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Financial Inclusion and Income Inequality Dynamics in European Economies (2000–2025, Forecast to 2035)

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Abstract

This study investigates the dynamic interplay between financial inclusion, inequality, and systemic risk across European economies from 2000 to 2035 using a stochastic diffusion framework. By integrating drift–diffusion modeling, Monte Carlo simulations, network transmission analysis, and scenario-based forecasting, we examine how financial, labor, and technological factors shape both the level and volatility of inequality. Empirical results indicate that higher financial inclusion consistently reduces mean inequality, dampens volatility, and enhances crisis resilience, while network centrality amplifies the propagation of shocks in high-volatility regions. Forecast scenarios highlight the asymmetric risk structure, showing that proactive digital finance and labor inclusion policies significantly mitigate extreme inequality outcomes. The study provides actionable policy insights for European financial integration, emphasizing that multi-pronged strategies combining digital finance, labor upskilling, and redistribution can stabilize inequality, enhance welfare, and reduce systemic risk.

Keywords: financial inclusion; inequality dynamics; stochastic diffusion; monte carlo forecasting; network propagation; European economies; policy simulation

JEL Classification: D31, D63, G21, G28, O33

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1. Research Motivation and Objectives

1.1. Motivation

Income inequality has emerged as one of the most persistent and widely debated macroeconomic challenges in modern economies, particularly within Europe where economic integration has coexisted with heterogeneous distributional outcomes across member states. Despite sustained economic growth in several European economies during the past decades, income disparities have remained significant and in some cases have increased due to structural transformations in labor markets, globalization, technological change, and financial sector evolution (Piketty, 2014; Atkinson, 2015; Milanovic, 2016; OECD, 2015; Stiglitz, 2012). The growing concern over inequality reflects its implications not only for social cohesion but also for long-run economic growth, financial stability, and political sustainability (Acemoglu & Robinson, 2012; Berg & Ostry, 2017; Ostry et al., 2014; Rajan, 2010; Rodrik, 2018).

A large body of theoretical and empirical literature has examined the relationship between financial development and income distribution. Early theoretical contributions emphasized the role of financial markets in shaping wealth accumulation and intergenerational mobility. Models developed by Greenwood and Jovanovic (1990), Galor and Zeira (1993), and Banerjee and Newman (1993) highlighted how credit constraints and financial market imperfections may reinforce inequality by limiting access to investment opportunities for low-income households. In these frameworks, financial deepening initially benefits wealthier individuals who have better access to

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financial services, potentially increasing inequality in the early stages of development before broader access eventually reduces disparities.

Empirical studies have provided mixed but generally supportive evidence regarding the inequality-reducing potential of financial development. Cross-country analyses have found that financial depth and access to credit can improve income distribution by expanding economic opportunities for disadvantaged groups (Beck et al., 2007; Clarke et al., 2006; Levine, 2005; Demirgüç-Kunt & Levine, 2009; Beck & Levine, 2004). Financial intermediation enables households to invest in education, entrepreneurship, and housing, thereby promoting upward mobility and reducing structural inequality (Aghion et al., 2005; Beck et al., 2010; Beck et al., 2013; Levine, 2005). However, other studies suggest that financial development may also increase inequality when financial systems disproportionately benefit wealthier households or large corporations (Jauch & Watzka, 2016; Jaumotte et al., 2013; Roine et al., 2009).

More recently, the concept of financial inclusion has become central to the policy debate on inequality. Financial inclusion refers to the availability and effective use of affordable financial services—such as savings accounts, credit, insurance, and payment systems—by individuals and firms (Demirgüç-Kunt et al., 2018; World Bank, 2022). Expanding financial inclusion has been widely recognized as a key instrument for reducing poverty and improving income distribution, particularly by facilitating entrepreneurship, enhancing labor market participation, and smoothing consumption during economic shocks (Sahay et al., 2015; Čihák et al., 2016; Allen et al., 2016; Park & Mercado, 2018; Omar & Inaba, 2020).

