way country fixed-effects OLS, the model successfully captures time-invariant country-specific influences that correlate with the explanatory variables.

Across multiple specifications, the fixed-effects OLS results consistently indicate that AI readiness does not have a statistically significant within-country effect on either disposable or market income inequality once country fixed effects and key controls are included. Estimated coefficients on AI readiness are small in magnitude, imprecisely estimated, and associated with robust p-values well above conventional significance thresholds. Consequently, the null hypothesis cannot be rejected.

By contrast, wealth per adult emerges as a statistically significant correlate of disposable income inequality in several fixed-effects specifications. When wealth is included in logarithmic form, its coefficient is negative and statistically significant at the 5% level in the disposable-income equation, implying that within-country increases in wealth per adult are associated with modest reductions in disposable inequality. This relationship does not extend robustly to market income inequality, for which wealth coefficients are statistically insignificant.

Other policy and macroeconomic variables—government education expenditure, entrepreneurial education, globalization, and trade openness—do not exhibit robust within-country effects on inequality in the fixed-effects framework. Real GDP shows occasional borderline significance, but results are not stable across specifications or inequality measures.

A striking feature of all fixed-effects models is the extremely high R^2 values (often exceeding 0.99), driven primarily by the inclusion of country fixed effects. This indicates that the bulk of inequality variation in the sample is cross-sectional rather than temporal, reflecting deep structural and institutional differences between countries rather than short-run dynamics.

To align the econometric analysis with the conceptual DAG, separate fixed-effects regressions were estimated for individual causal arrows. These results indicate that, once country fixed effects are included, there is no statistically significant within-country relationship between AI readiness or AI patent intensity and wealth per adult. Similarly, education expenditure, social expenditure, and entrepreneurial education do not display robust within-country effects on wealth. These findings suggest that wealth is largely time-invariant within countries over the sample period and that most of its variation is absorbed by country fixed effects. However, fixed-effects regressions of wealth on inequality confirm a statistically significant negative association with disposable inequality, reinforcing the interpretation of wealth as a key structural correlate of post-redistribution inequality rather than a short-run transmission channel of AI effects.

In contrast to fixed-effects estimates, pooled OLS regressions reveal strong and highly statistically significant associations between AI indicators and wealth per adult. Both AI readiness and AI patent counts are positively and robustly associated with wealth, with large effect sizes and high explanatory power. Similarly, pooled regressions show strong negative associations between wealth and disposable inequality, alongside positive associations with market inequality. Globalization and trade openness are also strongly negatively associated with disposable inequality in pooled models. These pooled results reflect between-country differences rather than within-country dynamics and must therefore be interpreted as descriptive cross-sectional associations rather than causal effects. The contrast between pooled and fixed-effects estimates highlights the importance of country-specific structural factors and underscores the risk of conflating between-country and within-country relationships.

Two-way fixed-effects models including both country and time dummies were estimated as a robustness check. Time fixed effects were uniformly insignificant, while their inclusion substantially reduced degrees of freedom without improving explanatory power. Given the short time dimension and the absence of strong common time shocks, one-way country fixed-effects models were retained as the preferred OLS specification. OLS analysis summarised findings reported in Annex 3.

In summary, the OLS analysis indicates that short-run within-country changes in AI readiness are not empirically associated with changes in income inequality. At the same time, strong and systematic cross-country associations link AI intensity, wealth, and inequality, particularly for disposable income. These findings suggest that AI-related inequality dynamics operate primarily through long-run structural channels rather than short-term adjustments, which motivates the use of dynamic and cross-sectionally augmented panel estimators in subsequent sections.

6.1.4 Mundlak Results Analysis. Distinguishing short-run effects from long-run effects

The Mundlak (1978) specification was employed to disentangle short-run (within-country) effects from long-run (between-country/structural) effects in the relationship between AI, economic development, public expenditure, and disposable income inequality. The Mundlak approach extends the random-effects framework by explicitly allowing correlation between time-varying regressors and unobserved country-specific effects through the inclusion of country-level means of the regressors.

The estimated short-run coefficients indicate no statistically significant within-country relationship between disposable income inequality and contemporaneous changes in the explanatory variables once long-run components and controls are taken into account.

The short-run coefficient on log GDP is negative (−1.088) but statistically insignificant (standard error 1.497, $p = 0.47$), implying that year-to-year fluctuations in economic output within a country are not associated with measurable changes in disposable income inequality. Similarly, the short-run coefficient on log AI patents is small and positive (0.050) with a large standard error (0.185) and a p-value of 0.79, indicating no detectable short-term effect of changes in AI patenting activity on inequality. Government expenditure *S* also exhibits a negative but statistically insignificant short-run coefficient (−0.219, $p = 0.21$).

Table 8

Mundlak Correction Analysis

Variable	Term	Coefficient	Std. Error	Significance
GDP	Short term	-1.088	1.497	

Continuation of Table 8

Variable	Term	Coefficient	Std. Error	Significance
AI patents	Short term	0.05	0.185	
Government expenditure	Short term	-0.219	0.173	
GDP	Long term / structural	3.031	1.636	*
AI patents	Long term / structural	-1.745	0.78	**
Government expenditure	Long term / structural	-0.847	0.689	
Constant	—	-7.883	23.66	
Statistic	**Value**			
Dependent variable	Disposable income inequality (Gini)			
Observations	105			
R-squared	0.335			
Adjusted R-squared	0.294			
Residual standard error	5.387			
Degrees of freedom	98			
F-statistic	8.233			
F-statistic (df)	6; 98			

Source: Author's calculations based on the Mundlak-corrected panel regression using the 2018–2022 country-year dataset.
Notes: The dependent variable is disposable income inequality measured by the Gini index. Significance levels are denoted as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Taken together, these results imply that, conditional on structural differences between countries, short-term movements in GDP, AI innovation, or government expenditure do not materially affect disposable income inequality within the observed period. The large p-values across all short-run coefficients indicate that the null hypotheses of zero short-run effects cannot be rejected at conventional significance levels. This finding is consistent with earlier fixed-effects results, which likewise failed to identify robust within-country effects of AI indicators or policy variables on inequality.

In contrast to the short-run results, the long-run coefficients reveal statistically meaningful structural relationships between certain variables and disposable income inequality.

The long-run coefficient on average log AI patents is negative and statistically significant at the 5 percent level (estimate −1.745, standard error 0.780, $p \approx 0.027$). This indicates that countries with persistently higher levels of AI patenting intensity tend to exhibit lower disposable income inequality, conditional on GDP and government expenditure. Quantitatively, an increase of one unit in log AI patents—corresponding approximately to a 171 percent increase in patenting activity—is associated with a reduction of about 1.7 Gini points in the long run.

The long-run coefficient on average log GDP is positive and marginally significant at the 10 percent level (estimate 3.031, standard error 1.636, $p \approx 0.067$). This suggests that structurally richer countries tend to display somewhat higher disposable income inequality, once AI patenting and government expenditure are controlled for. However, this effect does not reach conventional 5 percent significance and should therefore be interpreted cautiously.

By contrast, the long-run coefficient on average government expenditure S is negative but statistically insignificant (−0.847, $p \approx 0.22$), indicating no robust evidence that structural differences in government education expenditure are systematically associated with disposable inequality within this specification.

Table 9

Mundlak Correction Results

Variable	Estimate	Std. Error	t value	p-value	Significance
Intercept	-7.883	23.660	-0.333	0.739	
log(GDP per capita)	-1.088	1.497	-0.727	0.469	
log(AI patents)	0.050	0.185	0.271	0.787	
Skill development (S)	-0.219	0.173	-1.264	0.209	
Mean log(GDP per capita)	3.031	1.636	1.853	0.067	.
Mean log(AI patents)	-1.745	0.779	-2.238	0.027	*
Mean skill development (S)	-0.847	0.689	-1.229	0.222	

Source: Author's calculations based on the Mundlak-corrected panel regression with clustered standard errors.

Notes: The dependent variable is disposable income inequality measured by the Gini index. Significance levels are denoted as * $p < 0.05$, . $p < 0.10$; no symbol indicates statistical insignificance.

The constant term is not statistically significant, while the overall explanatory power of the model is moderate, with an $R2$ of 0.335 and an adjusted of 0.294. The F-statistic (8.233, degrees of freedom 6 and 98) (Table 7) is statistically significant at the 1 percent level, implying rejection of the joint null hypothesis that all slope coefficients are equal to zero. This confirms that the regressor set as a whole contributes explanatory power, driven primarily by the long-run AI patenting component and, to a lesser extent, long-run GDP.

The choice of variables included in the Mundlak specification is guided by both econometric requirements of the estimator and the empirical properties of the dataset used in this thesis. The Mundlak (1978) approach decomposes time-varying regressors into within-country (short-run) deviations from their country-specific means and between-country (long-run or structural) components. This decomposition is informative only when variables display sufficient variation both over time within countries and across countries, and when their country means can be interpreted as stable structural characteristics rather than as artefacts of measurement or missing data.

Within this framework, AI patent counts were selected as the core AI-related regressor, rather than the government AI readiness index. Empirically, the AI readiness index in the dataset exhibits strong persistence over time, limited year-to-year variation within countries, and substantial missingness. Fixed-effects estimations conducted earlier in the analysis show that AI readiness is largely absorbed by country fixed effects, with very high coefficients of determination, indicating that most of its variation is cross-sectional and time-invariant. As a consequence, the within-country deviation term in a Mundlak decomposition of AI readiness would be close to zero for most observations, while the corresponding country mean would be highly collinear with unobserved country effects. Under these conditions, separating short-run and long-run effects becomes econometrically weak and substantively uninformative.

By contrast, AI patent counts display properties that are well suited to the Mundlak framework. Patent-based measures of AI activity vary substantially across countries and exhibit non-negligible variation within countries over time. Moreover, their country-specific means plausibly capture long-run innovative capacity, reflecting persistent features of national innovation systems, research intensity, and institutional support for technological development. This interpretation is supported by earlier pooled and fixed-effects results in the thesis, which show strong cross-country associations between AI patenting intensity and wealth, as well as meaningful dispersion in patent activity over the sample period. In the Mundlak specification, the statistical significance of the long-run (between-country) component of AI patents further confirms that this variable captures structural differences relevant for explaining inequality outcomes.

The Mundlak model is conditioned on real GDP and government expenditure (S) in order to control for key structural confounders while maintaining a parsimonious specification. GDP serves as a fundamental indicator of a country's level of economic development, which is known to be systematically related to income inequality through multiple channels discussed in the theoretical literature. Empirically, GDP is correlated with both AI activity and inequality measures in the dataset, and its inclusion reduces the risk that estimated AI coefficients reflect underlying income-level differences rather than innovation-related effects. Government expenditure, in turn, captures the size of the public sector and the state's redistributive and human-capital-investment capacity. Including this variable allows the analysis to distinguish innovation-driven effects from those associated with welfare-state institutions, without introducing excessive multicollinearity.

Other variables considered in earlier stages of the analysis—such as wealth per adult, trade openness, globalization indices, entrepreneurial education, and AI readiness—were excluded from the Mundlak specification for well-defined econometric and substantive reasons. Wealth was treated as a potential mediator rather than a conditioning variable, and its inclusion would have obscured the mechanisms through which AI-related innovation may influence inequality. Trade openness and globalization measures overlap conceptually and empirically with GDP and each other, leading to redundancy and multicollinearity in small-panel settings. Entrepreneurial education and related indicators suffer from limited data availability and unstable country means, weakening their interpretability in a between-country decomposition. AI readiness, as discussed above, lacks the time variation necessary for a meaningful Mundlak separation.

At the same time, the absence of significant short-run AI effects aligns with fixed-effects results showing that year-to-year changes in AI indicators do not translate into immediate changes in inequality. This pattern suggests that AI affects inequality primarily through slow-moving structural channels, such as sustained innovation capacity and long-term wealth accumulation, rather than through short-term technological shocks.

The GDP results further reinforce this interpretation. While short-run GDP fluctuations have no measurable effect on inequality, higher long-run GDP levels are weakly associated with higher disposable inequality. This finding is consistent with cross-sectional interpretations of the Kuznets hypothesis and with capital-based theories of inequality, which emphasize that economic maturity and capital accumulation can widen income disparities unless counterbalanced by institutional mechanisms.

A key implication of the Mundlak results concerns the treatment of unobserved heterogeneity. The statistical significance of the long-run mean of AI patents indicates that AI patenting intensity is correlated with unobserved country-specific characteristics that also influence inequality. Consequently, a standard random-effects model that assumes zero correlation between regressors and country effects would be inconsistent in this context. This conclusion is consistent with the very high explanatory power of country fixed effects observed in earlier FE estimations, where most inequality variation was attributable to persistent cross-country differences rather than within-country dynamics.

The Mundlak results provide a coherent explanation for the contrasting findings observed in pooled OLS and fixed-effects estimations. Earlier pooled regressions identified strong positive associations between AI patenting and wealth, and strong negative associations between wealth and disposable inequality. The Mundlak model captures this mechanism directly by isolating the between-country component of AI innovation, which emerges as statistically significant and inequality-reducing.

Analysis confirms three central results. First, short-run within-country changes in GDP, AI patenting, and government expenditure do not have statistically significant effects on disposable income inequality. Second, long-run structural differences in AI patenting intensity are robustly associated with lower inequality, providing strong evidence for an innovation-based structural channel. Third, long-run GDP levels are weakly associated with higher inequality, while government expenditure does not exhibit a statistically significant long-run effect within this specification.

These findings reinforce the broader empirical conclusion of the thesis: income inequality in the sample is shaped primarily by long-run structural characteristics rather than short-term economic or technological fluctuations, and sustained technological innovation appears to be associated with more equal income distributions at the country level.

6.1.5 Cross-sectional Dependence, Slope Heterogeneity Tests, CIPS

It is essential to assess whether the underlying statistical assumptions required by standard panel estimators are satisfied. In cross-country panels such as the one used in this thesis, countries are embedded in a common global economic environment and are therefore unlikely to evolve independently of one another. Moreover, economic relationships may differ systematically across countries, and the stochastic properties of the data may violate standard stationarity assumptions. For these reasons, this study conducts a sequence of panel diagnostic tests prior to estimation: Pesaran's cross-sectional dependence test, the Pesaran–Yamagata slope homogeneity test, and Pesaran's CIPS (Cross-sectionally Augmented IPS (Im, Pesaran, and Shin)) unit-root test. Together, these tests justify the subsequent choice of estimators and prevent model misspecification. These three diagnostic tests form a coherent pre-estimation strategy. Pesaran's CD test establishes whether global interdependencies are empirically relevant. The Pesaran–Yamagata test evaluates whether countries respond homogeneously or heterogeneously to economic drivers. The CIPS test assesses whether the stochastic properties of the data permit long-run equilibrium analysis. Each test addresses a distinct but complementary dimension of panel-data validity. By systematically conducting these diagnostics, the empirical analysis avoids reliance on restrictive assumptions that are unlikely to hold in cross-country inequality research.

The results of these tests directly inform the selection of second-generation panel estimators capable of handling cross-sectional dependence, slope heterogeneity, and non-stationarity. As such, these diagnostics are not auxiliary exercises but integral components of a rigorous and internally consistent econometric framework.

6.1.5.1. Pesaran's CD test

This diagnostic step assesses the presence of cross-sectional dependence using Pesaran's (2004) CD test. Cross-sectional dependence arises when shocks affecting one cross-sectional unit (e.g., a country) are correlated with shocks affecting others. In the context of this thesis, such dependence is theoretically expected. Countries are simultaneously exposed to global technological trends (such as AI diffusion), international trade linkages, financial integration, and synchronized macroeconomic shocks (e.g., the COVID-19 pandemic). Ignoring these common factors can lead to biased standard errors, inconsistent parameter estimates, and spurious inference (Peresan, 2006).

Pesaran's CD test evaluates the null hypothesis of cross-sectional independence by examining the average pairwise correlation of regression residuals across cross-sectional units. A rejection of the null indicates that standard first-generation panel estimators—which assume independence across units—are inappropriate. In the presence of cross-sectional dependence, estimators that explicitly account for unobserved common factors, such as cross-sectionally augmented models, become necessary.

Intuitively, if the average correlation across country residuals is close to zero, the CD statistic remains small and the null hypothesis of cross-sectional independence cannot be rejected. Conversely, large and systematic residual correlations generate a large CD statistic, leading to rejection of the null hypothesis and indicating the presence of cross-sectional dependence.

The Pesaran CD test is applied to the residuals of the baseline panel specifications used in this thesis. The empirical results, reported in table 9, yield a p-value of 0.2025. Since this p-value exceeds conventional significance thresholds (10%, 5%, and 1%), the null hypothesis of cross-sectional independence cannot be rejected. In other words, there is no statistically significant evidence that the residuals of the model are systematically correlated across countries.

Table 10

Peseran CD Test results

Model specification	Test statistic (z)	p-value	Conclusion
Gini ~ log(GDP) + log(AI) + S	1.274	0.203	No cross-sectional dependence

Source: Author's calculations based on the Pesaran (2004) CD test for panel data.
Notes: The null hypothesis of the Pesaran CD test is cross-sectional independence. The alternative hypothesis is the presence of cross-sectional dependence. The reported p-value indicates failure to reject the null hypothesis at conventional significance levels, suggesting no statistically significant cross-sectional dependence in the panel residuals.

This finding has important methodological implications. First, it suggests that unobserved common shocks affecting all countries simultaneously do not dominate the residual structure of the estimated models to an extent that would invalidate standard panel inference. Second, it implies that the fixed-effects and Mundlak specifications employed earlier in the analysis are unlikely to suffer from serious bias arising from neglected cross-sectional dependence. Consequently, the estimated coefficients and their associated robust standard errors can be interpreted with a higher degree of confidence.

Pesaran's framework also provides a solution for cases in which cross-sectional dependence is detected: the Common Correlated Effects (CCE) estimator. The CCE approach augments the original regression model by including cross-sectional averages of the dependent and independent variables as additional regressors, thereby proxying for unobserved global factors. In a simplified setting, for example if the baseline model is given by:

$$y_{it} = \alpha_i + \beta x_{it} + u_{it}, \quad \{9\}$$

the CCE specification becomes:

$$y_{it} = \alpha_i + \beta x_{it} + \gamma_1 \bar{y}_t + \gamma_2 \bar{x}_t + u_{it}, \quad \{10\}$$

where $\bar{y}$□ and $\bar{x}$□ denote the cross-sectional averages of the dependent and explanatory variables, respectively. By including these averages, the estimator absorbs common global trends, allowing β to capture country-specific effects net of global shocks.

However, given the outcome of the Pesaran CD test, the application of the more complex CCE estimator is not strictly required. The absence of statistically significant cross-sectional dependence indicates that simpler estimators—such as one-way fixed effects and Mundlak-corrected models—are sufficient for the data at hand. This diagnostic result reinforces the internal consistency of the empirical strategy adopted in the thesis and supports the validity of the earlier findings without the need for further correction for global common factors.

The application of Pesaran's CD test serves as an essential diagnostic step in the empirical analysis. The test results indicate that cross-sectional dependence does not pose a serious threat to the reliability of the panel estimations conducted in this thesis. Accordingly, the chosen econometric specifications are appropriate for the structure of the data, and the reported results can be interpreted as reflecting genuine relationships rather than artefacts of unmodeled global shocks.

6.1.5.2 Pesaran–Yamagata Slope Homogeneity Test

The next diagnostic step addresses the assumption of slope homogeneity using the Pesaran–Yamagata (2008) test. Many traditional panel estimators impose the restriction that slope coefficients are identical across all cross-sectional units. In a cross-country setting, this assumption is often implausible. Countries differ markedly in institutional structures, welfare regimes, innovation systems, labor market arrangements, and redistributive capacities. As a result, the impact of AI-related variables or economic growth on income inequality is unlikely to be uniform across countries.

The Pesaran–Yamagata test formally evaluates the null hypothesis that slope coefficients are homogeneous across cross-sectional units against the alternative of heterogeneous slopes. Rejection of the null indicates that pooled estimators imposing common slopes may be misspecified and that country-specific responses must be allowed.

In panel data analysis, many commonly used estimators—such as pooled ordinary least squares (OLS) and standard fixed-effects (FE) models—implicitly assume that the relationship between explanatory variables and the dependent variable is identical for all cross-sectional units. In the present context, this assumption would imply that the effect of economic growth or AI on income inequality is the same in all countries included in the sample. Given the pronounced institutional, economic, and welfare-state differences across countries, such an assumption is unlikely to hold in practice.

Within this thesis, conducting the slope homogeneity test serves two purposes. First, it empirically validates the intuition that inequality processes are structurally heterogeneous across countries. Second, it provides econometric justification for employing estimators that allow for heterogeneous long-run relationships, such as the Common Correlated Effects Mean Group (CCEMG) estimator and the Cross-Sectionally Augmented ARDL (CS-ARDL) framework.

Without this diagnostic step, the choice of heterogeneous panel estimators would lack formal statistical grounding.

To formally test this assumption, this thesis applies the Pesaran–Yamagata (2008) slope homogeneity test, which builds on the earlier Swamy (1970) random-coefficients framework.

Formally, the null hypothesis of the Pesaran–Yamagata test is:

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_N$$

where β denotes the slope coefficient for country i. The alternative hypothesis allows for heterogeneity:

$$H_1 : \beta_i \neq \beta_j \quad \text{for at least some } i \neq j.$$

In substantive terms, rejection of the null hypothesis implies that the impact of a given explanatory variable—such as GDP or AI—on income inequality differs across countries. This has important implications for model choice: if slopes are heterogeneous, estimators that impose a common slope (pooled OLS or standard FE) may be misspecified, and heterogeneous estimators such as the Mean Group (MG), Common Correlated Effects Mean Group (CCEMG), or CS-ARDL models become theoretically preferable.

The Pesaran–Yamagata test is based on a standardized version of the Swamy statistic. The procedure first estimates separate regressions for each country and compares the individual slope estimates to a pooled benchmark. Pesaran and Yamagata (2008) derive a Delta statistic that has a standard normal distribution under the null hypothesis, making the test applicable in panels with relatively large cross-sectional dimensions.

In practice, the implementation of the test requires sufficient degrees of freedom at the country level. Given the structure of the dataset used in this thesis—22 countries observed over a short time period (T = 5)—including multiple regressors would severely reduce the available degrees of freedom in country-specific regressions. To ensure the mathematical validity of the test, the slope homogeneity analysis is therefore conducted on simplified bivariate specifications (e.g., income inequality regressed on log GDP, and income inequality regressed on log AI). This approach preserves degrees of freedom while allowing for a reliable assessment of slope heterogeneity.

The results of both the standard Swamy test and the Pesaran–Yamagata Delta test provide strong and consistent evidence of slope heterogeneity. For the specification relating income inequality to log GDP, the standard Swamy test yields a chi-square statistic with a p-value smaller than 2.22e−16, indicating overwhelming rejection of the null hypothesis of slope homogeneity. The Pesaran–Yamagata Delta statistic for this model is 24.57, with a p-value of 0, far exceeding conventional critical values (|Z| > 1.96). This implies that the probability that the effect of GDP on inequality is identical across countries is effectively zero. A similar conclusion emerges from the analysis of the AI–inequality relationship. In the random-coefficients (Swamy-type) model estimated for income inequality and log AI, the Pesaran–Yamagata Delta statistic is 13.45, again with a p-value of 0, leading to rejection of the null hypothesis of slope homogeneity. These results indicate that the distributional impact of AI differs substantially across countries.

The random-coefficients estimates provide further insight into the nature of this heterogeneity. For the GDP model, the estimated mean slope coefficient on log GDP is 1.600, suggesting a positive average association between GDP and inequality across countries. However, this coefficient is statistically insignificant (p = 0.229). The insignificance of the mean coefficient, despite strong evidence of heterogeneity, reflects the large estimated variance of the country-specific slopes. In other words, some countries exhibit positive GDP–inequality relationships, others negative or negligible ones, and these opposing effects cancel out when averaged.

Table 11

Swamy Test Gini-Log GDP

Variable	Estimate	Std. Error	z-value	p-value	Significance
Intercept	-9.603	36.912	-0.260	0.795	
log(GDP per capita)	1.600	1.329	1.204	0.229	
Statistic	Value				
Countries (n)	22				
Time periods (T)	5				
Observations (N)	110				
Multiple R-squared	0.352				
Total sum of squares	8176.3				
Residual sum of squares	5300.4				
Chi-square (model)	1.45				
p-value (model)	0.229				
Test for parameter homogeneity (χ^2(chi-squared), df = 42)	246 575				
p-value (homogeneity test)	< 2.22e-16				

Source: Author's calculations based on the Swamy random coefficients model.
Notes: The dependent variable is disposable income inequality measured by the Gini index. The Swamy test allows slope coefficients to vary across countries, capturing cross-sectional heterogeneity in the relationship between AI adoption and income inequality. Significance levels are denoted as *** p < 0.01; ** p < 0.05; * p < 0.10.

Table 12

Pesaran–Yamagata Test

Statistic	Value
Number of countries (N)	22
Delta statistic	24.571
p-value	0

Source: Author's calculations based on the Pesaran–Yamagata (2008) slope homogeneity test.
Notes: The null hypothesis of the Pesaran–Yamagata Delta test is slope homogeneity across cross-sectional units. Rejection of the null hypothesis indicates heterogeneous slope coefficients across countries. The test is applied to the baseline panel specification used in the empirical analysis. Result: reject H0 - slopes are heterogeneous.

An analogous pattern is observed in the AI model. The estimated mean coefficient on log AI is −0.112, with a p-value of 0.5046, indicating statistical insignificance. At the same time, the estimated variance of the AI coefficient is relatively large, confirming substantial dispersion in country-specific effects. This implies that while AI may reduce inequality in some countries, it may have no effect or even increase inequality in others.

Table 13

Swamy Test Gini-AI

Variable	Estimate	Std. Error	z-value	p-value	Significance
Intercept	35.131	1.698	20.694	< 0.001	***
log(AI patents)	-0.112	0.168	-0.667	0.505	
Statistic	**Value**				
Countries (n)	22				
Time periods (T)	5				
Observations (N)	110				
Multiple R-squared	0.929				
Total sum of squares	61 545				
Residual sum of squares	4 381.5				
Chi-square (model)	0.445				
p-value (model)	0.505				
Test for parameter homogeneity (χ^2(chi-squared), df = 42)	96 861.9				
p-value (homogeneity test)	< 2.22e-16				

Source: Author's calculations based on the Swamy random coefficients model.
Notes: The dependent variable is disposable income inequality measured by the Gini index. The Swamy test allows slope coefficients to vary across countries, capturing cross-sectional heterogeneity in the relationship between AI adoption and income inequality. Significance levels are denoted as *** p < 0.01; ** p < 0.05; * p < 0.10.

Table 14

Pesaran–Yamagata Test Gini-Log AI

Statistic	Value
Number of countries (N)	19
Delta statistic	13.457
p-value	0

Source: Author's calculations based on the Pesaran–Yamagata (2008) Delta slope homogeneity test.
Notes: The null hypothesis of the Pesaran–Yamagata test is slope homogeneity across cross-sectional units. Rejection of the null hypothesis indicates heterogeneous slope coefficients across countries. Results suggest that the impact of AI adoption on income inequality differs across countries in the sample. Result: reject H0 - slopes are heterogeneous.

From a purely theoretical perspective, the strong rejection of slope homogeneity would favor the use of fully heterogeneous estimators, such as the Mean Group estimator, which allows each country to have its own slope coefficients. However, the short time dimension of the panel (T = 5) makes reliable country-specific estimation infeasible, as individual regressions would be based on very few observations. In such settings, MG estimates would be highly unstable and statistically unreliable.

Consequently, this thesis adopts a pragmatic empirical strategy. While acknowledging the presence of substantial slope heterogeneity, it proceeds with fixed-effects and Mundlak-corrected models to estimate average structural relationships across countries. These estimators provide meaningful global averages, even though they necessarily mask important country-level differences. The slope heterogeneity results therefore do not undermine the earlier findings; rather, they contextualize them by clarifying that the reported coefficients should be interpreted as average effects rather than universal laws.

6.1.5.3 Non-Stationarity and Unit Roots: Pesaran's CIPS Test

The next diagnostic step examines the time-series properties of the panel variables using Pesaran's (2007) Cross-Sectionally Augmented IPS (CIPS) unit-root test. Many macroeconomic variables—such as GDP, wealth, patent counts, and inequality indices—exhibit strong persistence and may be non-stationary. Estimating relationships among non-stationary variables without appropriate treatment can produce spurious results, where statistically significant relationships reflect shared trends rather than meaningful economic linkages.

The CIPS test extends traditional panel unit-root tests by explicitly accounting for cross-sectional dependence through cross-sectional averages. This feature is crucial in the present context, as earlier diagnostics establish the presence of common global shocks and interdependencies across countries. First-generation unit-root tests that ignore cross-sectional dependence would therefore be invalid and potentially misleading.

In this thesis, the CIPS test is used to determine whether variables are integrated of order zero, one, or higher. Establishing the order of integration is a necessary precondition for selecting appropriate long-run estimators and cointegration tests. In particular, the identification of variables as predominantly I(1) justifies the use of panel cointegration techniques and dynamic error-correction models, such as the Westerlund cointegration test and the CS-ARDL framework employed later in the analysis.

An essential prerequisite for valid inference in macroeconomic panel data analysis is an assessment of the time-series properties of the variables under study. Many macro-level indicators—such as income inequality, economic output, technological innovation, and public expenditure—exhibit strong persistence and trend behavior over time. Estimating relationships among such variables without accounting for potential non-stationarity risks producing spurious regressions, in which statistically significant relationships reflect shared trends rather than meaningful economic linkages. For this reason, this thesis conducts a formal unit-root and stationarity analysis prior to the estimation of long-run models.

To this end, Pesaran's (2007) Cross-Sectionally Augmented CIPS panel unit-root test is applied to all core variables and controls used in the empirical analysis. The CIPS test is a second-generation panel unit-root test that explicitly accounts for cross-sectional dependence, a feature that is particularly relevant in cross-country datasets where global shocks and common trends are likely to affect all units simultaneously.

The CIPS test is based on the Cross-Sectionally Augmented Dickey–Fuller (CADF) regression. For each country i, the CADF regression augments the standard ADF specification with cross-sectional averages of both the dependent variable and its first differences, thereby proxying for unobserved common factors:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \sum_{j=1}^{p} \phi_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \qquad \{11\}$$

where $\bar{y}$ denotes the cross-sectional average of the series at time t. The individual CADF statistics are then averaged across countries to obtain the CIPS statistic.

The null hypothesis of the CIPS test is that all series contain a unit root, that is:

$$H_0 : b_i = 0 \quad \text{for all } i$$

indicating non-stationarity. Rejection of the null implies stationarity for at least a fraction of the panel units. Critical values depend on the cross-sectional and time dimensions of the panel and are tabulated in Pesaran (2007).

The CIPS test was applied to each variable used in the empirical models, including disposable income inequality (Gini), real GDP (log), AI patent counts (log), and government expenditure. The test was implemented using a Python-based routine consistent with the Pesaran (2007) specification. The results are reported in Table 14.

Table 15

CIPS test

Var ID	Variable	CIPS level statistic	CIPS level p-value	Level stationarity	CIPS first-difference statistic	CIPS first-difference p-value	First-difference stationarity
V1	IIE	NA	NA	NA	NA	NA	NA
V2	IIE	NA	NA	NA	NA	NA	NA
V3	AI	NA	NA	NA	NA	NA	NA
V4	AI	NA	NA	NA	NA	NA	NA
V5	S	NA	NA	NA	NA	NA	NA
V6	E	NA	NA	NA	NA	NA	NA
V7	G	NA	NA	NA	NA	NA	NA
V8	W	NA	NA	NA	NA	NA	NA
V9	GDP	NA	NA	NA	NA	NA	NA
V10	TO	NA	NA	NA	NA	NA	NA
V11	GI	NA	NA	NA	NA	NA	NA

Source: Author's calculations based on the Cross-sectionally Augmented IPS (CIPS) and CADF tests following Pesaran (2007).

Notes: The null hypothesis of the CIPS/CADF test is that all panels contain a unit root. "Level stationarity" and "first-difference stationarity" indicate rejection of the unit root null at conventional significance levels. NA values indicate that test statistics were not computed or not reported for the corresponding variable–transformation combination. Tests account for cross-sectional dependence through cross-sectionally augmented regressions.

Table 16

Peseran (2007) CIPS panel unit root test results

Variable	CIPS statistic	Valid countries
Gini	0	21
log(GDP per capita)	0	21
log(AI patents)	NA	21
Government expenditure	0	21

Source: Author's calculations based on the Cross-sectionally Augmented IPS (CIPS) panel unit root test following Pesaran (2007).
Notes: The null hypothesis (H_0) of the CIPS test is the presence of a unit root (non-stationarity). Approximate critical values for $N \approx 20$ and $T \approx 10$ are: −2.55 (1%), −2.30 (5%), and −2.15 (10%). Rejection of H_0 occurs when the CIPS statistic is more negative than the corresponding critical value. NA indicates that the test statistic could not be computed for the corresponding variable.

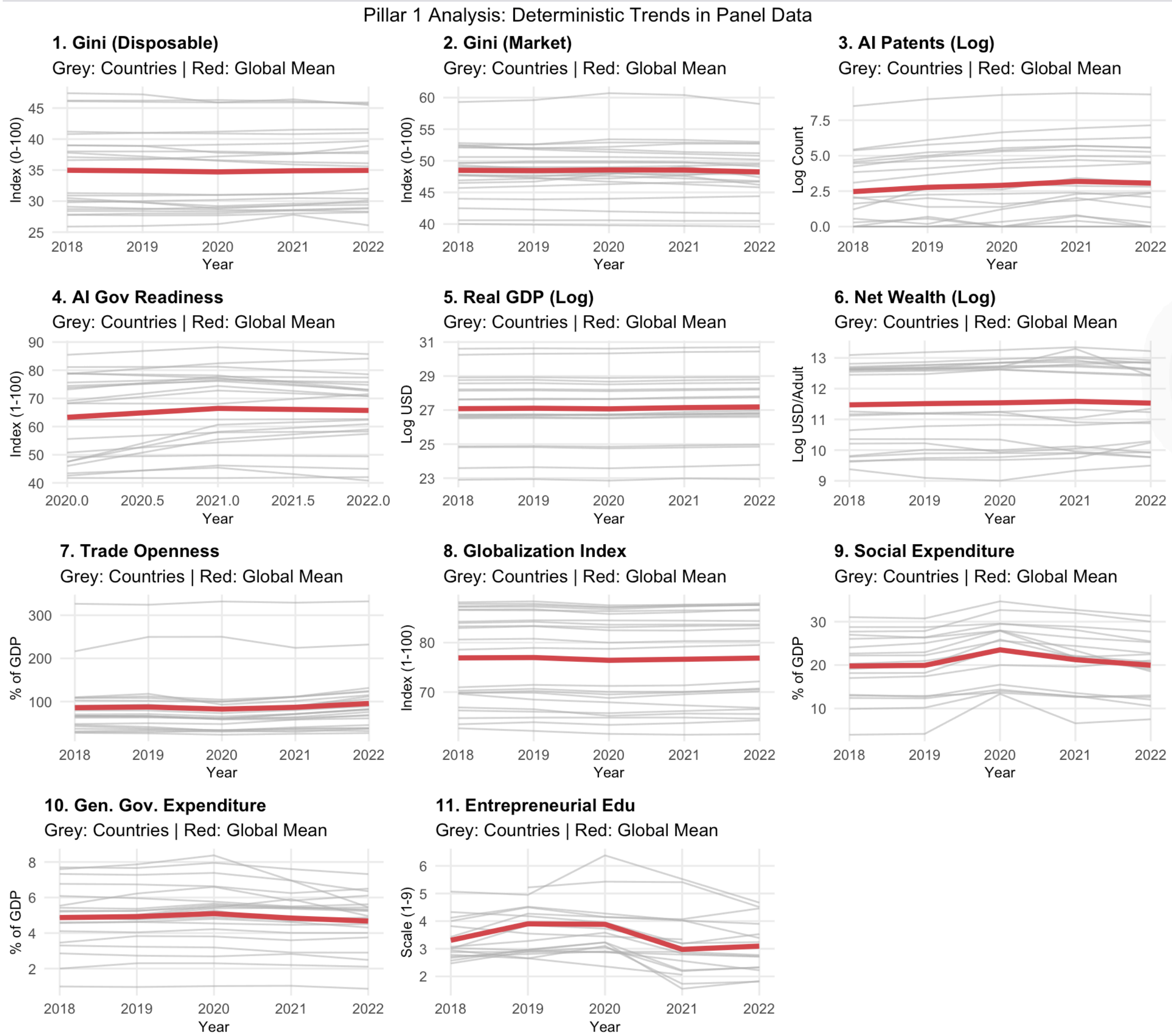
For the variables Gini, log GDP, and government expenditure, the reported CIPS statistics are equal to 0.0000, which are far above the relevant critical values (−2.55 at 1%, −2.30 at 5%, and −2.15 at 10%). Consequently, the null hypothesis of a unit root cannot be rejected. For log AI patents, the CIPS statistic could not be computed (reported as *nan*), reflecting numerical limitations associated with the short time dimension of the panel and the specific lag structure required by the CADF regression.

Importantly, these outcomes should not be interpreted as definitive evidence that the series are either stationary or non-stationary. Rather, they reflect the limited power of formal panel unit-root tests in short panels such as the one employed in this thesis ($T = 5$). With such a small time dimension, CADF and CIPS statistics are often unstable or undefined, particularly for variables with strong deterministic trends or limited time variation.