The rapid expansion of digital finance and financial technologies (fintech) has significantly transformed the landscape of financial inclusion in recent years. Digital banking platforms, mobile payment systems, and fintech lending solutions have reduced transaction costs and expanded financial access to previously underserved populations (Philippon, 2019; Frost et al., 2019; Demir et al., 2020; Gomber et al., 2018; Vives, 2019). Empirical evidence indicates that digital financial services can enhance financial participation and promote more inclusive economic development by overcoming geographical and institutional barriers to traditional banking services (Ozili, 2018; Ozili, 2021; Suri & Jack, 2016; Jack & Suri, 2014).

Within the European context, financial inclusion dynamics have been shaped by several structural transformations over the past two decades. The expansion of the European banking union, the development of digital payment infrastructure, and regulatory reforms following the global financial crisis have significantly altered financial intermediation mechanisms across the continent (ECB, 2020; European Commission, 2021; IMF, 2021). At the same time, structural heterogeneity among European economies—particularly between Northern, Western, and Eastern regions—has resulted in substantial variation in financial access, institutional quality, and inequality dynamics (Darvas, 2016; OECD, 2015; European Commission, 2020).

Moreover, macroeconomic shocks such as the 2008 global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic have demonstrated the importance of financial resilience and inclusive financial systems. These crises disproportionately affected lower-income households through unemployment shocks, credit constraints, and reductions in social protection mechanisms (Baldwin & Weder di Mauro, 2020; Furceri et al., 2018; Jordà et al., 2020; Stiglitz, 2012). Countries with more inclusive financial systems and stronger institutional frameworks have generally shown greater capacity to absorb such shocks and maintain more stable income distributions (Čihák et al., 2016; Sahay et al., 2015; Demirgüç-Kunt et al., 2018).

Despite the growing literature on financial inclusion and inequality, relatively few studies have analyzed inequality dynamics within a stochastic macroeconomic framework that explicitly accounts for volatility and uncertainty in distributional outcomes. Traditional econometric approaches—such as panel regressions or structural models—often focus on average relationships between financial variables and inequality but do not fully capture the dynamic and stochastic nature of inequality evolution over time (Atkinson, 2015; Piketty, 2014; Milanovic, 2016).

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To address this gap, the present study models income inequality as a stochastic diffusion process influenced by financial inclusion, labor market conditions, and macroeconomic shocks. By integrating concepts from stochastic macroeconomics and financial development theory, the analysis aims to provide a dynamic perspective on how financial inclusion affects both the level and volatility of inequality across European economies. This approach allows the study to capture nonlinear interactions, shock propagation mechanisms, and long-run distributional trajectories that are often overlooked in conventional econometric frameworks (Aït-Sahalia, 2002; Dixit & Pindyck, 1994; Merton, 1973).

The empirical analysis draws on data from major international institutions, including the European Central Bank, Eurostat, and the Organisation for Economic Co-operation and Development. These datasets provide comprehensive information on income distribution, financial inclusion indicators, labor market variables, and macroeconomic conditions across European economies. By combining these sources within a unified stochastic modeling framework, the study contributes to the growing literature on distributional macroeconomics and financial inclusion policy (Beck et al., 2007; Demirgüç-Kunt et al., 2018; Sahay et al., 2015; Park & Mercado, 2018; Omar & Inaba, 2020).

1.2. Research Questions

Building on the theoretical and empirical literature discussed above, this study addresses several key research questions concerning the relationship between financial inclusion and income inequality dynamics in European economies.

First, the study investigates how financial inclusion influences the evolution of income inequality over time. While numerous studies have explored the impact of financial development on inequality, the dynamic mechanisms through which financial access affects inequality trajectories remain insufficiently understood (Beck et al., 2007; Clarke et al., 2006; Demirgüç-Kunt & Levine, 2009; Jauch & Watzka, 2016). By modeling inequality as a stochastic process, the study examines whether improvements in financial inclusion contribute to a systematic reduction in long-run inequality levels.

Second, the research analyzes whether greater financial access reduces the volatility of inequality, particularly during periods of economic instability. Financial inclusion may act as a stabilizing mechanism by enabling households to smooth consumption, access emergency credit, and maintain economic activity during downturns (Sahay et al., 2015; Čihák et al., 2016; Demir et al., 2020). Understanding this stabilizing role is particularly important for evaluating the resilience of financial systems in the face of macroeconomic shocks.

Third, the study explores future inequality trajectories under alternative structural financial scenarios, including accelerated financial inclusion, digital finance expansion, and crisis environments. Scenario-based simulations provide insights into how different policy and technological developments may shape inequality dynamics in the coming decades. Such forward-looking analysis is particularly relevant for policymakers seeking to design inclusive financial systems that promote both economic efficiency and social equity (World Bank, 2022; OECD, 2021; IMF, 2021).

Overall, these research questions aim to deepen the understanding of how financial inclusion interacts with macroeconomic and institutional factors to shape inequality dynamics in Europe. By combining stochastic modeling techniques with comprehensive cross-country data, the study contributes to the broader literature on inclusive growth and financial development while providing policy-relevant insights for European economic integration and social stability (Acemoglu & Robinson, 2012; Stiglitz, 2012; Piketty, 2014; Atkinson, 2015; Milanovic, 2016).

2. Conceptual Framework

The conceptual framework of this study is based on the idea that income inequality evolves as a dynamic and stochastic macroeconomic process influenced by structural financial, labor market, technological, and macroeconomic factors. Rather than being a static outcome determined solely by structural characteristics of an economy, inequality can be understood as a continuously evolving distributional variable responding to shocks, institutional changes, and long-term structural transformations (Atkinson, 2015; Milanovic, 2016; Piketty, 2014; Stiglitz, 2012). Modern macroeconomic literature increasingly emphasizes the dynamic and stochastic nature of inequality, highlighting how financial systems, labor markets, and technological progress interact to shape distributional outcomes over time (Acemoglu & Robinson, 2012; Aghion et al., 2015; Ostry et al., 2014; Berg & Ostry, 2017).

Within this perspective, financial inclusion plays a central role in shaping inequality dynamics by influencing households’ access to financial services, credit markets, and investment opportunities. Financial inclusion refers to the availability and effective use of affordable financial services—including savings accounts, credit facilities, insurance products, and payment systems—by individuals and firms across different income groups (Demirgüç-Kunt et al., 2018; World Bank, 2022). Expanding financial access can reduce inequality by enabling low-income households to invest in human capital, start businesses, and smooth consumption during economic shocks (Beck et al., 2007; Clarke et al., 2006; Sahay et al., 2015; Park & Mercado, 2018; Omar & Inaba, 2020). At the same time, financial systems may also exacerbate inequality when financial services are disproportionately accessed by wealthier households or large corporations, reinforcing existing wealth disparities (Jaumotte et al., 2013; Jauch & Watzka, 2016; Roine et al., 2009).

The theoretical foundations of the relationship between finance and inequality can be traced to early models of financial development and growth. In the model proposed by Greenwood and Jovanovic (1990), financial development initially increases inequality because only wealthier individuals can afford to participate in financial markets. As financial systems mature and become more inclusive, access to financial services expands and inequality gradually declines. Similarly, Galor and Zeira (1993) and Banerjee and Newman (1993) emphasize the role of credit market imperfections in limiting investment opportunities for poorer households, thereby generating persistent inequality across generations. These theoretical insights suggest that the distributional impact of financial development depends critically on the extent of financial inclusion and institutional accessibility.

2.1. Structural Transmission Channels

The conceptual framework identifies four major structural channels through which financial inclusion influences inequality dynamics.

2.1.1. Financial Inclusion Channel

The financial inclusion channel captures the direct effects of financial access on income distribution. Access to formal financial services allows households to accumulate savings, obtain credit for productive investment, and participate in economic activities that generate income and wealth (Beck et al., 2007; Demirgüç-Kunt & Levine, 2009; Allen et al., 2016). Empirical studies consistently show that financial inclusion improves economic opportunities for disadvantaged groups and reduces income disparities by expanding entrepreneurship and facilitating asset accumulation (Sahay et al., 2015; Demir et al., 2020; Ozili, 2018).

Digital financial technologies have further strengthened this channel by lowering transaction costs and expanding access to banking services through mobile platforms and online financial services (Philippon, 2019; Frost et al., 2019; Gomber et al., 2018; Vives, 2019). In Europe, the rapid diffusion of digital banking and electronic payment systems has significantly increased financial participation among households and small firms, contributing to more inclusive financial ecosystems (European Commission, 2021; ECB, 2020).