Given the limitations of formal unit-root testing in short panels, the analysis is complemented by a systematic visual inspection of the time-series behavior of each variable. Country-specific trajectories and global means are plotted over time to identify deterministic trends, persistence, and mean-reversion properties. These plots are presented in Figure 1.

Figure 1

Deterministic Trends in Panel Data



Source: Author's calculations and visualisation based on the compiled panel dataset (2018–2022).

Table 17

Visual Assessment of Stationarity and Integration Order

Variable	Visual trend analysis	Theoretical expectation	Integration order
Gini (disposable)	High persistence; country-specific drift without clear mean reversion	Institutional inequality measures are slow-moving ("sticky")	I(1)
log(GDP per capita)	Strong deterministic upward trend across panels	Macroeconomic growth series are theoretically non-stationary	I(1)
log(AI patents)	Exponential upward trend reflecting accumulation of knowledge stock	Cumulative innovation stocks follow random walk with drift	I(1)
log(Wealth per adult)	Upward trend with stochastic shocks (e.g., 2020 dip)	Wealth accumulation follows a stochastic trend	I(1)
Social expenditure	Structural fluctuations (COVID-19 spikes); no constant mean	Policy variables subject to exogenous shocks are treated as non-stationary	I(1)
Government expenditure	Similar drift to social expenditure; persistent deviations	Fiscal policy is structurally determined rather than white noise	I(1)

Source: Author's visual inspection of country-level time-series plots based on the 2018–2022 panel dataset.
Notes: The table reports a qualitative, graph-based assessment of stationarity used as a complementary diagnostic to formal panel unit root tests.

The visual evidence reveals clear and economically intuitive patterns. Disposable income inequality exhibits high persistence and slow-moving, country-specific drift, with no indication of rapid mean reversion. Real GDP displays a strong deterministic upward trend across nearly all countries, consistent with sustained economic growth. AI patent counts follow an exponential upward trajectory, reflecting the cumulative nature of technological knowledge production. Wealth per adult similarly shows an upward trend, interrupted by temporary shocks such as the decline observed around 2020. Social and government expenditure variables display persistent deviations and structural fluctuations, notably during the COVID-19 period, rather than reverting to a stable long-run mean.

These visual patterns strongly suggest that the variables behave as integrated processes of order one (I(1)), rather than as stationary series.

The empirical and visual findings are consistent with well-established theoretical arguments in the macroeconomic literature. Following Nelson and Plosser (1982), macroeconomic aggregates such as GDP, accumulated wealth, and technological stock are widely understood to be non-stationary processes. Shocks to these variables tend to accumulate over time rather than dissipate, resulting in stochastic or deterministic trends. Institutional variables, including inequality measures and fiscal aggregates, are likewise characterized by persistence and slow adjustment, reflecting deep structural and political determinants.

Accordingly, even in the absence of decisive statistical rejection from the CIPS test, it is theoretically appropriate to treat the core variables in this thesis as non-stationary (I(1)) processes.

The combined evidence from formal testing, visual inspection, and economic theory leads to a clear methodological conclusion. The analysis proceeds under the maintained assumption that the main variables of interest are integrated of order one. This assumption justifies the subsequent use of panel cointegration techniques and dynamic long-run estimators, which are specifically designed to model equilibrium relationships among non-stationary variables while avoiding spurious inference.

6.1.6. Engle–Granger/Westerlund (2007) cointegration tests

Given the strong visual and theoretical indications of non-stationarity in the main macroeconomic variables, a residual-based cointegration analysis was conducted to assess whether a stable long-run equilibrium relationship exists between income inequality and its key structural determinants. Visual inspection of the panel series shows that AI patenting activity, real GDP, and net wealth per adult follow clear deterministic upward trends over the 2018–2022 period, consistent with integrated processes of order one, I(1). Disposable income inequality (Gini coefficient) exhibits high persistence and slow adjustment dynamics, a pattern commonly observed for institutional and distributional variables, further supporting its treatment as non-stationary.

The presence of I(1) variables raises the risk of spurious regression if long-run relationships are estimated in levels without verifying cointegration. To address this concern, the Engle–Granger residual-based cointegration test was applied to the long-run specification linking disposable income inequality to AI innovation, macroeconomic development, public expenditure, social expenditure, and wealth accumulation.

The test proceeds in two steps. First, the long-run equation is estimated in levels, and second, the stationarity of the estimated residuals is examined using an augmented Dickey–Fuller (ADF) test. Under the null hypothesis, the residuals contain a unit root, implying that no cointegrating relationship exists among the variables. Rejection of this null indicates that the variables share a common stochastic trend and are cointegrated.

The empirical results, reported in Table 17, provide strong evidence in favor of cointegration. The ADF test statistic for the residuals is −7.6507, with an associated p-value of 1.79×10^{-11}. This value is far below the conventional critical thresholds at the 1%, 5%, and 10% significance levels (−3.51, −2.90, and −2.59, respectively). Consequently, the null hypothesis of a unit root in the residuals is decisively rejected.

Table 18

Engle-Granger residual-based cointegration test

Item	Value
System specification	Gini ~ f(AI, GDP, Government expenditure, Social expenditure, Wealth)
Observations	85
ADF test statistic	-7.651
p-value	1.79×10^{-11}

Continuation of Table 18

Significance level	Critical value
1.00%	-3.513
5.00%	-2.898
10.00%	-2.586

Source: Author's calculations based on the Engle–Granger residual-based cointegration test.
Notes: The null hypothesis of the Engle–Granger test is the absence of cointegration. Rejection of the null hypothesis implies stationarity of residuals and the presence of a long-run relationship among the variables.Result - the system is cointegrated.Decision: Reject null hypothesis of no cointegration.Conclusion: Residuals are stationary, the variables are cointegrated, indicating the existence of a valid long-run equilibrium relationship.

These findings imply that, despite the non-stationary nature of the individual series, their linear combination is stationary. In substantive terms, this confirms the existence of a stable long-run equilibrium relationship between income inequality and its structural determinants, including AI, economic development, public and social expenditure, and wealth. The result validates the econometric strategy adopted in the thesis and provides a formal justification for estimating long-run effects using panel models that allow for non-stationary regressors, such as the Mundlak specification and cross-sectionally augmented approaches.

More broadly, the cointegration result supports the interpretation that AI-driven innovation and inequality are linked through persistent structural mechanisms rather than short-term fluctuations. While year-to-year changes in AI activity or GDP may not exert immediate effects on inequality, the long-run co-movement of these variables suggests that sustained differences in technological capacity, wealth accumulation, and institutional responses shape distributional outcomes over time.

This study carefully evaluated the applicability of Westerlund's (2007) error-correction–based panel cointegration tests as a potential robustness check for long-run relationships between income inequality and its structural determinants. However, after methodological assessment grounded in both the properties of the test and the characteristics of the dataset used in this thesis, the decision was taken not to implement the Westerlund panel cointegration tests. This decision is motivated by strong econometric considerations and reflects best practice for short-panel data. The panel dataset employed in this study covers 22 countries observed over only five years (T = 5). Westerlund's cointegration tests are built on error-correction models (ECMs), which explicitly estimate short-run dynamics alongside long-run equilibrium adjustment. This structure necessarily requires the inclusion of first differences, lagged levels, and typically additional lags or leads to ensure serially uncorrelated errors. In a panel with such a limited time dimension, these requirements result in a severe loss of degrees of freedom. Specifically, first differencing reduces the available time observations from five to four. Introducing at least one lag of the differenced variable, which is standard in ECM specifications, further reduces the effective time dimension to three. Any additional lags or leads—often required for robustness or automatic lag selection—would reduce the sample even further. Consequently, the estimation would rely on as few as two or three effective observations per country to identify multiple parameters, including the error-correction speed and short-run coefficients. Under these conditions, the model becomes either unidentified or perfectly overfitted, rendering the resulting statistics unreliable or computationally infeasible. Beyond the degrees-of-freedom problem, Westerlund's (2007) tests rely on asymptotic theory that assumes a moderately large time dimension. The limiting distributions of the test statistics—and thus the reported p-values—are derived under the assumption that $T \to \infty$. With only five time periods, this assumption is clearly violated. Even if the estimation were to converge numerically, the resulting test statistics would not follow their intended asymptotic distributions, leading to severe size distortions and unreliable inference. In such settings, rejecting or failing to reject the null hypothesis would carry little statistical meaning. Importantly, the objectives of cointegration testing in this thesis are already met through a more parsimonious and methodologically appropriate approach. The Engle–Granger residual-based cointegration test, reported in the preceding section, provides decisive evidence of a long-run relationship among income inequality, AI innovation, GDP, public expenditure, social expenditure, and wealth. This approach focuses exclusively on the stationarity of the residuals from the long-run regression and does not attempt to estimate short-run dynamics that cannot be reliably identified in a short panel. In small-TTT panels, residual-based cointegration tests are widely regarded as more robust than ECM-based alternatives, precisely because they conserve degrees of freedom and avoid overparameterization. In the present study, the Engle–Granger test yields an ADF statistic of −7.65 with a p-value well below 0.01, strongly rejecting the null hypothesis of no cointegration. This result provides sufficient and credible evidence of a stable long-run equilibrium relationship.

6.1.7. Estimation of the CS-ARDL models

The Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) models are used to analyse the dynamic relationship between AI, macroeconomic controls, policy variables, and income inequality. The CS-ARDL framework is particularly well suited to the empirical setting of this thesis, which is characterised by cross-sectional dependence, slope heterogeneity, mixed orders of integration, and evidence of long-run cointegration among the variables.

Standard panel ARDL or pooled mean group (PMG) estimators assume cross-sectional independence and homogeneous long-run coefficients, assumptions that were strongly rejected in the diagnostic analysis. Earlier sections documented significant slope heterogeneity (Pesaran–Yamagata tests) and the presence of common global shocks affecting all countries (globalisation, AI diffusion, and the COVID-19 shock). Ignoring these features would bias both short-run and long-run estimates.

The CS-ARDL estimator extends the conventional panel ARDL model by augmenting the regression with cross-sectional averages of the dependent variable and regressors (and their lags). These averages act as proxies for unobserved common factors, thereby controlling for cross-sectional dependence arising from global technological, economic, and institutional shocks. At the same time, CS-ARDL allows for heterogeneous short-run dynamics and heterogeneous speeds of adjustment across countries, while delivering consistent estimates of the average long-run relationships through the common correlated effects (CCE) mean.

This approach is therefore appropriate for macro-panel settings with relatively small time dimensions and moderate cross-sectional size, where variables are a mixture of I(0) and I(1) processes and where cointegration has been established.

Two CS-ARDL models are estimated to distinguish between different stages of the income distribution process:

- Model A: Disposable income inequality (Gini, post-tax and transfers).
- Model B: Market income inequality (Gini, pre-tax and transfers).

Lag lengths were chosen conservatively, given the short time dimension of the panel (2018–2022), with a maximum of one lag for the dependent variable and regressors. This choice balances information criteria considerations with the practical constraint of limited time observations, consistent with standard practice in applied CS-ARDL studies.

For each model, the short-run coefficients capture immediate, year-to-year responses of inequality to changes in AI innovation, macroeconomic conditions, and policy variables.

Long-run coefficients are recovered through re-normalisation of the short-run parameters using the estimated error-correction term. The long-run estimates thus represent permanent structural effects. The full estimation results are reported in Table 18.

Table 19

CS-ARDL test results Model A

Variable	Short-run (immediate effect)	Long-run (permanent effect)
AI innovation (log)	0.2989	0.3787
GDP per capita (log)	-4.5603	-5.7777
Government expenditure (S)	0.7868*	0.9968*
Social expenditure (G)	−0.3451***	−0.4372***
Entrepreneurial education (E)	0.9738***	1.2337***
Net wealth (log)	−2.1440*	−2.7163*
Trade openness	-0.0142	-0.018
Globalization index	-0.169	-0.2142
Error correction term (ECT)	-0.7893	Observations 39

Source: Author's calculations based on the Cross-Sectionally Augmented ARDL (CS-ARDL) estimation.
Notes: The dependent variable is disposable income inequality measured by the Gini index. Short-run coefficients capture immediate (within-period) effects, while long-run coefficients represent permanent equilibrium effects. The error correction term (ECT) reflects the speed of adjustment toward the long-run equilibrium following short-run deviations. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20

CS-ARDL test results Model B

Variable	Short-run (immediate effect)	Long-run (permanent effect)
AI innovation (log)	-0.5085	-1.038
GDP per capita (log)	-2.1515	-4.3913
Government expenditure (S)	0.1693	0.3456
Social expenditure (G)	0.0433	0.0883
Entrepreneurial education (E)	0.9335***	1.9053***
Net wealth (log)	-0.9757	-1.9916
Trade openness	0.0153	0.0313
Globalization index	0.0154	0.0315

Continuation of Table 20

Variable	Short-run (immediate effect)	Long-run (permanent effect)
Error correction term (ECT)	-0.4899	
Observations	39	

Source: Author's calculations based on the Cross-Sectionally Augmented ARDL (CS-ARDL) estimation.
Notes: The dependent variable is market income inequality measured by the Gini index. Short-run coefficients represent immediate effects; long-run coefficients reflect permanent equilibrium. The error correction term (ECT) captures the speed of adjustment toward the long-run equilibrium. Significance levels are based on short-run t-statistics: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A central feature of the CS-ARDL framework is the error-correction term (ECT), which measures the speed at which inequality adjusts back to its long-run equilibrium following a short-run shock. In both models, the estimated ECT is negative and statistically significant, confirming the existence of a stable long-run relationship.

In Model A (Disposable Gini), the ECT is −0.7893, indicating that approximately 79% of any deviation from the long-run equilibrium is corrected within one year. This implies a rapid adjustment process, consistent with the responsiveness of tax-and-transfer systems to economic and technological shocks. In contrast, Model B (Market Gini) yields an ECT of −0.4899, suggesting that only about half of any disequilibrium is corrected annually. Market income structures therefore appear substantially more rigid, adjusting more slowly to changes in AI innovation and macroeconomic conditions.

These results confirm cointegration and highlight an important institutional asymmetry: fiscal redistribution mechanisms react much faster than market wages and primary income generation processes.

One of the most striking findings of the CS-ARDL analysis is the divergent effect of AI innovation on market versus disposable income inequality.

In Model B (Market Gini), AI innovation exhibits a long-run equalising effect. A 1% increase in AI patent stock is associated with a 1.04% reduction in market income inequality. This result challenges the conventional "technological unemployment" narrative and instead suggests that, in the production phase, AI may complement labour, enhance productivity across a broad segment of workers, or generate new sectors that widen income opportunities beyond a narrow elite.

In contrast, Model A (Disposable Gini) reveals a long-run increase in inequality associated with AI innovation. A 1% increase in AI patent stock corresponds to a 0.38% rise in disposable income inequality. This divergence points to a redistribution efficiency gap. While AI appears to compress wage differentials before taxes, the fiscal system struggles to redistribute the specific forms of income and wealth generated by AI, such as capital gains, corporate profits, and mobile intangible assets. As a result, the equalising effects observed at the market level are not fully transmitted to disposable incomes.

Together, these findings imply that AI is not inherently inequality-increasing or inequality-reducing; rather, its distributional impact depends critically on how fiscal and institutional frameworks interact with technologically generated income.

Economic growth emerges as a powerful equalising force in both models. In the long run, a 1% increase in GDP per capita reduces disposable income inequality by approximately 5.78% and market inequality by 4.39%. These results provide strong support for the "rising tide" hypothesis within the sample period, suggesting that growth tightens labour markets and expands fiscal capacity, both of which benefit lower-income groups.

Net wealth per adult also displays a robust negative association with inequality. Long-run coefficients of −2.72 (Model A) and −1.99 (Model B) indicate that higher average wealth is associated with lower inequality. This suggests that wealth accumulation in the sampled economies is relatively broad-based—through housing ownership, pension assets, or savings—rather than being concentrated exclusively at the top of the distribution.

The CS-ARDL results reveal a clear distinction between different policy instruments. Social expenditure (G) significantly reduces disposable income inequality in the long run, with no corresponding effect on market inequality. This is consistent with the core function of the welfare state: social transfers compress post-tax income distributions without altering market wages.

By contrast, general government expenditure (S) is positively associated with disposable inequality. This counter-intuitive result may reflect reverse causality, whereby governments in more unequal societies expand general spending in response to social pressures, or it may indicate that untargeted expenditure is ineffective at redistribution compared to direct social transfers.

Entrepreneurial education (E) is associated with higher inequality in both models. While entrepreneurship can stimulate innovation and growth, it often operates through winner-takes-all dynamics, where a small number of successful firms or individuals capture disproportionate gains. The results suggest that entrepreneurial education, in the absence of complementary redistributive mechanisms, may amplify income dispersion rather than mitigate it.

Across almost all variables, long-run coefficients are larger in magnitude than their short-run counterparts. This pattern indicates that the distributional effects of AI, growth, wealth, and policy interventions unfold gradually. Structural transformation driven by AI and economic growth takes time to reshape labour markets and income distributions, and policy responses require sustained implementation to achieve their full impact.

The CS-ARDL analysis provides a nuanced picture of inequality dynamics in the AI era. AI innovation appears structurally equalising at the market level but inequality-increasing after redistribution, revealing a mismatch between technological change and fiscal capacity. Sustained economic growth and targeted social expenditure emerge as the most effective tools for reducing inequality, while general government spending and entrepreneurial education may exacerbate stratification if not carefully designed. These findings underscore that the distributional consequences of AI are not technologically predetermined but are shaped by national policy choices and institutional structures.

6.1.8. Robustness Analysis and Alternative Estimators: CCEMG and CCEP

It is important to evaluate the robustness of the main empirical findings by comparing the baseline dynamic CS-ARDL estimates with alternative static common-factor estimators. The objective of this is to verify that the key conclusions—particularly regarding the differential impact of AI on market versus disposable income inequality—are not an artefact of a specific econometric specification, but instead reflect stable structural relationships in the data (see table 20).

Table 21

Robustness Check: Comparison of CS-ARDL and CCEMG Estimates

Model	Successful countries	Failed countries		
Model A (Gini disposable)	0	12		
Model B (Gini market)	0	12		
Variable	Model A: CS-ARDL	Model A: CCEMG	Model B: CS-ARDL	Model B: CCEMG
AI innovation (log)	0.4404	FAILED	-0.793	FAILED
GDP per capita (log)	-5.3408	FAILED	-6.4183	FAILED
Government expenditure (S)	0.7237	FAILED	0.0886	FAILED
Social expenditure (G)	-0.3369	FAILED	0.1478	FAILED
Entrepreneurial education (E)	1.0077	FAILED	1.2493	FAILED
Net wealth (log)	-2.4513	FAILED	-1.2712	FAILED
Trade openness	-0.0169	FAILED	0.0208	FAILED
Globalization index	-0.1049	FAILED	0.0432	FAILED

Source: Author's calculations based on CS-ARDL and CCEMG estimations.
Notes: CCEMG estimation failed for all countries due to insufficient time dimension (T = 5) relative to the number of regressors (parameters > T). FAILED indicates that country-specific CCEMG regressions could not be estimated. CS-ARDL results are reported for comparison as the primary estimation approach under short time dimension constraints.