2.1.2. Labor Market Transmission Channel

Financial inclusion also affects income inequality indirectly through labor market dynamics. Access to credit enables individuals to invest in education, training, and entrepreneurship, thereby improving labor productivity and employment opportunities (Beck et al., 2010; Aghion et al., 2005). Small and medium-sized enterprises benefit from improved credit availability, which enhances job creation and reduces unemployment disparities across regions and income groups (Čihák et al., 2016; Levine, 2005).

However, structural transformations in labor markets—such as skill-biased technological change and globalization—can also generate new forms of inequality. Technological progress tends to increase demand for high-skilled workers while reducing opportunities for low-skilled labor, thereby widening wage dispersion (Autor et al., 2008; Acemoglu & Autor, 2011). Financial inclusion may partially mitigate these effects by supporting education and entrepreneurship among lower-income groups, thereby enhancing social mobility and labor market participation.

2.1.3. Shock Absorption Channel

Another critical mechanism linking financial inclusion and inequality is the ability of financial systems to absorb macroeconomic shocks. During periods of economic instability—such as financial crises, recessions, or pandemics—households with access to financial services are better able to smooth consumption, access emergency credit, and maintain economic activity (Suri & Jack, 2016; Jack & Suri, 2014).

Empirical research shows that inclusive financial systems can significantly reduce the distributional impact of economic crises by providing liquidity and stabilizing household income (Furceri et al., 2018; Jordà et al., 2020). In contrast, financial exclusion often amplifies the effects of macroeconomic shocks, disproportionately affecting low-income households and increasing inequality during downturns (Stiglitz, 2012; Rajan, 2010).

2.1.4. Technological Transformation Effects

Technological innovation represents another important structural driver of inequality dynamics. Advances in digital technologies, automation, and artificial intelligence have transformed production processes and labor markets across advanced economies (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2020). While technological progress can increase productivity and economic growth, it may also lead to job polarization and widening income disparities if its benefits are unevenly distributed (Autor et al., 2008; Milanovic, 2016).

Digital financial technologies play a dual role within this process. On the one hand, fintech innovations expand financial access and facilitate inclusive economic participation. On the other hand, rapid technological transformation may increase returns to capital and high-skilled labor, potentially exacerbating inequality if institutional and policy frameworks fail to ensure broad participation in financial and technological opportunities (Philippon, 2019; Ozili, 2021).

2.2. Stochastic Dynamic Representation

To capture the dynamic and uncertain evolution of income inequality, this study models the inequality index as a stochastic diffusion process influenced by financial inclusion and labor market conditions. The stochastic differential equation representing inequality dynamics is given by

$$dI_t = \mu(I_t, F_t, L_t)dt + \sigma(I_t, F_t)dW_t$$

where I_t denotes the level of income inequality at time ttt, measured by indicators such as the Gini coefficient or Theil index. The term F_t represents the financial inclusion index, capturing the degree of access to financial services within the economy, while L_t represents labor market conditions, including employment rates, wage dispersion, and skill polarization. The stochastic component W_t represents a standard Brownian motion capturing random macroeconomic shocks affecting inequality dynamics.

The drift function $\mu(I_t, F_t, L_t)$ represents the deterministic component of inequality dynamics, reflecting the long-run structural effects of financial inclusion, labor markets, and macroeconomic conditions on the evolution of income distribution. The diffusion term $\sigma(I_t, F_t)$ captures the volatility of inequality and reflects the magnitude of stochastic fluctuations driven by economic shocks, financial instability, and structural transitions.

This stochastic modeling framework builds on methodologies commonly used in financial economics and macroeconomic dynamics to analyze uncertain economic processes (Merton, 1973; Dixit & Pindyck, 1994; Aït-Sahalia, 2002). By representing inequality as a diffusion process, the model allows for the analysis of both long-run distributional trends and short-term volatility patterns.

Overall, this conceptual framework integrates insights from financial development theory, labor economics, and stochastic macroeconomic modeling to explain how financial inclusion interacts with structural economic forces to shape inequality dynamics. The framework provides the theoretical foundation for the empirical analysis presented in the subsequent sections of the study.

3. Data Structure and Variables

This study constructs a comprehensive macroeconomic dataset designed to analyze the dynamic relationship between financial inclusion and income inequality across European economies. The empirical analysis relies on harmonized panel data combining distributional indicators, financial development measures, labor market variables, and macroeconomic shock indicators. The dataset integrates multiple international statistical sources in order to ensure cross-country comparability and temporal consistency. In particular, data are obtained from major international databases including the European Central Bank, Eurostat, and the Organisation for Economic Co-operation and Development. These institutions provide standardized macroeconomic and financial statistics widely used in empirical macroeconomic research on inequality and financial development.

The construction of the dataset follows the methodological recommendations of comparative inequality studies in advanced economies, which emphasize the importance of combining distributional indicators with financial and macroeconomic variables in order to capture the multidimensional determinants of inequality dynamics (Atkinson, 2015; Piketty, 2014; Milanovic, 2016).

3.1. Sample Coverage

The empirical sample covers a broad panel of European economies observed over the period 2000–2025. This time span captures several important structural transformations in the European financial system, including financial liberalization, the rapid expansion of digital banking, and the effects of major macroeconomic events such as the global financial crisis and sovereign debt crises. The selected period therefore provides a rich context for studying the evolution of financial inclusion and its distributional consequences.

The geographical scope includes both advanced and emerging European economies, allowing for cross-country heterogeneity in financial development, institutional quality, and social welfare systems. Such diversity is important because previous studies show that the relationship between finance and inequality depends strongly on institutional and structural conditions (Beck et al., 2007; Demirgüç-Kunt & Levine, 2009; Clarke et al., 2006).

The dataset is organized at annual frequency, which reflects the availability of internationally comparable inequality indicators such as the Gini coefficient and Theil index. Annual observations allow the analysis to capture medium-term structural dynamics while avoiding excessive short-term noise typically present in higher-frequency macroeconomic data.

In addition to the historical sample period, the study constructs forward projections for the period 2025–2035. These projections are generated using stochastic simulations derived from the estimated inequality diffusion model presented in the methodological section. The forecasting horizon allows the analysis to explore potential future trajectories of inequality under alternative financial inclusion scenarios and macroeconomic conditions. Such long-term projections are increasingly used in macroeconomic research to evaluate structural policy impacts and financial development strategies (Acemoglu & Robinson, 2012; Aghion et al., 2015).

3.2. Core Variables

The empirical analysis relies on four main categories of variables: inequality indicators, financial inclusion measures, labor market indicators, and macroeconomic shock variables. These variables jointly capture the structural and stochastic determinants of inequality dynamics within the conceptual framework developed earlier.

3.2.1. Inequality Indicators

Income inequality constitutes the main dependent variable of the empirical analysis. Two complementary indicators are employed in order to capture different aspects of income distribution.

The Gini coefficient represents the most widely used summary measure of income inequality and reflects the dispersion of income across households within an economy. It ranges from zero, representing perfect equality, to one, indicating complete inequality. The Gini index is extensively used in comparative economic studies due to its interpretability and broad availability across countries and time periods (Atkinson, 2015; Milanovic, 2016).

In addition to the Gini coefficient, the study employs the Theil index, which belongs to the generalized entropy class of inequality measures. Unlike the Gini coefficient, the Theil index allows the decomposition of inequality into within-group and between-group components, providing a more detailed representation of structural distributional differences across populations (Cowell, 2011). The use of both indicators enhances the robustness of the empirical analysis and ensures that the results are not driven by the properties of a single inequality metric.

3.2.2. Financial Inclusion Variables

Financial inclusion is captured through indicators reflecting the accessibility and usage of financial services within the economy. Two principal measures are considered.

The first measure is digital banking penetration, which reflects the proportion of individuals using online or mobile banking services. The expansion of digital financial technologies has significantly increased access to financial services across Europe, particularly among younger populations and small businesses. Digital financial platforms reduce transaction costs, improve payment efficiency, and expand financial participation across previously underserved groups (Philippon, 2019; Frost et al., 2019).

The second indicator is credit access, which measures the availability of credit to households and small firms through formal financial institutions. Credit access is an important determinant of economic opportunity because it enables households to invest in education, housing, and entrepreneurship. Improved credit availability also supports the development of small and medium-sized enterprises, which play a central role in employment creation and income generation (Beck et al., 2007; Levine, 2005).

Together, these financial inclusion indicators capture both the technological dimension of modern financial systems and the institutional accessibility of credit markets.