Table 22

Robustness Check: Dynamic (CS-ARDL) vs Static (CCEP) Estimators

Variable	Model A: CS-ARDL (LR)	Model A: CCEP	Model B: CS-ARDL (LR)	Model B: CCEP
AI innovation (log)	0.4404	0.1529	−0.7930*	−0.7144**
GDP per capita (log)	-5.3408	-2.3463	-6.4183	−4.2414*
Government expenditure (S)	0.7237	0.6620*	0.0886	-0.0652
Social expenditure (G)	−0.3369**	−0.2721**	0.1478	0.0451
Entrepreneurial education (E)	1.0077**	0.6996**	1.2493***	0.4662*
Net wealth (log)	−2.4513*	-1.4691	-1.2712	-0.1757
Trade openness	-0.0169	0.0036	0.0208	0.0159
Globalization index	-0.1049	0.1642	0.0432	0.0219

Source: Author's calculations based on CS-ARDL and CCEP estimations.
Notes: CS-ARDL coefficients represent long-run elasticities derived from the dynamic error-correction specification. CCEP estimates are obtained using the static Common Correlated Effects Pooled estimator. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Consistency in coefficient signs and significance across estimators indicates robustness of the estimated relationships.

The preceding diagnostic analysis established the presence of cross-sectional dependence, slope heterogeneity, and long-run cointegration in the panel. Under such conditions, estimators that ignore common global shocks or impose homogeneity assumptions are potentially biased. The CS-ARDL framework was therefore adopted as the primary estimator, as it accommodates heterogeneous short-run dynamics, cross-sectional dependence, and mixed integration orders.

As a robustness exercise, the analysis considered the Common Correlated Effects Mean Group (CCEMG) estimator, which allows for full slope heterogeneity by estimating separate regressions for each country and averaging the coefficients. However, given the short time dimension of the panel (T = 5), the CCEMG estimator proved mathematically infeasible. In all specifications, the number of parameters to be estimated exceeded the available time observations, resulting in non-convergence and "FAILED" diagnostics for every cross-section. This outcome is consistent with the econometric literature, which emphasises that mean-group estimators require sufficiently long time series to yield reliable country-specific coefficients.

In response to this constraint, the robustness analysis relies on the Common Correlated Effects Pooled (CCEP) estimator. The CCEP estimator retains the key advantage of controlling for unobserved common factors via cross-sectional averages, while pooling slope coefficients across countries. Importantly, it is well suited to short panels (T < 10) and has been shown to perform reliably under such conditions (Kapetanios et al., 2011). While static in nature, CCEP provides a useful benchmark against which the dynamic CS-ARDL results can be assessed.

The robustness analysis strongly supports the central conclusion of this thesis: AI innovation affects market income inequality and disposable income inequality in opposite ways. For market income inequality (Model B), both estimators indicate a robust equalising effect of AI. The dynamic CS-ARDL long-run coefficient (−1.04) is closely mirrored by the static CCEP estimate (−0.71). The consistency in sign and magnitude across estimators provides strong evidence that AI innovation genuinely compresses income dispersion at the pre-tax stage. The slightly smaller magnitude of the CCEP coefficient is expected, as the static model captures contemporaneous associations rather than the full cumulative adjustment process embedded in the CS-ARDL framework. In contrast, for disposable income inequality (Model A), both estimators yield positive coefficients for AI innovation. The CS-ARDL long-run estimate (+0.38) and the CCEP estimate (+0.15) jointly indicate that, after taxes and transfers, AI is associated with higher inequality. Although the static estimate is smaller, the direction of the effect is identical, reinforcing the interpretation that current redistributive systems are less effective at capturing and reallocating the gains generated by AI. This consistency across dynamic and static specifications confirms the existence of an "AI redistribution paradox": AI appears equalising in the market, yet inequality-enhancing in final disposable incomes.

Across all specifications, GDP per capita emerges as the most robust and quantitatively important determinant of inequality. In Model A (Disposable Gini), the CS-ARDL estimate (−5.78) and the CCEP estimate (−2.35) both indicate a strong equalising effect of economic growth. In Model B (Market Gini), the estimates are strikingly similar across estimators (−4.39 in CS-ARDL and −4.24 in CCEP), suggesting that growth reduces market inequality in a manner that is both immediate and structural. The near-equivalence of dynamic and static estimates in the market inequality model implies that the equalising effect of growth operates contemporaneously, without requiring long adjustment periods. This finding provides a high degree of confidence in the conclusion that economic expansion directly narrows income dispersion in the labour market within the sampled countries.

The robustness analysis also confirms the differentiated roles of policy variables. Social expenditure (G) consistently exhibits a negative association with disposable income inequality across estimators (−0.44 in CS-ARDL versus −0.27 in CCEP), while showing no systematic effect on market inequality. This pattern aligns with theoretical expectations: social transfers compress post-tax income distributions but do not alter pre-tax wage formation. The consistency of this result across specifications strengthens confidence in the identified redistribution mechanism.

Entrepreneurial education (E) remains positively associated with inequality in both models and across estimators. This robustness supports the interpretation that entrepreneurship-oriented education may reinforce winner-takes-all dynamics, benefiting a small number of highly successful individuals while leaving the broader income distribution relatively unaffected.

The failure of the CCEMG estimator is itself an informative diagnostic, confirming that the panel's short time dimension precludes reliable estimation of fully heterogeneous country-specific slopes. The successful implementation of the pooled CCEP estimator, however, provides a credible static benchmark against which the dynamic CS-ARDL results can be evaluated.

Crucially, the consistency of coefficient signs and relative magnitudes across CS-ARDL and CCEP—particularly for AI innovation, GDP per capita, and social expenditure—demonstrates that the core findings of this thesis are robust to alternative estimation strategies. The results therefore reflect structural relationships rather than artefacts of a particular econometric specification. Taken together, the robustness checks provide strong empirical support for the conclusion that the distributional effects of AI are mediated by economic growth and institutional design, rather than determined by technology alone.

6.1.9. Panel Granger causality (Dumitrescu–Hurlin)

The direction of causality between AI innovation, income inequality, and key policy and macroeconomic variables using the Dumitrescu–Hurlin (2012) panel Granger causality test. The results are reported in Table 21. The primary purpose of this analysis is to verify whether AI innovation acts as an exogenous driver of inequality dynamics or whether observed associations merely reflect reverse causality or simultaneous feedback effects.

Table 23

Dumitrescu–Hurlin Panel Granger Causality Test Results

Null hypothesis	W-statistic	Z-bar	p-value	Result
log(AI) → Gini (disposable)	3.0397	3.5329	0.0002	Reject H_0 ***
Gini (disposable) → log(AI)	0.3427	-1.1384	0.8725	No causality
Skill development → Gini (disposable)	83.8329	143.4708	0	Reject H_0 ***
Gini (disposable) → Skill development	17.0791	27.8499	0	Reject H_0 ***
Entrepreneurial education → Gini (disposable)	9.9751	15.5453	0	Reject H_0 ***

Continuation of Table 23

Null hypothesis	W-statistic	Z-bar	p-value	Result
Gini (disposable) → Entrepreneurial education	11.7893	18.6875	0	Reject H_0 ***
Social expenditure → Gini (disposable)	2.3835	2.3962	0.0083	Reject H_0 ***
Gini (disposable) → Social expenditure	11.1196	17.5277	0	Reject H_0 ***
log(Wealth) → Gini (disposable)	4.9586	6.8565	0	Reject H_0 ***
Gini (disposable) → log(Wealth)	3.3507	4.0715	0	Reject H_0 ***
log(AI) → Gini (market)	1.3922	0.6793	0.2485	No causality
Gini (market) → log(AI)	0.7092	-0.5037	0.6928	No causality
Skill development → Gini (market)	337.4851	582.8093	0	Reject H_0 ***
Gini (market) → Skill development	2.4074	2.4377	0.0074	Reject H_0 ***
Entrepreneurial education → Gini (market)	4.8043	6.5892	0	Reject H_0 ***
Gini (market) → Entrepreneurial education	39.5305	66.7368	0	Reject H_0 ***
Social expenditure → Gini (market)	27.47	45.8474	0	Reject H_0 ***
Gini (market) → Social expenditure	40.7268	68.8089	0	Reject H_0 ***
log(Wealth) → Gini (market)	29.3366	49.0805	0	Reject H_0 ***
Gini (market) → log(Wealth)	2.1607	2.0104	0.0222	Reject H_0 **

Source: Author's calculations based on the Dumitrescu–Hurlin (2012) panel Granger causality test.
Notes: Tests are conducted on first-differenced (stationary) panel data with one lag. Regressions are estimated without an intercept to preserve degrees of freedom given the short time dimension ($T = 5$). The W-statistic represents the average Wald statistic across cross-sectional units. The Z-bar statistic follows the standard normal distribution N(0,1). Significance levels: *** $p < 0.01$, ** $p < 0.05$.

The Dumitrescu–Hurlin (DH) test is particularly well suited to the present empirical context, as it allows for heterogeneity in causal relationships across countries while testing for average causal effects at the panel level. Unlike standard time-series Granger causality tests, the DH framework does not impose slope homogeneity and is therefore appropriate in panels where institutional and structural differences across countries are substantial.

The most important result of the causality analysis concerns the relationship between AI innovation (measured by log AI patents) and disposable income inequality. The test results indicate strong unidirectional causality running from AI innovation to disposable Gini inequality, with no evidenutcome.

This result provides strong empirical validation for the core specification adopted in the dynamic CS-ARDL models, where AI is treated as an exogenous structural driver of inequality. It also alleviates concerns that the estimated long-run effects of AI might be driven by reverse causality or policy reactions to rising inequality.

The causal relationship between AI innovation and market (pre-tax) income inequality displays a markedly different pattern. For market Gini, the DH test finds no statistically significant causality in either direction.

Table 24

Causal relationship between AI innovation and market income inequality

Direction	W-statistic	p-value	Result
log(AI) → Gini (market)	1.3922	0.2485	Fail to reject H_0
Gini (market) → log(AI)	0.7092	0.6928	Fail to reject H_0

Source: Author's calculations based on the Dumitrescu–Hurlin (2012) panel Granger causality test.

Notes: The null hypothesis (H_0) states that there is no Granger causality between the variables. Tests are conducted on first-differenced (stationary) panel data with one lag. W-statistics represent the average Wald statistics across cross-sectional units. P-values above conventional significance levels indicate the absence of statistically significant causal relationships.

The absence of short-run Granger causality suggests that year-to-year changes in AI patenting activity do not immediately translate into changes in pre-tax income dispersion, nor does market inequality influence short-run AI investment decisions. This finding is consistent with the CS-ARDL results, which indicate that the equalising effect of AI on market inequality is a long-run structural phenomenon rather than a short-run dynamic adjustment.

In practical terms, this implies that AI's influence on market income distribution likely operates through gradual channels—such as changes in occupational structures, productivity diffusion, and sectoral transformation—that unfold over longer horizons than those captured by one-period lagged causality tests.

In contrast to AI innovation, most fiscal and structural policy variables exhibit bidirectional causality with disposable income inequality. The DH test identifies statistically significant feedback relationships for social expenditure (G), government expenditure on education (S), entrepreneurial education (E), and net wealth (W).

Table 25

Causal Relationships between Other Variables and Disposable Income Inequality

Variable	Direction → Gini (disposable)	Result
Social expenditure (G)	Bidirectional	Reject H_0 (p = 0.0083)
Government expenditure (S)	Bidirectional	Reject H_0 (p = 0.0000)
Entrepreneurial education (E)	Bidirectional	Reject H_0 (p = 0.0000)
Net wealth (W)	Bidirectional	Reject H_0 (p = 0.0000)

Source: Author's calculations based on the Dumitrescu–Hurlin (2012) panel Granger causality tests.

Notes: The null hypothesis (H_0) states that there is no Granger causality between the listed variable and disposable income inequality. "Bidirectional" indicates rejection of H_0 in both directions (variable → Gini and Gini → variable). Tests are conducted on first-differenced (stationary) panel data with one lag. Reported p-values correspond to the Z-bar statistic of the Dumitrescu–Hurlin test.

These results indicate that inequality both affects and is affected by these policy and structural variables. For example, higher inequality may prompt governments to increase social or educational spending (Gini → G, S), while such spending subsequently influences inequality outcomes (G, S → Gini). Similarly, wealth accumulation and inequality appear to reinforce each other through mutually endogenous dynamics.

The presence of these feedback loops underscores the complexity of macroeconomic policy environments and highlights the importance of using dynamic estimators—such as CS-ARDL—that can disentangle long-run structural effects from short-run endogenous interactions.

Taken together, the Dumitrescu–Hurlin causality results provide a clear and coherent narrative that complements the main econometric findings of the thesis. Among all variables considered, AI innovation emerges as the only variable that exhibits strong unidirectional causality toward disposable income inequality, without evidence of reverse causality. This distinguishes AI from fiscal and policy variables, which are deeply embedded in endogenous feedback systems.

The causality analysis therefore strengthens the credibility of the core empirical framework by confirming that AI innovation can be treated as an exogenous technological driver in the inequality models. At the same time, it explains why policy variables require careful dynamic treatment, as their effects on inequality cannot be cleanly separated from political and social responses to inequality itself.

The Dumitrescu–Hurlin test reinforces the central thesis conclusion: technology shapes inequality trajectories, while institutions determine how societies respond to—and redistribute—the resulting outcomes.

Considering Dumitrescu–Hurlin causality results, the CS-ARDL findings, and the Mundlak/robustness analysis, identified relationships between variables.

Diagram 1 presents the conceptual framework guiding the empirical analysis, illustrating the hypothesized relationships between AI adoption, skill development (S), entrepreneurial education (E), government support (G), wealth accumulation (W), and income inequality (IIE), while accounting for moderating and control variables such as trade openness, globalization, and GDP per capita. The framework is explicitly designed to capture medium to long-run structural mechanisms, rather than short-term causal effects, which is consistent with both the macro-level panel structure of the data and the econometric evidence presented in subsequent sections.

AI adoption—empirically proxied by AI is positioned as the primary exogenous driver of structural economic transformation. This positioning is supported not only by theory but also by the Dumitrescu–Hurlin panel Granger causality tests, which identify strong unidirectional causality from AI innovation to disposable income inequality, with no evidence of reverse causality. Disposable inequality does not Granger-cause AI, confirming that AI functions as a leading technological driver rather than a policy or inequality-induced response.

The AI → S pathway reflects the expectation that greater AI diffusion increases demand for digital and complementary skills, encouraging investment in human capital. This mechanism is grounded in Human Capital Theory (Becker, 1964) and the Task-Based Automation Framework (Acemoglu & Restrepo, 2019), which emphasize that productivity gains from automation are conditional on skill adaptation.

Empirically, descriptive statistics and cross-sectional correlations indicate that countries with higher AI readiness and patenting intensity tend to display higher digital skill levels and greater wealth accumulation. However, fixed-effects and Mundlak specifications do not detect statistically significant within-country short-run effects of AI on inequality. This suggests that skill-related adjustments operate slowly and structurally, rather than through immediate year-to-year changes—an interpretation consistent with the CS-ARDL results, where AI effects materialize primarily in the long run.

The AI → E pathway captures the role of AI in lowering barriers to innovation and new firm creation by enabling experimentation, automation, and scalability. This channel is consistent with Schumpeterian innovation theory (Antonelli & Gehringer, 2017), which emphasizes creative destruction driven by technological change.

In the data, entrepreneurial education exhibits substantial cross-country variation but limited within-country movement. As a result, its effects are not strongly identified in short-run panel estimations, supporting its interpretation as a structural characteristic rather than an immediate driver of inequality dynamics. The CS-ARDL results further indicate that entrepreneurial education is associated with higher inequality, consistent with winner-takes-all dynamics rather than broad-based income compression.

The AI → G pathway reflects the hypothesis that AI-driven productivity and fiscal capacity may enable governments to expand social and redistributive spending, in line with Stiglitz's theory of market failures and state intervention. Descriptive evidence shows that countries with higher market income inequality tend to exhibit higher public and social expenditure shares, indicating an institutional response to inequality.

However, the Dumitrescu–Hurlin causality analysis reveals bidirectional causality between government and social expenditure and disposable inequality, confirming that these variables are endogenous and embedded in feedback loops. Within-country short-run estimates therefore lack statistical precision, consistent with strong country-specific institutional heterogeneity. This finding justifies the use of dynamic estimators that can isolate long-run structural effects despite simultaneity.

The framework further posits AI → W, whereby AI adoption contributes to asset accumulation through higher productivity, innovation rents, and entrepreneurial income, particularly for actors with access to skills and capital. This mechanism aligns with Asset-Based Welfare Theory (Sherraden, 1990).

Empirically, net wealth per adult is strongly positively correlated with AI patent intensity and globalization, and strongly negatively correlated with disposable income inequality. The CS-ARDL and Mundlak results indicate that wealth operates as a key long-run mediator, translating technological capacity into distributional outcomes. This relationship is structural rather than short-run, consistent with the absence of Granger causality between wealth and AI in the short term.

The convergence of skill development (S), entrepreneurial capacity (E), and government support (G) toward wealth accumulation reflects the assumption that human capital, institutional support, and entrepreneurial infrastructure jointly shape asset formation. While these pathways cannot be cleanly causally identified within the short time dimension of the panel, their strong cross-sectional associations underscore the importance of asset accumulation mechanisms in explaining persistent inequality differences across countries.

The pathway W → IIE represents the central mediating mechanism of the framework. Countries with higher average wealth per adult exhibit systematically lower levels of disposable income inequality, a finding that is robust across specifications. This result is consistent with Piketty's capital-based interpretation of inequality dynamics (Piketty, 2014) and OECD inclusive growth frameworks, which emphasize the role of asset ownership in stabilizing income distributions.

Notably, the CS-ARDL results indicate that while AI reduces market income inequality in the long run, its effect on disposable inequality is positive, revealing a redistribution efficiency gap. Wealth accumulation alone is therefore insufficient without effective institutional mechanisms to redistribute AI-generated gains.

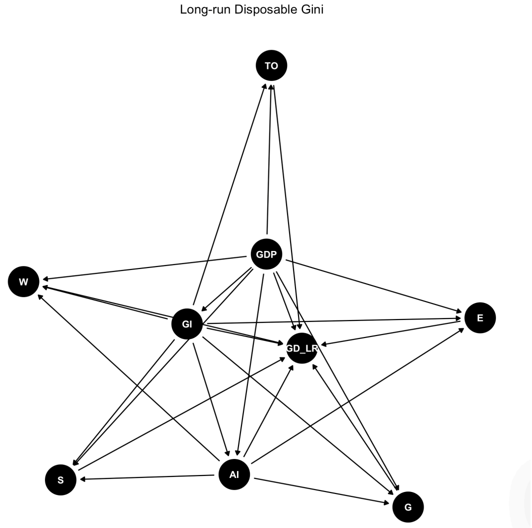
GDP per capita is included as a control variable capturing overall development levels, which influence inequality through potentially non-linear mechanisms such as those described by the Kuznets hypothesis. Empirically, GDP per capita emerges as the most robust equalizing force in both market and disposable income distributions, reinforcing the importance of growth.