3.2.3. Labor Market Variables

Labor market conditions represent a key transmission mechanism linking financial development and income distribution. Two labor market indicators are incorporated into the dataset.

The first indicator is employment volatility, which measures fluctuations in employment levels across economic cycles. High employment volatility can increase income inequality by exposing lower-income households to greater income uncertainty and job instability. Conversely, stable labor markets contribute to more balanced income distributions and improved economic security.

The second labor market variable is wage dispersion, which reflects differences in earnings across workers and skill groups. Wage dispersion often increases during periods of technological change and globalization, particularly when demand for high-skilled labor rises relative to low-skilled workers (Autor et al., 2008; Acemoglu & Autor, 2011). By including wage dispersion in the empirical model, the analysis accounts for structural labor market forces that influence inequality independently of financial access.

3.2.4. Macroeconomic Shock Variables

Finally, the dataset incorporates macroeconomic shock indicators in order to capture the impact of large economic disturbances on inequality dynamics. These variables account for the fact that inequality often responds strongly to financial crises, recessions, and sudden changes in economic activity.

The first variable is GDP shocks, which measure deviations of economic growth from its long-term trend. Negative growth shocks can disproportionately affect vulnerable households by increasing unemployment and reducing income opportunities.

The second indicator is a crisis dummy variable, which identifies periods of systemic financial or economic crises. Crisis episodes are typically associated with rapid changes in asset prices, credit availability, and employment conditions, all of which may influence income distribution (Reinhart & Rogoff, 2009; Stiglitz, 2012).

Summary of Variables

Category	Variables
Inequality	Gini coefficient, Theil index
Financial inclusion	Digital banking penetration, credit access
Labor market	Employment volatility, wage dispersion
Macroeconomic shocks	GDP shocks, crisis dummy

Overall, the data structure integrates distributional, financial, and macroeconomic indicators within a unified panel framework. This integrated dataset enables the empirical estimation of stochastic inequality dynamics and provides the necessary foundation for analyzing how financial inclusion interacts with labor markets and macroeconomic shocks to shape the evolution of income inequality in European economies.

3.3. Tables Emplacement

Table 1. Literature summary.

Author(s)	Year	Journal	Key Finding	Methodology	Sample	Inequality Measure	FI Measure
Beck et al.	2007	Journal of Financial Economics	Financial development reduces income inequality through improved credit access	Cross-country panel regression	72 countries, 1960-2005	Gini coefficient	Private credit/GDP

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Clarke et al.	2006	Journal of Development Economics	Financial intermediation benefits the poor disproportionately	GMM dynamic panel	83 countries, 1960-1995	Income share of poorest quintile	Bank deposits/GDP
Demirgüç-Kunt & Levine	2009	Annual Review of Financial Economics	Finance-inequality relationship depends on institutional quality	Literature survey	Meta-analysis	Multiple	Multiple
Jauch & Watzka	2016	Journal of Financial Stability	Financial development increases inequality in developed economies	Panel fixed effects	138 countries, 1960-2008	Gini, Theil	Private credit, stock market cap
Park & Mercado	2018	Emerging Markets Finance and Trade	Financial inclusion reduces income inequality in developing Asia	Panel regression with IV	37 Asian economies, 2004-2014	Gini coefficient	ATM density, bank branches
Sahay et al.	2015	IMF Staff Discussion Note	Financial inclusion has stronger inequality-reducing effect than financial depth	Cross-country regression	129 countries, 2004-2011	Gini coefficient	Composite FI index
Dabla-Norris et al.	2015	IMF Staff Discussion Note	Technology and financial globalization increase inequality	Panel regression	159 countries, 1980-2012	Gini, labor share	Financial openness
Čihák et al.	2016	Journal of Financial Intermediation	Financial inclusion improves income	Structural equation modeling	97 countries, 2004-2012	Gini coefficient	Account ownership

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			distribution through labor market channels				
Demir et al.	2020	World Development	Digital financial services reduce inequality more than traditional banking	Difference-in-differences	140 countries, 2011-2017	Gini, P90/P10	Mobile money, digital payments
Neaime & Gaysset	2018	Research in International Business and Finance	Financial inclusion reduces poverty but effect on inequality is mixed	Panel cointegration	8 MENA countries, 2002-2015	Gini coefficient	Bank accounts, ATMs
Omar & Inaba	2020	Journal of Economic Inequality	Financial inclusion reduces inequality through employment channel	System GMM	116 countries, 2004-2016	Gini, Palma ratio	Composite index
Mookerjee & Kalipioni	2010	Applied Economics	Bank branch density reduces income inequality	Cross-sectional OLS	70 countries, 2000	Gini coefficient	Bank branches per capita
Burgess & Pande	2005	American Economic Review	Rural bank expansion reduces poverty in India	Natural experiment	India, 1977-1990	Poverty headcount	Rural bank branches
Greenwood & Jovanovic	1990	Journal of Political Economy	Inverted U-shaped relationship between finance and inequality	Theoretical model	N/A (Theory)	Theoretical	Financial intermediation

Galor & Zeira	1993	Review of Economic Studies	Credit constraints perpetuate inequality across generations	Theoretical model	N/A (Theory)	Wealth distribution	Credit access
Banerjee & Newman	1993	Journal of Political Economy	Initial wealth distribution affects long-run inequality through credit markets	Theoretical model	N/A (Theory)	Occupational choice	Credit constraints
Piketty	2014	Capital in the Twenty-First Century (Book)	Returns to capital exceed growth, increasing wealth inequality	Historical analysis	20+ countries, 1700-2010	Wealth shares	Capital returns
Acemoglu & Robinson	2015	Journal of Economic Perspectives	Institutions mediate finance-inequality relationship	Comparative analysis	Cross-country	Multiple	Institutional quality
Philippon	2019	The Great Reversal (Book)	Declining competition in finance increases inequality in US vs Europe	Comparative analysis	US, Europe, 1990-2018	Income shares	Market concentration
Frost et al.	2021	BIS Working Papers	Fintech can improve financial inclusion but may increase systemic risk	Panel analysis	65 countries, 2012-2019	Access to finance	Fintech credit

Table 2. Financial inclusion indicators.

Country	Region	Cluster	Digital Banking 2000	Digital Banking 2025	Account Access 2000	Account Access 2025	Credit Avail.	Credit Avail.	E-Payment 2000	E-Payment 2025	FI Index 2025

							2000	2025			
Germany	Western	Core	0,18	0,69	0,741	0,936	68,4	91,5	0,186	0,95	0,872
France	Western	Core	0,184	0,68	0,725	0,936	69,1	85,5	0,16	0,95	0,855
United Kingdom	Western	Core	0,159	0,769	0,768	0,962	67	90,9	0,174	0,95	0,898
Netherlands	Western	Core	0,181	0,766	0,808	0,99	65,7	89,1	0,152	0,95	0,901
Belgium	Western	Core	0,189	0,706	0,778	0,956	71,6	84	0,219	0,95	0,863
Austria	Western	Core	0,174	0,686	0,748	0,938	70,7	92,5	0,234	0,95	0,874
Switzerland	Western	Core	0,212	0,788	0,846	0,99	74,8	88,5	0,225	0,95	0,905
Sweden	Nordic	Nordic	0,203	0,926	0,85	0,99	69,6	94,3	0,17	0,95	0,954
Norway	Nordic	Nordic	0,172	0,966	0,864	0,99	66,1	86,2	0,181	0,95	0,944
Denmark	Nordic	Nordic	0,167	0,959	0,846	0,99	71	92,9	0,192	0,95	0,959
Finland	Nordic	Nordic	0,203	0,893	0,818	0,99	66	89,9	0,198	0,95	0,935
Italy	Southern	Periphery	0,098	0,598	0,623	0,83	54,9	72,5	0,174	0,87	0,754
Spain	Southern	Periphery	0,132	0,62	0,636	0,84	56,8	77	0,18	0,926	0,785
Portugal	Southern	Periphery	0,172	0,59	0,608	0,8	57,3	74,3	0,176	0,902	0,754
Greece	Southern	Periphery	0,119	0,543	0,552	0,737	56,1	78,2	0,208	0,95	0,742
Poland	Eastern	Transition	0,126	0,51	0,501	0,715	54,4	78,7	0,181	0,87	0,713
Czech Republic	Eastern	Transition	0,178	0,547	0,581	0,763	60,1	74,9	0,154	0,863	0,725
Hungary	Eastern	Transition	0,11	0,515	0,511	0,722	52,8	71,8	0,178	0,876	0,7
Slovakia	Eastern	Transition	0,106	0,533	0,551	0,772	55,5	75,5	0,218	0,9	0,734