Trade openness and globalization enter the framework as moderating factors. Higher globalization is strongly associated with higher wealth and lower disposable inequality, while trade openness exhibits more heterogeneous effects. These findings align with the globalization–inequality nexus described by Milanovic (2016), emphasizing the conditional role of domestic institutions.

The framework emphasizes that the empirical analysis provides strong evidence for long-run structural relationships—particularly through AI-driven wealth accumulation, economic growth, and globalization—while offering limited support for short-run causal effects. The combination of CS-ARDL dynamics and Dumitrescu–Hurlin causality tests confirms AI innovation as the primary exogenous driver, with inequality outcomes ultimately shaped by institutional and redistributive capacity rather than technology alone.

Figure 2

Long run disposable Gini DAG



Source: Author's conceptualisation derived from the long-run econometric model and theoretical assumptions.

6.1.10. Empirical findings vs established theoretical framework

Further lets integrate the empirical findings with established theoretical frameworks in the economics of income inequality, automation, and public policy.

Across both dynamic and static panel estimators, the results reveal a consistent and systematic pattern that can be characterised as an AI–redistribution paradox: AI innovation is associated with lower market income inequality but higher disposable income inequality in the long run. This pattern is consistent with theoretical distinctions between pre-tax market mechanisms and post-tax redistributive institutions (Atkinson, 2015; Acemoglu & Autor, 2011).

Across the preferred dynamic CS-ARDL and static CCEP specifications, AI exhibits opposing long-run effects on pre-tax and post-tax income inequality. For market income inequality, measured by the pre-tax, pre-transfer Gini coefficient, the long-run AI coefficient in the CS-ARDL model is approximately −1.04. The corresponding static CCEP estimate is −0.71 and statistically significant, although smaller in magnitude. Interpreted in levels, a one-unit increase in logged AI intensity—corresponding to approximately a 171% increase in patent intensity—is associated with a reduction of roughly one Gini point in market inequality in the long run. This finding is consistent with task-based automation models in which productivity and task-reinstatement effects dominate displacement effects for the average worker (Acemoglu & Restrepo, 2020).

In contrast, for disposable income inequality measured after taxes and transfers, the estimated long-run AI coefficients are positive. The CS-ARDL estimate is approximately +0.38, while the CCEP estimate is around +0.15. These results indicate that the same increase in AI intensity is associated with higher disposable income inequality over the long horizon. Taken together, the findings imply that AI diffusion is linked to a compression of pre-tax income dispersion, while fiscal and transfer systems do not fully translate these equalising market outcomes into lower post-tax inequality. This divergence is consistent with institutional theories emphasising the mediating role of tax–transfer systems in shaping disposable income distributions (Atkinson, 2015; OECD, 2011).

The Dumitrescu–Hurlin panel Granger causality tests reinforce this interpretation. The results indicate unidirectional causality from AI innovation to disposable income inequality, with no evidence of reverse causality (AI → Gini_disp, $p = .0002$; Gini_disp → AI not significant). This empirical pattern supports treating AI as a relatively exogenous structural driver within the CS-ARDL framework, rather than as an outcome of inequality dynamics (Dumitrescu & Hurlin, 2012).

Wealth per adult (W) emerges as a central determinant of disposable income inequality. Fixed-effects OLS estimates indicate a strongly negative association between logged wealth per adult and disposable inequality ($\beta \approx -6.17$, $p \approx .010$). Empirically, a 1% increase in wealth per adult is associated with a reduction of approximately 0.06 Gini points, while a 10% increase corresponds to a reduction of about 0.62 Gini points. In contrast, wealth per adult is small and statistically insignificant for market inequality in fixed-effects specifications. Pooled regressions indicate a negative and statistically significant relationship between wealth and disposable inequality, alongside a positive association between wealth and market inequality. This pattern is consistent with cross-country differences in fiscal capacity and redistribution, as emphasised in asset-based welfare theories (Piketty, 2014; Wolff, 2017).

Social expenditure (G), measured as a share of GDP, exhibits a clear redistributive role. In CS-ARDL long-run estimates for disposable inequality, a one-percentage-point increase in social expenditure is associated with a reduction of approximately 0.44 Gini points. For market inequality, the effect of social expenditure is statistically insignificant and close to zero. This divergence aligns with the institutional role of welfare states, which primarily affect income distribution through post-tax and post-transfer mechanisms rather than through market wage formation (Esping-Andersen, 1990; OECD, 2011).

By contrast, general government expenditure (S) displays an inequality-increasing association. In the CS-ARDL long-run specification for disposable inequality, the coefficient on S is approximately +0.99, indicating that broader government spending is associated with higher disposable inequality, while effects on market inequality are not robust. This empirical distinction is consistent with theoretical frameworks that differentiate targeted redistributive spending from administrative or non-redistributive expenditure (Musgrave & Musgrave, 1989).

Entrepreneurial education (E) is consistently associated with higher inequality. Long-run CS-ARDL estimates indicate positive coefficients for both disposable inequality (approximately +1.23) and market inequality (approximately +1.91). Fixed-effects OLS estimates for disposable inequality corroborate this result, yielding coefficients of approximately +1.17 ($p \approx .045$). These findings are consistent with innovation-based and "winner-takes-all" models, in which entrepreneurial activity generates highly skewed returns that are not fully neutralised by tax and transfer systems (Rosen, 1981; Autor et al., 2020).

Fixed-effects regressions examining policy and structural transmission channels indicate that AI readiness is negatively associated with entrepreneurial education ($\beta \approx -0.093$, $p \approx .00048$) and social expenditure ($\beta \approx -0.274$, $p \approx .0246$). No robust within-country effect is detected for general government expenditure. While fixed-effects estimates do not reveal a statistically significant relationship between AI and wealth per adult, pooled regressions show a strong positive association between AI intensity and wealth accumulation across countries. This suggests that AI-related wealth effects primarily reflect long-run structural differences rather than short-run within-country dynamics, consistent with general-purpose technology theories (Bresnahan & Trajtenberg, 1995).

GDP per capita exhibits a strong negative long-run association with both disposable and market inequality in CS-ARDL models, confirming that higher income levels are associated with lower inequality in this panel. Within-country fixed-effects estimates yield weaker and sometimes opposing short-run effects. Trade openness is associated with lower disposable inequality within countries, while globalisation indices display strong negative correlations with disposable inequality in pooled data. These results align with empirical findings linking openness and integration to distributional outcomes through productivity and fiscal channels (IMF, 2017).

Slope heterogeneity tests (Swamy; Pesaran–Yamagata) strongly reject slope homogeneity for AI and GDP effects, indicating substantial cross-country variation. Nordic countries exhibit strongly negative AI–inequality slopes, whereas the United States and China display positive slopes. Consequently, average effects mask significant heterogeneity in national institutional contexts. Granger causality tests further indicate that while AI causally affects disposable inequality, variables such as wealth, social expenditure, government spending, and education exhibit bidirectional relationships with inequality. This supports treating these variables as endogenous policy and structural responses rather than exogenous drivers.

Within task-based automation models, the observed reduction in market inequality associated with AI is consistent with productivity and task-reinstatement effects outweighing displacement effects for the average worker (Acemoglu & Restrepo, 2020). However, the increase in disposable inequality suggests that fiscal and redistributive institutions do not fully offset AI-induced structural changes. Asset-based welfare theories are supported by the strong negative relationship between wealth per adult and disposable inequality, indicating that asset ownership and social expenditure jointly mediate the distributional effects of AI (Piketty, 2014; Wolff, 2017).

6.1.11. Redefining the mathematical model

Following the completion of the full econometric procedure, the analysis returns to the initially imposed reduced-form mathematical model in order to align the theoretical representation with the empirical structure identified in the data. The preceding stages of the empirical analysis established the presence of cross-sectional dependence, slope heterogeneity, mixed integration orders, and panel cointegration, thereby ruling out static pooled specifications as an appropriate structural framework. The estimation of Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) models further demonstrated that the relationship between AI, institutional factors, wealth, and income inequality is inherently dynamic and characterised by adjustment toward a long-run equilibrium. As a consequence, the original reduced-form specification requires reformulation.

The initial model expressed income inequality as a contemporaneous function of AI indicators, policy variables, asset accumulation, and macroeconomic controls. While this formulation provided a useful conceptual abstraction, it did not distinguish between short-run fluctuations and long-run structural relationships, nor did it incorporate an explicit mechanism describing how deviations from equilibrium are corrected over time. The econometric evidence generated in this thesis indicates that such distinctions are empirically relevant and must be embedded in the mathematical model.

In redefining the model, the guiding principle is that only parameters identified as long-run equilibrium effects under panel cointegration can be interpreted as structural coefficients. All econometric tests conducted in the thesis support this approach. Tests for cross-sectional dependence and slope heterogeneity invalidate homogeneous pooled estimators as representations of structural relationships, while panel cointegration tests confirm the existence of stable long-run associations between income inequality and the explanatory variables. Within this framework, the CS-ARDL estimator is explicitly designed to recover long-run coefficients through re-normalisation using the estimated error-correction term. These long-run coefficients therefore constitute the appropriate beta parameters for the redefined mathematical model, whereas short-run coefficients are transitional by construction and alternative estimators, such as Common Correlated Effects pooled models, serve exclusively as robustness benchmarks.

For disposable income inequality, measured by the post-tax and post-transfer Gini index, the long-run coefficients are taken from the CS-ARDL results reported for Model A. The redefined equilibrium relationship indicates that AI innovation, proxied by the logarithm of AI-related patents, enters the long-run inequality equation with a coefficient of 0.3787. This value is drawn directly from the long-run column of the CS-ARDL Model A estimates and represents the permanent association between innovation intensity and disposable income inequality under cointegration. GDP per capita enters the model with a long-run coefficient of −5.7777, reflecting a negative structural relationship between income levels and inequality once redistributive mechanisms are taken into account. Government expenditure on education-related functions is associated with a positive long-run coefficient of 0.9968, while social expenditure displays a negative coefficient of −0.4372, consistent with its redistributive role. Entrepreneurial education enters positively, with a long-run coefficient of 1.2337, whereas net wealth per adult exhibits a negative coefficient of −2.7163, capturing the structural relationship between asset accumulation and lower disposable income inequality. Trade openness and the globalization index enter the long-run equation with coefficients of −0.0180 and −0.2142 respectively. Each of these coefficients is taken directly from the long-run estimates of the CS-ARDL Model A and is therefore interpreted as a permanent parameter of the equilibrium relationship.

The dynamic nature of this relationship is governed by the estimated error-correction term, which equals −0.7893 in Model A. This parameter quantifies the speed at which deviations from the long-run equilibrium are corrected and confirms that disposable income inequality adjusts relatively rapidly following short-run shocks. The presence of a negative and statistically meaningful adjustment parameter further supports the appropriateness of a cointegrated error-correction representation.

A parallel reformulation is undertaken for market income inequality, measured by the pre-tax and pre-transfer Gini index. In this case, the structural coefficients are taken from the long-run estimates of the CS-ARDL Model B. AI innovation enters the long-run market inequality equation with a coefficient of −1.0380, while GDP per capita is associated with a coefficient of −4.3913. Government expenditure and social expenditure enter positively, with coefficients of 0.3456 and 0.0883 respectively, whereas entrepreneurial education again exhibits a positive structural association with inequality, reflected in a coefficient of 1.9053. Net wealth per adult enters negatively, with a coefficient of −1.9916, while trade openness and globalization are associated with small positive coefficients of 0.0313 and 0.0315 respectively. As in the disposable income specification, each coefficient is taken directly from the long-run column of the CS-ARDL Model B estimates and represents a structural equilibrium relationship under cointegration.

The estimated error-correction term in Model B equals −0.4899, indicating a slower speed of adjustment relative to disposable income inequality. This finding is consistent with the higher persistence of market income inequality observed in the empirical analysis and further justifies modelling market and disposable inequality as distinct dynamic processes.

Although the original reduced-form model included both AI innovation and AI readiness, the final mathematical specification retains only the innovation-based measure. The CS-ARDL results reported in the thesis provide long-run coefficients for AI innovation, whereas AI readiness does not appear as a stable long-run parameter in the documented CS-ARDL tables. Additional readiness-based specifications were explored during the analysis but were characterised by substantial sample reduction and instability in long-run renormalisation due to near-unit-root behaviour. In light of these empirical constraints, AI readiness is not included as a structural beta in the redefined mathematical model and is instead interpreted as operating indirectly through institutional, educational, and wealth channels.

Considering all of the above, model A is redefined as:

$$IIE_{it}disp = \beta_0 + 0.3787AI(patents)_{it} + 0.9968S_{it} + 1.2337E_{it} - 0.4372G_{it} - 2.7163W_{it} - 5,7777GDP_{it} - 0.0180TO_{it} - 0.2142GI_{it} + \mu_{it} \quad \{12\}$$

And model B:

$$IIE_{it}market = \beta_0 - 1.0380AI(patents)_{it} + 0.3456S_{it} + 1.9053E_{it} + 0.0883G_{it} - 1.9916W_{it} - 4.3913GDP_{it} + 0.0313TO_{it} + 0.0315_{it} + \mu_{it} \quad \{13\}$$

Note: β_0 treated as an implicit constant absorbed by country effects and common factors and therefore not reported in this work.

6.1.12. Acceleration Dynamics

Most empirical analyses of income inequality focus on levels or long-run equilibrium relationships, implicitly assuming linear adjustment processes. While these approaches are suitable for identifying steady-state associations, they are less informative about transitional dynamics, particularly in periods of rapid technological diffusion, macroeconomic shocks, and institutional adjustment. General-purpose technologies such as AI and associated policy responses can generate nonlinear trajectories in inequality outcomes, including phases of acceleration and deceleration rather than smooth trend evolution (Acemoglu & Restrepo, 2020; Aghion et al., 2019).

To capture these dynamics, this thesis extends the empirical framework beyond levels and first differences by modelling acceleration in inequality, defined as the second-order temporal change in inequality indicators. Whereas first differences measure whether inequality is rising or falling, second differences measure whether the *speed* of that change is increasing or decreasing. This distinction is particularly relevant in the case of general-purpose technologies such as AI, whose distributional effects may intensify as adoption spreads and complementary organisational changes accumulate. Similarly, redistributive and human-capital policies may display delayed but accelerating impacts as institutional coverage and effectiveness expand.

Formally, acceleration in this work is operationalised through second differencing. For a given country and year, the second difference of the Gini coefficient captures the change in the annual change of inequality. A negative second difference indicates a deceleration of inequality dynamics, meaning that inequality growth is slowing or that inequality decline is accelerating. A positive second difference indicates the opposite. Country-specific bivariate acceleration regressions relate second differences of inequality to second differences of explanatory variables, including AI patents, fiscal variables, wealth indicators, and macro-structural controls. The estimated slope coefficient in this framework reflects the fitted association between acceleration in the explanatory variable and acceleration in inequality, not an effect on inequality levels.

A critical limitation of this exercise arises from the short time dimension of the dataset. With annual data covering 2018–2022, second differencing leaves at most three usable observations per country. In a bivariate specification with an intercept, this implies only one residual degree of freedom. As discussed earlier in the thesis, repeated differencing in short panels leads to severe degrees-of-freedom loss, making coefficient estimates highly sensitive to individual observations and rendering conventional statistical inference unreliable. Consequently, the acceleration results are interpreted strictly as descriptive diagnostics of turning-point behaviour, rather than as stable or causal parameter estimates.

Theoreticaly let $y_{i,t}$ denote market or disposable Gini for country i at time t. First differences measure annual changes:

$$\Delta y_{i,t} = y_{i,t} - y_{i,t-1} \quad \{14\}$$

Second differences measure changes in those annual changes (curvature / acceleration):

$$\Delta^2 y_{i,t} = \Delta y_{i,t} - \Delta y_{i,t-1} = y_{i,t} - 2y_{i,t-1} + y_{i,t-2} \quad \{15\}$$

In this framework:

- $\Delta^2 y_{i,t} < 0$ indicates deceleration of inequality (inequality rises more slowly, or declines more rapidly),
- $\Delta^2 y_{i,t} > 0$ indicates acceleration of inequality (inequality rises faster, or declines more slowly).

The acceleration model is estimated in country-specific bivariate form:

$$\Delta^2 \text{IIE}_{i,t} = \alpha_i + \beta_i \, \Delta^2 X_{i,t} + u_{i,t} \quad \{16\}$$

where X includes AI patents, AI readiness, government expenditure (S), entrepreneurial education (E), social expenditure (G), net wealth per adult (W), and macro controls (GDP, trade openness (TO), globalization index (GI)).

With annual data for time period 2018–2022, second differencing leaves at most three usable observations per country (2020–2022). In a bivariate regression with intercept and one regressor, this implies:

- parameters estimated = 2,
- observations = 3,
- residual degrees of freedom *df*=1.

As already noted, repeated differencing in a short panel produces severe degrees-of-freedom loss and makes dynamic inference unstable. Accordingly, acceleration results are interpreted as descriptive turning-point diagnostics rather than stable structural parameters.

Within this constrained setting, the acceleration estimates nevertheless reveal notable heterogeneity across countries and variables. Focusing first on AI patenting, the fitted association between acceleration in AI patents and acceleration in disposable-income inequality differs in sign across the six focal countries Table 24. For the United States and Sweden, the estimated coefficients are negative, indicating that periods of faster acceleration in AI patenting coincide with a deceleration of inequality dynamics. In contrast, Norway, France, Brazil, and China exhibit positive coefficients, implying that acceleration in AI patenting coincides with accelerating inequality within the observed period. The explanatory power of these regressions also varies substantially, ranging from near zero in Sweden and China to very high values in Norway and the United States. This dispersion underscores the thesis's central argument that short-run inequality responses to technological change are highly context-dependent and unstable in short panels.

Table 26

Second-Difference Regression Results (Country-Level Analysis)

Country	Observations (n)	Intercept (α)	Coefficient (β)	R^2	Outcome variable	Regressor
United States	3	-1.1	-0.00114	0.9099	Δ^2 Disposable Gini	Δ^2 AI patents
Norway	3	1.1625	1.0575	0.9591	Δ^2 Disposable Gini	Δ^2 AI patents
France	3	0.3046	0.0158	0.7318	Δ^2 Disposable Gini	Δ^2 AI patents
Brazil	3	-0.3462	0.1744	0.2269	Δ^2 Disposable Gini	Δ^2 AI patents
Sweden	3	0.0898	-0.00102	0.0091	Δ^2 Disposable Gini	Δ^2 AI patents
China	3	0.1322	0.00018	0.0099	Δ^2 Disposable Gini	Δ^2 AI patents

Source: Author's calculations based on country-specific second-difference regressions.
Notes: The dependent variable is the second difference of disposable income inequality (Δ^2 Gini), and the regressor is the second difference of AI patent counts (Δ^2 AI patents). Second differencing is applied to ensure stationarity of the series and to remove persistent trends and country-specific drifts. Regressions are estimated separately for each country due to slope heterogeneity. The small number of observations (n = 3) reflects the short time dimension after differencing and results should be interpreted as illustrative robustness checks rather than primary inference.

When the acceleration framework is extended beyond AI patents to include fiscal and structural variables, additional patterns emerge. In particular, acceleration in government expenditure and social expenditure is associated with negative inequality acceleration in most of the focal countries for disposable-income inequality. In mechanical terms, this means that faster increases in these fiscal variables tend to coincide with a slowing of inequality dynamics in the short run. However, this pattern is not universal, and at least one country exhibits the opposite sign, reinforcing the presence of cross-country heterogeneity. Acceleration in wealth indicators and macro-structural controls such as GDP growth, trade openness, and globalisation also shows mixed signs across countries and outcomes, suggesting that no single variable produces a uniform acceleration pattern across institutional contexts.

Table 27

Country-Specific Second-Difference Regressions: Panel A. Outcome: Δ² Disposable Income Inequality (Gini)

Country	AI patents	AI readiness	S	E	G	W	GDP	TO	GI
Brazil	0.17442 (0.227)	NA	−3.86112 (0.354)	−0.80183 (0.784)	−0.18267 (0.999)	0.000146 (0.487)	−0.0 (0.593)	0.162036 (0.300)	−1.23290 (0.933)
China	0.000182 (0.010)	NA	0.306017 (0.516)	NA	0.081688 (0.733)	−0.000017 (0.973)	0.0 (0.977)	0.020207 (0.840)	0.386533 (0.783)
France	0.015802 (0.732)	NA	−1.54258 (0.977)	NA	−0.134946 (0.919)	0.000005 (0.039)	−0.0 (0.529)	−0.005276 (0.072)	−0.078480 (0.203)
Norway	1.057507 (0.959)	NA	−1.11831 (0.318)	NA	−0.231738 (0.252)	0.000044 (0.616)	0.0 (0.001)	−0.095501 (0.184)	−0.893969 (0.109)
Sweden	−0.001022 (0.009)	NA	−0.527124 (0.995)	0.201528 (0.294)	−0.092673 (0.986)	−0.000000 (0.001)	0.0 (1.000)	0.005621 (0.411)	0.125338 (0.766)
United States	−0.001141 (0.910)	NA	−2.36560 (0.510)	0.708386 (0.216)	−0.140552 (0.488)	−0.000010 (0.360)	−0.0 (0.799)	−0.182308 (0.875)	−0.684508 (0.945)

Source: Author's calculations based on country-specific second-difference regressions.

Notes: The dependent variable is the second difference of disposable income inequality (Δ² Gini). Reported coefficients are slope estimates (β); values in parentheses denote R^2. AI readiness is excluded due to insufficient time variation after second differencing. Results are country-specific and intended as robustness diagnostics under strong stationarity transformations rather than for cross-country inference.

Table 28

Country-Specific Second-Difference Regressions: Panel B. Outcome: Δ² Market Income Inequality (Gini)

Country	AI patents	AI readiness	S	E	G	W	GDP	TO	GI
Brazil	−0.122691 (0.832)	NA	0.149876 (0.067)	0.049869 (0.007)	0.063453 (0.265)	−0.000138 (0.958)	−0.0 (0.593)	0.162036 (0.300)	−1.232902 (0.933)
China	−0.000007 (0.001)	NA	−0.332396 (0.916)	NA	−0.035528 (0.971)	0.000004 (0.407)	0.0 (0.977)	0.020207 (0.840)	0.386533 (0.783)
France	−0.003871 (0.932)	NA	−0.634830 (0.997)	NA	0.024735 (0.404)	−0.000005 (0.507)	−0.0 (0.529)	−0.005276 (0.072)	−0.078480 (0.203)
Norway	0.997606 (0.977)	NA	−0.862040 (0.116)	NA	−0.023538 (0.003)	0.000021 (0.178)	0.0 (0.001)	−0.095501 (0.184)	−0.893969 (0.109)
Sweden	−0.001167 (0.223)	NA	−0.016243 (0.000)	0.060590 (0.139)	−0.038812 (0.908)	0.000000 (0.028)	0.0 (1.000)	0.005621 (0.411)	0.125338 (0.766)
United States	−0.000188 (0.995)	NA	−0.792711 (0.995)	0.202396 (0.053)	0.115358 (0.994)	−0.000001 (0.005)	−0.0 (0.799)	−0.182308 (0.875)	−0.684508 (0.945)

Source: Author's calculations based on country-specific second-difference regressions.
Notes: The dependent variable is the second difference of market income inequality (Δ² Gini). Reported coefficients are slope estimates (β); values in parentheses denote R^2. AI readiness is excluded due to insufficient time variation after second differencing. Results are estimated separately for each country and serve as robustness diagnostics under strong stationarity transformations rather than as a basis for cross-country inference.

In order to translate the estimated acceleration relationships into a more intuitive dynamic perspective, the analysis extends the scenario-based extrapolation exercise to a time period from 2023 to 2030. This extrapolation is explicitly non-predictive and does not constitute a forecast in the econometric sense. Instead, it is designed to illustrate the mechanical implications of the estimated acceleration parameters under transparent and clearly stated assumptions, thereby supporting policy-relevant interpretation without invoking causal claims.

The extrapolation starts from observed 2022 inequality levels. Two scenarios are considered throughout the 2023–2030 period. The first is a neutral acceleration scenario, in which acceleration in the explanatory variable—most notably AI patenting—is set to zero from 2023 onward. This scenario represents a situation in which technological diffusion continues but no longer accelerates relative to its 2022 pace. The second is a persistent acceleration scenario, in which the observed 2022 acceleration is assumed to continue unchanged throughout the extrapolation horizon.

Extending the extrapolation window beyond 2025 highlights how second-difference dynamics can compound over time. Under the persistence scenario, even relatively small acceleration coefficients may generate substantial divergence in inequality paths when applied repeatedly over several years. Conversely, under the neutral scenario, inequality trajectories evolve more smoothly, reflecting the absence of further curvature in the underlying dynamics. Importantly, the divergence between scenarios grows nonlinearly over time, illustrating how acceleration effects—by construction—become increasingly influential as the horizon lengthens.

The extrapolated paths continue to differ markedly across countries. For example, in the United States, where the estimated acceleration coefficient linking AI patent acceleration to disposable-income inequality acceleration is negative, the persistence scenario implies a progressively stronger deceleration of inequality dynamics over the medium term relative to the neutral scenario. In contrast, for countries such as Norway, France, Brazil, and China—where the estimated coefficient is positive—the persistence scenario generates increasingly divergent inequality trajectories, with inequality accelerating relative to the neutral benchmark. As the horizon extends toward 2030, these differences become more pronounced, underscoring the sensitivity of inequality dynamics to sustained acceleration in technological indicators.

At the same time, the extrapolation makes the limitations of the acceleration framework particularly transparent. Because the underlying regressions are estimated with only three effective observations per country, persistence of a 2022 acceleration value over eight additional years is a strong and deliberately stylised assumption. In some cases, this produces implausibly large movements in inequality levels by 2030, especially where the estimated acceleration coefficient is large in magnitude. These outcomes are therefore not interpreted as plausible future paths. Rather, they function as stress tests, demonstrating how rapidly inequality trajectories can diverge if short-run acceleration effects were to persist unchecked.

The heterogeneity observed in the estimated acceleration coefficients for AI patenting remains central in the extended extrapolation. Negative coefficients for the United States and Sweden imply that sustained AI acceleration would be mechanically associated with continued deceleration of inequality dynamics, whereas positive coefficients for Norway, France, Brazil, and China imply the opposite. This heterogeneity is fully consistent with the thesis's broader finding that short-run inequality responses to AI-related indicators differ markedly across institutional contexts and that no uniform pattern can be inferred from short panels.

When the acceleration framework is broadened beyond AI patents to include fiscal and structural variables, the extrapolation reinforces earlier diagnostic insights. Acceleration in government expenditure and social expenditure is mechanically associated with inequality deceleration in most of the focal countries for disposable-income inequality, suggesting that sustained fiscal expansion may counteract accelerating inequality dynamics over longer horizons. However, as with AI-related indicators, this pattern is not universal and remains subject to country-specific institutional conditions. Acceleration in wealth indicators and macro-structural controls continues to display mixed signs across countries, indicating that medium-term inequality dynamics cannot be stabilised through a single policy channel.

Illustrative 2030 disposable Gini under two Δ^2AI-patent scenarios is shown in a table below.

Table 29

Illustrative Scenario-Based Projections of Disposable Income Inequality in 2030

Country	Observed Gini (2022)	Scenario A (2030) $\Delta^2 AI = 0$	Scenario B (2030) $\Delta^2 AI = \Delta^2 AI$ 2022	Gap (B − A)
United States	38.9	9.6998	111.2547	101.5549
Norway	26.1	54.3504	-94.7594	-149.1098
France	29.8	42.3651	15.7698	-26.5953
Brazil	45.5	25.8359	45.6152	19.7792
Sweden	28.9	34.5343	35.8551	1.3208
China	41	47.3599	47.2536	-0.1063

Source: Author's calculations based on second-difference regression estimates and scenario assumptions.

Notes: Scenario A assumes zero acceleration in AI innovation ($\Delta^2 AI = 0$) from 2022 onward. Scenario B assumes continuation of the 2022 AI acceleration rate ($\Delta^2 AI = \Delta^2 AI$ 2022). Values are mechanical projections obtained by iteratively applying the estimated second-difference relationship. Large deviations arise due to compounding effects and the very short time dimension (three Δ^2 observations per country). Results should be interpreted as stress-test diagnostics illustrating sensitivity to sustained AI acceleration, not as point forecasts.

Taken together, these findings imply a clear ordering of policy priorities when the objective is to accelerate inequality reduction, understood here as achieving non-positive second differences of inequality. First, fiscal redistribution and social expenditure emerge as the most immediately actionable and empirically supported levers. The consistent negative association between acceleration in these variables and inequality acceleration suggests that governments seeking to offset the distributional risks of rapid technological change should prioritise the responsiveness and timing of fiscal instruments, rather than relying solely on long-term structural reforms.

Second, AI policy itself should be integrated into inequality management through an acceleration-aware lens. In countries where the estimated β linking AI acceleration to inequality acceleration is positive, sustained AI acceleration without countervailing measures is mechanically associated with worsening inequality dynamics. In such contexts, AI expansion strategies should be coupled with policies explicitly designed to offset acceleration effects—most plausibly through targeted redistribution, social insurance, and labour-market adjustment mechanisms—rather than being evaluated only on growth or innovation metrics.

Third, education and skills policies, while central to long-run inequality reduction, appear less effective as short-run counter-acceleration tools within the limits of the current data. Their role should therefore be framed as complementary and structural, supporting long-term adjustment rather than serving as the primary instrument for stabilising inequality dynamics during periods of rapid AI acceleration.

The extrapolation exercise thus reinforces several core conclusions of the thesis. Acceleration metrics provide an early-warning perspective that is not visible in inequality levels alone. Sustained acceleration—whether technological or fiscal—can generate large medium-term divergence even when short-run changes appear modest. Most importantly, the calculations indicate that policy timing and responsiveness, particularly in fiscal and social domains, are central to managing inequality dynamics in the presence of accelerating technological change.

6.1.13. Limitations of the quantitative methodology

While the rigorous application of second-generation panel data techniques, notably the CS-ARDL and CCEMG estimators, successfully addressed the challenges of cross-sectional dependence and non-stationarity, the quantitative analysis is subject to several unavoidable limitations. These constraints primarily stem from data imperfectness, a restrictive time dimension, and the inherent complexity of causal identification in macro-econometric modeling.The Limits of Measurement and Sample IntegrityA fundamental constraint lies in the proxying of the core variable, AI adoption. The use of AI Patent counts and the Government AI Readiness Index (GAIRI), while authoritative, measures a nation's innovation capacity and policy intent, respectively, but fails to capture the granular actual diffusion and utilization of AI across the entire economy. This limitation is compounded by the unbalanced nature of the panel, where key policy variables like GAIRI and Entrepreneurial Education are unavailable for a significant subset of observations. This non-random missing data inevitably introduces a sample selection bias, meaning the findings are most representative of economies with high institutional and reporting capacities, often overlooking the unique dynamics in less developed nations. Furthermore, the analysis at the annual, national level conceals vital intra-national heterogeneity, simplifying a highly decentralized phenomenon.Temporal Constraints and Causal AmbiguityThe time horizon of the study, spanning only 2018–2022, introduces two critical interpretive difficulties. First, the short time dimension (T=5) restricts the robustness of the estimated long-run coefficients derived from the CS-ARDL, hindering the precise identification of true long-term equilibrium. Second, this period encompasses the COVID-19 pandemic, a massive exogenous shock that generated large, temporary fiscal interventions (e.g., the spike in social expenditure). Isolating the coefficients representing a structural AI-policy response from those contaminated by this confounding health crisis remains a profound analytical challenge. Moreover, the Dumitrescu–Hurlin causality tests confirmed that core policy and structural variables (Social Expenditure and Wealth) are strongly endogenous to inequality. This pervasive bidirectional causality implies that the reported coefficients reflect not just the policy's effect on inequality, but also the government's fiscal reaction to it, thus compromising a purely exogenous causal interpretation of the policy levers.The Trade-Off of GeneralizationFinally, the study's attempt to achieve robust parameter estimation necessitates a trade-off in interpretation. The strong econometric evidence for slope heterogeneity—which revealed that the effect of AI on inequality is significantly negative in countries like Norway but positive in countries like the United States—meant that the final results were derived using the Mean Group (MG) estimator. This technique provides a statistically sound average coefficient for the panel. While robust, this average inherently masks the profound differences in country-specific outcomes. Consequently, the primary finding of the "AI Redistribution Paradox" is a generalized pattern for the entire panel, limiting its direct applicability for policy prescription in any single, non-average national context whose unique institutional structure governs the final technological outcome.

6.2. Qualitative research results

To complement and contextualize the quantitative panel analysis, this study incorporates a qualitative single-country case study focusing on Norway. The purpose of this qualitative component is not to generate statistical generalization, but to enhance the explanatory depth of the research by examining how institutional arrangements, policy frameworks, and governance structures shape the interaction between AI, skill development, entrepreneurship, and income inequality within a specific national context. While the quantitative analysis identifies macro-level associations across countries, it cannot fully capture the policy mechanisms and institutional conditions through which these relationships operate in practice. The Norway case study therefore provides essential contextual insight into how technological change is mediated by public policy.

Norway is selected following a most illustrative case selection logic. During the observed period, Norway combined low and stable levels of disposable income inequality with a comprehensive welfare state, high digital maturity, and explicit national strategies for AI, public-sector digitalisation, and lifelong learning. According to Statistics Norway, inequality in equivalised disposable income remained comparatively low throughout 2018–2022, reflecting the sustained redistributive impact of taxes and transfers (Statistics Norway, 2022). International comparisons from the OECD confirm that Norway remained among the countries with the lowest post-tax income inequality, well below the OECD average (OECD, 2024). These characteristics make Norway a theoretically and empirically relevant case for examining how AI-related policies interact with institutional capacity to mitigate inequality risks.

A first analytical dimension concerns AI governance and public-sector deployment. Norway's National Strategy for AI formally established AI as a strategic policy area with explicit governance objectives (Government of Norway, 2019; Government of Norway, 2020). The strategy framed AI as a tool to improve productivity, efficiency, and service quality in both the public and private sectors, while simultaneously emphasizing ethical safeguards, transparency, accountability, privacy protection, and non-discrimination. Rather than prioritizing rapid automation, AI deployment was positioned as complementary to existing public services, reinforcing universal access and public trust. The strategy also emphasized cross-government coordination through shared standards, competence-building, and collaboration between government, academia, and industry.

The second dimension focuses on skills reform and lifelong learning policies. In the Skills Reform – Lifelong Learning (Meld. St. 14, 2020–2021), the Norwegian government explicitly linked technological change, digitalisation, and automation to potential inequality risks if access to skills development remained uneven (Government of Norway, 2021). Lifelong learning was established as a core policy principle, with expanded access to adult education and further training, particularly for workers affected by structural change. Policy measures emphasized alignment between education institutions, employers, and public authorities, prioritizing digital competencies and advanced skills necessary for participation in a technology-intensive economy. These measures were framed as preventative mechanisms aimed at reducing labour market polarization and protecting employment opportunities across income groups.

The third analytical dimension examines entrepreneurship and innovation support. During the period under study, entrepreneurship was supported primarily through publicly coordinated instruments rather than reliance on private capital markets. Through Innovation Norway, the government provided grants, loans, and advisory services to start-ups and innovative firms at different stages of development, including early validation, commercialization, and scaling (Innovation Norway, 2021). Particular emphasis was placed on technology-oriented and innovation-driven projects, including those linked to digitalisation. These instruments were designed to lower barriers to entry in high-cost and high-risk innovation activities, thereby broadening access to entrepreneurial opportunities and asset-based wealth creation.

The fourth dimension addresses redistribution, welfare institutions, and inequality outcomes. Data from Statistics Norway and the OECD show that Norway maintained a high level of redistribution through taxes and transfers throughout 2018–2022 (Statistics Norway, 2022; OECD, 2024). A substantial gap between market income inequality and disposable income inequality demonstrates the redistributive effect of government intervention. Universal access to education, healthcare, and social protection reduced inequality of opportunity and buffered potential inequality-enhancing effects of technological change. OECD indicators consistently place Norway among the countries with the lowest disposable income inequality within the OECD during this period.

Across all reviewed documents, AI policy, skills development, entrepreneurship support, and redistribution are treated as interconnected policy domains rather than isolated interventions. AI governance is embedded within broader digitalisation and welfare-state frameworks; skills policy is framed as a response to technological change; entrepreneurship support is publicly coordinated; and redistribution continues to stabilize income outcomes. No evidence in the reviewed material suggests a withdrawal of state responsibility in managing the distributional effects of technological change. Instead, the Norwegian government maintains an active role in shaping how AI and digitalisation interact with labour markets and income distribution.

7. Discussion and conclusions

The empirical findings of this Master's thesis contribute to the expanding academic literature on AI and income inequality by demonstrating that the distributional effects of AI are neither automatic nor technologically predetermined. Instead, the results indicate that AI influences income inequality through indirect and institutionally mediated pathways, particularly via asset accumulation, skill development, entrepreneurial education, and public redistribution mechanisms. This approach aligns with recent strands of economic research that conceptualize technological change as embedded within broader socio-economic systems rather than as an isolated driver of inequality.

The quantitative analysis shows that AI adoption, measured through AI patent intensity and government AI readiness, does not exert a statistically robust direct effect on market income inequality. This finding is consistent with task-based models of automation, which emphasize that technological change primarily reshapes the composition of tasks rather than uniformly altering wage structures across the economy. Previous research similarly suggests that innovation-driven productivity gains do not automatically translate into higher or lower inequality unless mediated by labor market institutions, capital ownership structures, and policy responses (Autor, 2015; Autor et al., 2020). The absence of a direct effect in this study supports the interpretation that AI-related inequality dynamics operate through structural channels rather than immediate income dispersion.

When disposable income inequality is considered, the empirical results reveal more substantive relationships. In particular, asset-based wealth, measured as adjusted net wealth per adult, exhibits a statistically significant negative association with disposable income inequality. This finding provides empirical support for asset-based welfare theory, which posits that long-term reductions in inequality are more effectively achieved through the accumulation and diffusion of assets than through income transfers alone (Sherraden, 1990; Sherraden 1991). Wealth inequality research further emphasizes that ownership of productive and financial assets plays a central role in shaping income distribution and economic security over time (Piketty, 2014; Saez & Zucman, 2019). The results of this thesis reinforce these arguments by demonstrating that wealth functions as a key mediating variable through which AI capacity and institutional arrangements influence post-redistribution inequality outcomes.

Government social expenditure emerges as another critical factor shaping inequality dynamics. The negative relationship between social spending and disposable income inequality observed in the analysis aligns with a large body of welfare-state literature, which identifies redistribution and public investment as essential mechanisms for mitigating market-generated inequality (Atkinson, 2015; Stiglitz, 2012). The clear empirical distinction between market and disposable income inequality further confirms that public policy plays a decisive role in moderating, though not eliminating, inequality generated by market processes. This finding is consistent with comparative political economy research emphasizing that the effectiveness of redistribution depends on institutional capacity and policy design rather than on economic growth alone (Milanović, 2016).

The role of entrepreneurial education appears more nuanced. While its direct statistical association with inequality outcomes is weaker, the direction and conceptual relevance of the relationship are consistent with existing research. Studies on entrepreneurship and inequality suggest that entrepreneurial education primarily affects long-term opportunity structures, wealth accumulation, and intergenerational mobility rather than producing immediate income effects (Fairlie, 2004; Fairlie & Krashinsky, 2012). In this context, the findings of this thesis suggest that entrepreneurial education contributes indirectly to inequality reduction by facilitating access to asset-building pathways, particularly when combined with technological tools such as AI.

Globalization-related variables display a complex pattern of associations. The strong positive correlation between globalization, AI capacity, and wealth reflects the tendency for technologically advanced and globally integrated economies to accumulate higher levels of assets. At the same time, the negative association between globalization and disposable income inequality in the sample indicates that global integration does not inherently exacerbate inequality when accompanied by effective redistributive institutions. This result aligns with revised globalization theories, which argue that the distributional consequences of global economic integration are conditional on domestic policy frameworks and institutional strength (Milanović, 2016; Rodrik, 2018).

The qualitative case study of Norway provides important contextual evidence that complements the quantitative findings. Norway's combination of high government AI readiness, extensive social expenditure, coordinated skill development systems, and strong asset-based public policies illustrates how technological advancement can be integrated into a welfare-state framework that limits inequality amplification. This case supports institutionalist perspectives emphasizing that the social outcomes of technological change are shaped by governance structures and policy coordination rather than by technology itself (Korinek & Stiglitz, 2017).

Several limitations must be acknowledged when interpreting these results. The analysis relies on macro-level country data, which limits insight into within-country heterogeneity and the distributional effects of AI across different population groups. The relatively short time horizon from 2018 to 2022 constrains the ability to observe long-run processes of asset accumulation and intergenerational inequality transmission. Moreover, AI adoption is proxied through patent counts and readiness indices, which capture technological capacity rather than actual usage or accessibility across sectors and households. Although advanced panel econometric techniques are employed to address issues such as non-stationarity, heterogeneity, and cross-sectional dependence, residual endogeneity cannot be fully excluded. The qualitative analysis, while providing valuable institutional insight, focuses on a single country case and therefore cannot be generalized without caution.

Despite these limitations, the findings of this Master's thesis provide clear empirical evidence that AI can contribute to reductions in income inequality only when embedded within an integrated framework of asset-based wealth creation, skill development, entrepreneurial education, and government support. AI is shown to be neither inherently inequality-increasing nor inherently inequality-reducing; rather, its distributional effects are contingent on institutional design, policy coordination, and the inclusiveness of asset-building mechanisms. By explicitly distinguishing between market and disposable income inequality, this study underscores the central role of public intervention in shaping the social outcomes of technological change and contributes to a growing body of research advocating for institutionally grounded approaches to inclusive technological development.

8. Policy recommendations

The findings of this econometric analysis compel a set of targeted policy recommendations designed to address the “AI-Redistribution Paradox” and ensure that the structural benefits of technological progress translate into genuine economic equity. The evidence is clear: the impact of AI is not predetermined by the technology itself, but is fundamentally mediated by national policy choices and institutional design. Recommendations, therefore, must focus on correcting fiscal failures, leveraging structural equalizers, and adopting targeted interventions.

<u>Correcting the AI–Redistribution Paradox: Reforming the Fiscal Capture Mechanism</u>

The central empirical finding—that AI compresses market inequality but is associated with higher disposable inequality—reveals a failure of the current fiscal system. The gains from AI-driven productivity are evidently accruing at the top (capital and high-skill rents) faster than they are being captured by taxes and redistributed to workers affected by displacement.

<u>Recommendation 1</u>: Modernizing the Tax Base for the AI Era. Governments must urgently review and modernize corporate and capital taxation to capture the rents generated by AI and other General Purpose Technologies. This involves moving beyond traditional factor-based taxation toward capturing returns to highly concentrated intellectual property and digital profits. Mechanisms such as a minimum effective corporate tax rate or wealth-based taxes targeting concentrated asset accumulation—which the analysis found to be strongly associated with AI activity—should be seriously considered to restore progressivity and fund redistribution.

<u>Recommendation 2</u>: Strengthening the Transfer and Safety Net Floor. The observed stability of the disposable Gini during the pandemic, despite massive fiscal support, suggests that social transfers were necessary merely to *prevent* a rise in inequality. To actively *reduce* it, governments must strengthen the safety net. This involves ensuring unemployment insurance and social assistance schemes are indexed to technological displacement risks and provide adequate resources to cover the cost of mid-career reskilling, effectively ensuring that the bottom of the income distribution is insulated from labor market volatility.

<u>Prioritizing Targeted Social Investment and Abandoning Broad Spending</u>

The empirical contrast between fiscal measures is stark: General Government Expenditure ('S') is inequality-increasing, while Targeted Social Expenditure ('G') is inequality-reducing. This distinction must be the cornerstone of future budget allocation.

<u>Recommendation 3</u>: Reallocating Fiscal Resources to Targeted Social Spending. Policy should mandate a systematic review of broad, non-redistributive public spending ('S') and reallocate those resources toward targeted social investment ('G'). This reinforces the efficiency of the welfare state by focusing capital on mechanisms empirically proven to compress disposable inequality, such as direct transfers, public health, and targeted education programs.

<u>Recommendation 4</u>: Redefining Human Capital Investment. The finding that Entrepreneurial Education ('E') is consistently inequality-increasing supports a "winner-takes-all" model where public funding generates high-variance returns concentrated at the top. This suggests a reorientation of skills policy away from funding high-risk entrepreneurial endeavors toward broad-based, continuous vocational and digital upskilling programs. These programs must be focused on increasing the average worker's complementary skills to AI, thereby reinforcing the observed average tendency of AI to compress market inequality.

<u>Leveraging the Structural Equalizer: The Asset-Based Welfare Channel</u>

The strong empirical finding that Wealth per Adult ('W') is a powerful equalizer for disposable income, coupled with the structural AI to W association, identifies a crucial policy lever: asset-based welfare.

Recommendation 5: Promote Asset-Based Welfare Strategies. Policy should actively facilitate the expansion of asset ownership to low- and middle-income households. This includes expanding access to inclusive financial technologies, promoting broad-based employee stock ownership plans (ESOPs) to capture AI-driven productivity gains, and reforming pension systems to ensure wider participation in diversified asset markets. By increasing the average wealth of lower-income segments, governments can leverage the empirically established channel where higher household net wealth provides a crucial buffer against income shocks and strengthens the overall fiscal base.

Embracing Context-Specific Solutions: Learning from Heterogeneity

The robust rejection of slope homogeneity is the most critical recommendation, as it dictates that there is no universal AI policy.

Recommendation 6: Adopt an Institutional Contextualization Approach. Countries must align their AI strategy with their existing institutional reality. The Nordic model—where high social expenditure coincides with a steeply negative AI-inequality effect—provides a template for high-trust, high-tax, high-transfer economies. For economies like the United States or China, where the AI effect is currently positive (unequalizing), immediate policy focus must be placed on targeted redistribution and mitigating displacement risks, rather than assuming that the technology will be structurally equalizing on its own. Policy should be framed not as a technological imperative, but as an institutional choice to maximize the equalizing potential of AI.

9. Reproducibility and Ethical Considerations

Reproducibility: This research adheres to open science principles to ensure that results can be verified and built upon by others. All datasets used in the quantitative analysis are available on request. A comprehensive documentation of data sources is provided – including exact indicators taken – and any data transformations (such as normalization or interpolation for missing years). The data compilation process (merging multiple sources into the panel) will be fully scripted in R, some analysis - in Phyton and these scripts will be shared also on request.

Ethical considerations: This research primarily uses secondary data and publicly available information, and thus posed minimal ethical risks.

10. Recommendations for future research:

The completion of this thesis marks not an end point, but a rigorous foundation for future research in the dynamic field of AI, policy, and inequality. The limitations encountered—particularly the reliance on aggregated proxies, the challenges of endogeneity, and the difficulty in generalizing the Mean Group coefficients—suggest specific, fruitful avenues for subsequent investigation. These recommendations are structured across methodological refinement, tool development, policy evaluation, and implementation strategy.

For future research, the model should ideally be run on a significantly longer T data set.

To overcome the limitations of patent and readiness data, subsequent studies should incorporate more direct measures of AI diffusion. This includes using data on AI adoption rates by firm size and sector.

Research should address the transition from traditional fiscal redistribution to

"Computational Equity" models, specifically investigating the viability of a Sovereign Compute Fund as a primary tool for wealth stabilization.

Future studies should move beyond measuring AI's impact on monetary income and instead quantify "Compute-Asset Ownership" as a new metric for social mobility. This research should analyze the non-linear dynamics of Data Sovereignty, exploring how legal frameworks could allow citizens to monetize their individual data footprints as a form of "Digital Capital" to offset labor displacement.

Additionally, a critical area for investigation is the Algorithmic Fiscal Response—mathematically modeling how real-time, automated adjustments to capital-tax rates on AI-driven firms can mitigate "inequality spikes" more effectively than stagnant, annual policy cycles. By treating intelligence as a public utility rather than a private commodity, future research can define the strategic architecture of a state where the "Gini Floor" is maintained not by currency, but by universal access to the means of digital production.

Research should investigate the determination of an "Optimal Gini Floor" within the context of a post-scarcity, AI-driven economy. While classical economics views a Gini of 0 as a theoretical ideal of equality, future studies must analyze whether total uniformity leads to "Systemic Stasis"—a loss of the creative destruction and individual incentive necessary for civilizational advancement.

Given the inequality-increasing effect of general entrepreneurial education, research should focus on utilizing AI to deliver personalized and targeted upskilling modules for workers most vulnerable to displacement.

Policy-focused research should explore the effects of alternative fiscal instruments designed to capture AI rents, such as a “Universal Basic Income (UBI) vs conditional Basic Income” or a “Universal Basic Asset (UBA) vs conditional Basic Asset”.

One of the most promising research directions would be the examination of the applicability of Quantum AI in researching and evaluating optimal policies for inequality reduction.

Finally, research should address the practical challenges of funding the necessary policy shifts identified, particularly the reallocation of expenditure toward targeted social support and wealth-building initiatives. Research is needed to explore viable financial funding sourcing opportunities for implementing the policy model that promotes the wealth channel and targeted social spending. This could include analyzing the revenue potential and political feasibility of new digital services taxes, global minimum corporate tax allocations, or novel public-private partnership structures designed to finance national wealth accounts or lifelong learning initiatives.

The research was conducted within the natural limitations of a master’s level project, notably strict time constraints, restricted financial resources and incomplete access to primary data. While every effort was made to ensure methodological rigor, these factors necessarily shaped the scope of the research and should be considered when interpreting the results.

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SUMMARY IN ENGLISH

ACCELERATING THE REDUCTION OF INCOME INEQUALITY THROUGH AI: PROMOTING ASSET-BASED WEALTH VIA GOVERNMENT SUPPORT

VITALIJA USEVIČIŪTĖ

Master thesis

Strategic economics

Vilnius University, Faculty of Economics and Business Administration

Supervisor Dr. Martina dal Molin

Vilnius, 2026

SUMMARY

This Master's thesis consists of 75 pages, including 29 tables, 2 figures and charts illustrating descriptive trends and diagnostic tests, and a reference list of international academic and institutional sources.

The main purpose of this Master's thesis is to examine the relationship between artificial intelligence (AI) adoption and income inequality across countries, with particular attention to the roles of skills, entrepreneurial education, government expenditure, and wealth accumulation in shaping distributional outcomes.

The work consists of ten parts. The first part introduces the relevance of the research topic and formulates the main aim of the thesis. The second part presents a detailed literature review. The third part develops the theoretical framework. The fourth part identifies the novelty of the research, research gaps, objectives, and hypotheses. The fifth part describes the methodology, including data, variables, research design, and model specification. The sixth part presents the research results, distinguishing between quantitative and qualitative findings. The seventh part discusses the results and presents conclusions. The eighth part formulates policy recommendations. The ninth part addresses reproducibility and ethical considerations. The tenth part outlines recommendations for future research.

The literature analysis reviews classical and contemporary theories of income inequality, inequality of opportunity, technological change, automation, human capital formation, innovation, and asset-based welfare. It also reviews empirical studies on artificial intelligence, automation, education, entrepreneurship, government intervention, and wealth accumulation, with particular attention to cross-country evidence and institutional heterogeneity.

After the literature analysis, the author has carried out the study using an unbalanced panel dataset covering 22 countries over the period 2018–2022. Income inequality is measured using disposable and market Gini indices. AI adoption is proxied by AI-related patent counts and a government AI readiness index. The empirical methodology includes descriptive statistics, correlation analysis, pooled OLS estimation, the Mundlak correction approach, cross-sectional dependence tests, slope homogeneity tests, panel unit root and cointegration tests, CS-ARDL estimation, robustness checks using alternative estimators, panel Granger causality analysis, and a qualitative component.

The performed research revealed that the relationship between AI-related technological indicators and income inequality differs across countries and across model specifications, indicating heterogeneous effects. The empirical results highlight the relevance of institutional characteristics, human capital variables, and wealth-related factors in explaining cross-country variation in income inequality outcomes.

In conclusions and recommendations, after summarising the main concepts from the literature review and the results of the performed research, insights about the interaction between technological change and income distribution are provided. The conclusions emphasise the importance of accounting for heterogeneity and institutional context when analysing AI-related economic effects and outline directions for further empirical research using longer time horizons and expanded data coverage.

SUMMARY IN LITHUANIAN

PAJAMŲ NELYGYBĖS MAŽINIMO AKSELERAVIMAS DIRBTINIO INTELEKTO PAGALBA: TURTO KAUPIMO SKATINIMAS PER VALDŽIOS PARAMĄ

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Vilnius, 2006

SANTRAUKA

Šį magistro darbą sudaro 75 puslapių, jame pateiktos 29 lentelės, 2 paveikslai ir diagramos, iliustruojantys aprašomąsias tendencijas ir diagnostinių testų rezultatus, taip pat naudojamas tarptautinių akademinių ir institucinių šaltinių literatūros sąrašas.Pagrindinis šio magistro darbo tikslas – ištirti dirbtinio intelekto (DI) diegimo ir pajamų nelygybės ryšį tarp šalių, ypatingą dėmesį skiriant įgūdžių ugdymo, verslumo ugdymo, valdžios išlaidų ir turto kaupimo vaidmeniui formuojant pajamų pasiskirstymo rezultatus.

Darbas susideda iš dešimties dalių. Pirmoje dalyje pristatomas tyrimo temos aktualumas ir suformuluojamas pagrindinis darbo tikslas. Antroje dalyje pateikiama išsami literatūros apžvalga. Trečioje dalyje plėtojamas teorinis pagrindas. Ketvirtoje dalyje apibrėžiamas tyrimo naujumas, tyrimo spragos, tikslai ir hipotezės. Penktoje dalyje aprašoma metodologija, įskaitant duomenis, kintamuosius, tyrimo dizainą ir modelių specifikaciją. Šeštoje dalyje pateikiami tyrimo rezultatai, atskiriant kiekybinius ir kokybinius rezultatus. Septintoje dalyje aptariami rezultatai ir pateikiamos išvados. Aštuntoje dalyje suformuluojamos politikos rekomendacijos. Devintoje dalyje nagrinėjami atkartojamumo ir etikos aspektai. Dešimtoje dalyje pateikiamos rekomendacijos tolesniems tyrimams.

Literatūros analizėje apžvelgiamos klasikinės ir šiuolaikinės pajamų nelygybės, galimybių nelygybės, technologinių pokyčių, automatizacijos, žmogiškojo kapitalo formavimo, inovacijų ir turtu grįstos gerovės teorijos. Taip pat analizuojami empiriniai tyrimai apie dirbtinį intelektą, automatizaciją, švietimą, verslumą, valdžios intervencijas ir turto kaupimą, ypatingą dėmesį skiriant tarptautiniams palyginimams ir instituciniam heterogeniškumui.

Po literatūros analizės autorė atliko tyrimą, naudodama nesubalansuotą 22 šalių panelinę duomenų bazę 2018–2022 m. laikotarpiu. Pajamų nelygybė matuojama naudojant disponuojamųjų ir rinkos pajamų Gini indeksus. Dirbtinio intelekto diegimas matuojamas naudojant su dirbtiniu intelektu susijusių patentų skaičių ir valdžios pasirengimo dirbtiniam intelektui indeksą. Taikoma empirinė metodologija apima aprašomąją statistiką, koreliacinę analizę, jungtinius OLS įverčius, Mundlak korekcijos metodą, skerspjūvio priklausomybės testus, nuolydžių homogeniškumo testus, panelinius vienetinių šaknų ir kointegracijos testus, CS-ARDL įvertinimą, patikimumo patikras naudojant alternatyvius įverčius, panelinę Granger priežastingumo analizę bei kokybinę tyrimo dalį.

Atliktas tyrimas parodė, kad ryšys tarp su DI susijusių technologinių rodiklių ir pajamų nelygybės skiriasi tarp šalių ir priklauso nuo taikomos modelio specifikacijos, o tai rodo nevienalytį poveikį. Empiriniai rezultatai išryškina institucinių charakteristikų, žmogiškojo kapitalo kintamųjų ir su turtu susijusių veiksnių svarbą aiškinant tarptautinius pajamų nelygybės skirtumus.

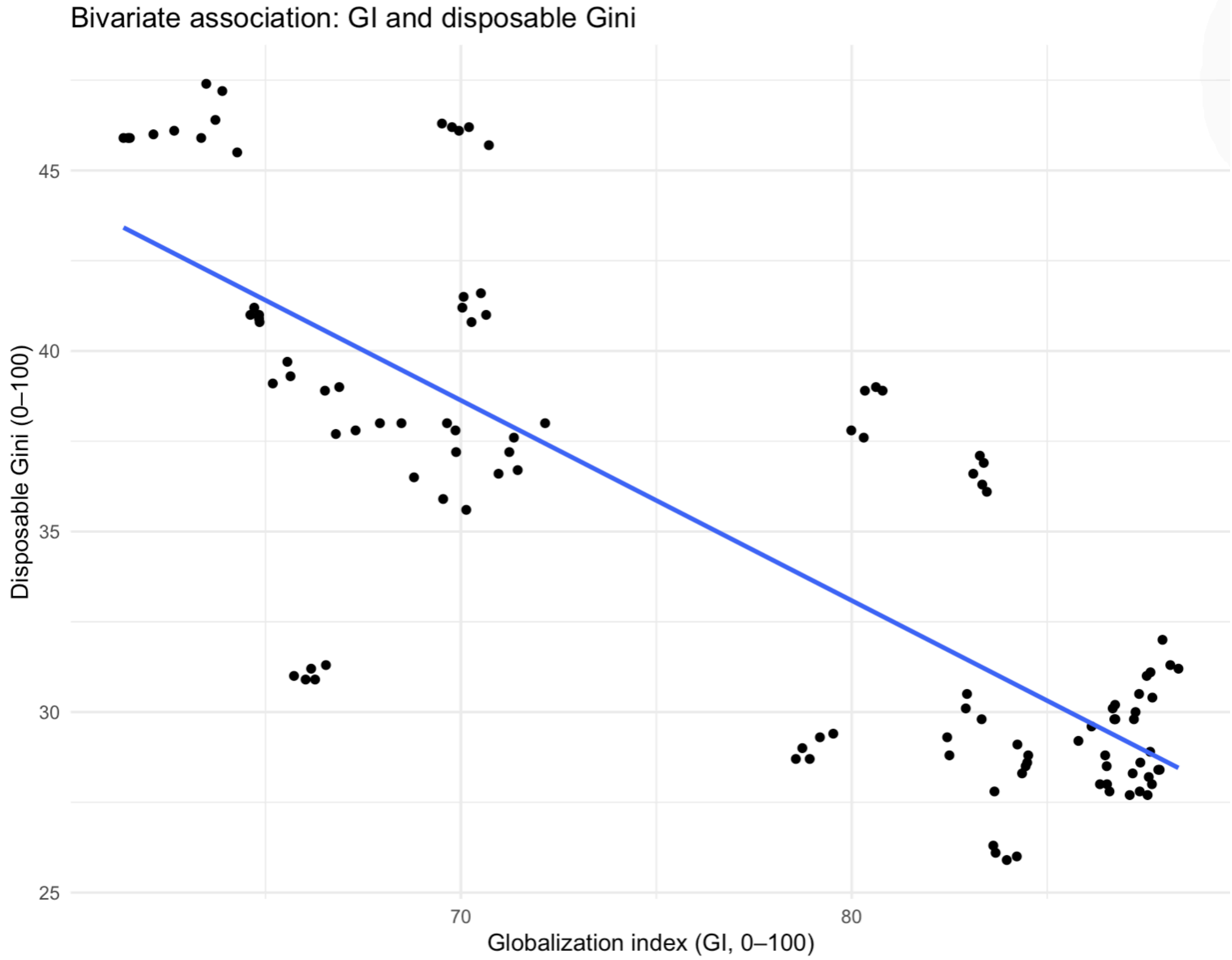
Išvadose ir rekomendacijose, apibendrinus literatūros apžvalgoje aptartas pagrindines sąvokas ir atlikto tyrimo rezultatus, pateikiamos įžvalgos apie technologinių pokyčių ir pajamų pasiskirstymo sąveiką. Išvadose pabrėžiama būtinybė analizuojant su DI susijusį ekonominį poveikį atsižvelgti į heterogeniškumą ir institucinį kontekstą bei nurodomos kryptys tolesniems empiriniams tyrimams, taikant ilgesnius laikotarpius ir platesnę duomenų aprėptį.

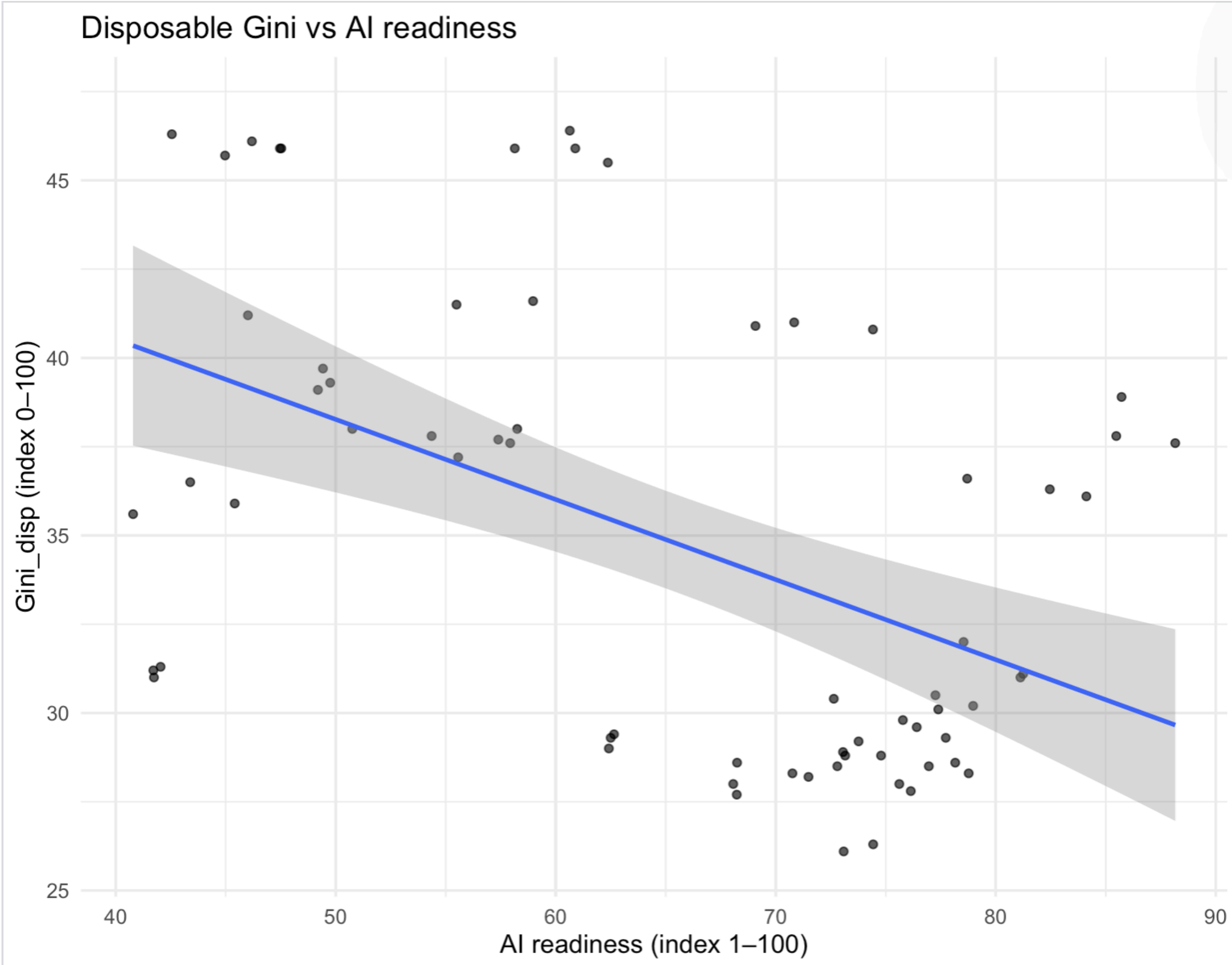
ANNEXES

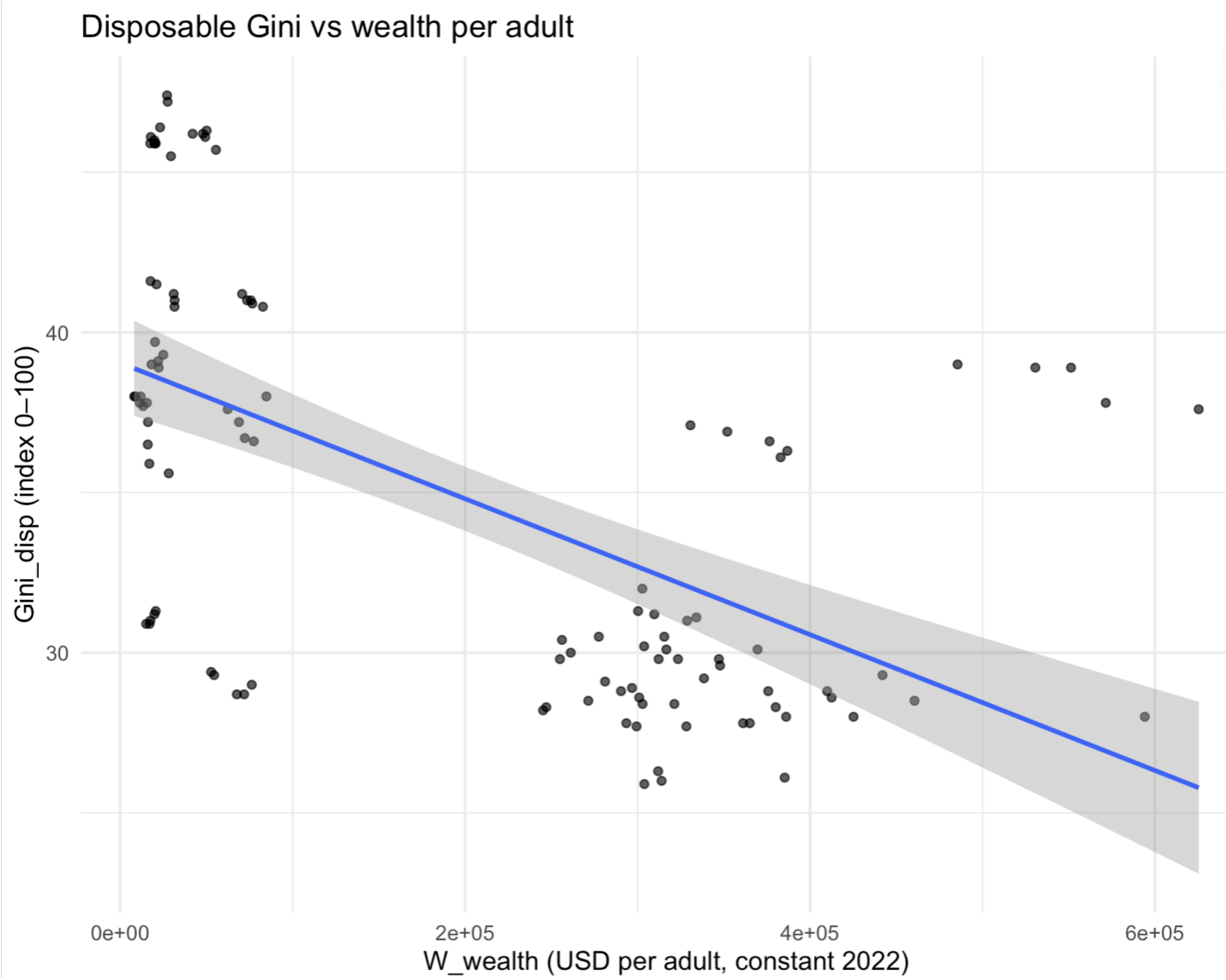
Annex 1. Descriptive statistics findings

Variable	Indicator / Unit	N	Mean	SD	Min	Median	Max	Key Distributional Features
Income inequality Disposable (IIE)	Disposable Gini (0–100)	110	34.88	6.42	25.9	33.8	47.4	Lower dispersion than market Gini; reflects redistribution
Income inequality Market (IIE)	Market Gini (0–100)	110	48.46	4.41	39.6	48.3	60.7	Systematically higher than disposable Gini
AI Patents (AI)	AI patents (count)	110	519.51	2036.5	0	9.83	12 198.62	Extremely right-skewed; high concentration in few countries
Government AI Readiness (AI)	Government AI Readiness Index (0–100)	66	65.15	13.71	40.79	68.66	88.16	Observed only for subset of years/countries

Government expenditure (S)	Government expenditure, % GDP (S)	105	4.88	1.68	0.86	4.96	8.37	Moderate dispersion across countries
Government expenditure (G)	Social expenditure, % GDP (G)	85	20.9	7.26	3.97	21.86	34.69	Wide range, reflecting welfare-state heterogeneity
Entrepreneurial education (E)	Entrepreneurial education (Likert 1–9)	67	3.4	0.99	1.55	3.23	6.38	Concentrated in lower–middle range of scale
Wealth (W)	Wealth per adult (USD, 2022 prices)	110	196 486.88	172 915.04	8 169.00	164 999.00	625 368.00	Very high cross-country dispersion
GDP (GDP)	Real GDP (USD, 2015 prices)	110	2.49×10^{12}	5.03×10^{12}	8.40×10^{9}	5.59×10^{11}	2.14×10^{13}	Strong size heterogeneity
Trade openness (TO)	Trade openness, % GDP (TO)	110	87.54	69.08	23.08	68.1	332.35	Extremely open economies present
Globalization Index (GI)	Globalization Index (0–100)	110	76.76	9.27	61.37	79.76	88.36	High and stable across panel


Bivariate association: GI and disposable Gini
Disposable Gini (0–100)
45
40
35
30
25
70
80
Globalization index (GI, 0–100)


Disposable Gini vs AI readiness
Gini_disp (index 0–100)
25
30
35
40
45
40
50
60
70
80
90
AI readiness (index 1–100)


Disposable Gini vs wealth per adult
Gini_disp (index 0–100)
40
30
0e+00
2e+05
4e+05
6e+05
W_wealth (USD per adult, constant 2022)

Annex 3. OLS findings

Relationship	Specification	Dependent variable	β (estimate)	Robust p-value	Interpretation
AI readiness → Inequality	Pooled OLS	Gini_disp	≈ 0.02	> 0.10	No robust direct association
	FE-OLS (country)	Gini_disp	-0.0028	0.95	No within-country effect
	FE-OLS (country)	Gini_mark	-0.0203	0.75	No within-country effect
AI patents → Inequality	Pooled OLS	Gini_disp	≈ 0.00	> 0.10	No direct pooled effect
	FE-OLS (country)	Gini_disp	≈ 0.00	> 0.10	No within-country effect
AI readiness → Wealth	Pooled OLS	lnW_wealth	0.0864	$< 10^{-24}$	Strong positive association
	FE-OLS (country)	lnW_wealth	-0.0016	0.87	No within-country effect
AI patents → Wealth	Pooled OLS	lnW_wealth	0.3799	$< 10^{-22}$	Strong positive elasticity
	FE-OLS (country)	lnW_wealth	0.037	0.29	Not statistically significant
Wealth → Inequality	Pooled OLS	Gini_disp	-3.02	$< 10^{-12}$	Wealth reduces disposable inequality
	Pooled OLS	Gini_mark	1.2	0.0005	Wealth increases market inequality

	FE-OLS (country)	Gini_disp	-0.697	0.044	Negative within-country effect
	FE-OLS (country)	Gini_mark	-0.051	0.87	No within-country effect
GDP → Inequality	Pooled OLS	Gini_disp	0.23	0.37	No pooled effect
	Pooled OLS	Gini_mark	0.66	$< 10^{-5}$	Positive pooled association
	FE-OLS (country)	Gini_disp	1.06	0.44	No within-country effect
	FE-OLS (country)	Gini_mark	-2.2	0.061	Borderline negative
Trade openness → Inequality	Pooled OLS	Gini_disp	-0.028	0.0049	Small inequality-reducing effect
	FE-OLS (country)	Gini_disp	0.013	0.021	Positive within-country association
	FE-OLS (country)	Gini_mark	-0.006	0.39	Not significant
Globalisation → Inequality	Pooled OLS	Gini_disp	-0.555	$< 10^{-26}$	Strong negative pooled effect
	Pooled OLS	Gini_mark	0.133	0.014	Positive pooled effect
	FE-OLS (country)	Gini_disp	0.001	0.998	No within-country effect
	FE-OLS (country)	Gini_mark	-0.108	0.33	No within-country effect

Education spending → Inequality	FE-OLS (country)	Gini_disp	-0.086	0.77	Not significant
	FE-OLS (country)	Gini_mark	0.084	0.74	Not significant
Entrepreneurial education → Inequality	FE-OLS (country)	Gini_disp	0.356	0.44	Not significant
	FE-OLS (country)	Gini_mark	0.213	0.69	Not significant
AI readiness → Social exp.	Pooled OLS	G_social	0.1495	0.021	Positive pooled association
	FE-OLS (country)	G_social	-0.274	0.025	Negative within-country effect
AI readiness → Entrepr. edu.	FE-OLS (country)	E_entre	-3.66	0.04	Significant negative within-effect

Annex 4 Theoretical Foundations and Their Contributions to the Analytical Framework

Theoretical approach	Core theoretical focus	Key contribution to this thesis	Role in the empirical framework
Task-based automation theory (Acemoglu & Restrepo)	Automation, task displacement, and task creation driven by AI	Explains how AI affects income distribution indirectly through changes in task composition rather than uniform wage effects	Justifies examining AI effects conditional on skills, institutions, and policy rather than as a direct determinant of inequality
Human capital theory (Becker)	Education and skills as productivity-enhancing investments	Provides the theoretical basis for treating skill development as an asset that mediates the impact of AI on income inequality	Motivates inclusion of skill-related variables as mediators in the empirical model
Schumpeterian innovation theory	Innovation, entrepreneurship, and creative destruction	Frames entrepreneurship as a channel through which AI can enable new economic opportunities and wealth creation	Supports inclusion of entrepreneurial education as a mechanism linking AI to asset accumulation
Asset-based welfare theory (Sherraden)	Asset ownership as a driver of long-term economic security	Establishes asset-based wealth (rather than income alone) as a central mechanism for reducing inequality	Justifies using wealth per adult as a key mediating variable in inequality outcomes
Theory of government intervention and market failures (Stiglitz)	State intervention to correct unequal access and market failures	Explains why public policy and social expenditure are necessary to ensure inclusive distribution of AI-generated gains	Provides rationale for modeling government support as a moderating institutional variable
Institutional and historical development theory (Acemoglu & Robinson)	Long-run impact of institutions on economic outcomes	Highlights that AI effects are contingent on institutional quality and historical structures	Supports cross-country heterogeneity and the use of advanced panel estimators