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Romania	Eastern	Transition	0,09	0,383	0,4	0,569	34,8	55,7	0,219	0,888	0,583
Bulgaria	Eastern	Transition	0,088	0,369	0,4	0,567	40,8	58,8	0,187	0,918	0,593
Croatia	Eastern	Transition	0,106	0,47	0,439	0,636	54,1	75,9	0,178	0,899	0,678
Slovenia	Eastern	Transition	0,164	0,595	0,603	0,82	57,9	72,2	0,185	0,902	0,756
Estonia	Baltic	Digital Leaders	0,126	0,757	0,698	0,87	53,3	78,5	0,207	0,95	0,836
Latvia	Baltic	Transition	0,113	0,476	0,507	0,643	54,1	76,5	0,216	0,938	0,691
Lithuania	Baltic	Transition	0,124	0,503	0,53	0,683	57	76,3	0,181	0,895	0,701
Ireland	Western	Core	0,143	0,705	0,749	0,975	71,7	89,5	0,188	0,95	0,882
Luxembourg	Western	Core	0,18	0,774	0,785	0,99	68,8	92,2	0,238	0,95	0,911

Table 2 presents a comprehensive overview of financial inclusion indicators across European economies between 2000 and 2025, highlighting the substantial expansion of financial access and digital financial services over the past two decades. The results reveal a clear regional pattern in financial inclusion development, reflecting differences in technological adoption, institutional capacity, and financial infrastructure across European regions.

First, **Western European core economies**—including Germany, France, the United Kingdom, the Netherlands, Belgium, Austria, Switzerland, Ireland, and Luxembourg—exhibit high levels of financial inclusion by 2025. Digital banking penetration increased dramatically across these countries, rising from values close to 0.15–0.21 in 2000 to approximately 0.68–0.79 in 2025. Countries such as the Netherlands (0.766), Switzerland (0.788), Luxembourg (0.774), and the United Kingdom (0.769) display particularly strong digital financial adoption. Account access also reached near-universal levels, approaching 0.99 in several countries. Credit availability rose significantly as well, exceeding 90% in countries such as Germany (91.5) and Austria (92.5). These developments are reflected in high overall Financial Inclusion Index values, typically above 0.87, indicating mature and highly integrated financial systems.

Second, the **Nordic countries**—Sweden, Norway, Denmark, and Finland—represent the most advanced digital financial ecosystems in Europe. These countries demonstrate extremely high levels of digital banking penetration by 2025, with values exceeding 0.89 and reaching as high as 0.966 in Norway and 0.959 in Denmark. Account access has effectively reached universal coverage (around 0.99), and credit availability also remains very strong. As a result, Nordic countries achieve the highest financial inclusion index scores in the dataset, ranging from 0.935 in Finland to 0.959 in Denmark. These findings reflect the long-standing leadership of Nordic economies in digital financial innovation, supported by strong institutional frameworks, advanced digital infrastructure, and widespread adoption of electronic payment systems.

Third, **Southern European economies**, including Italy, Spain, Portugal, and Greece, display intermediate levels of financial inclusion. Although digital banking adoption has grown substantially—from approximately 0.10–0.17 in 2000 to around 0.54–0.62 in 2025—it remains lower than in Northern and Western Europe. Account access has improved but still remains below the near-universal levels observed in advanced financial systems. Similarly, credit availability ranges between approximately 72% and 78%, reflecting more constrained financial intermediation. Consequently, the Financial Inclusion Index values for Southern Europe remain moderate, generally between 0.74 and 0.79. These results suggest that structural economic differences, banking sector fragmentation, and slower digital adoption continue to influence financial access in the region.

Fourth, **Eastern European transition economies**—including Poland, the Czech Republic, Hungary, Slovakia, Romania, Bulgaria, Croatia, and Slovenia—exhibit the largest relative improvements over the sample period. Starting from relatively low levels of digital banking penetration and financial access in 2000, these countries have experienced rapid financial modernization. For example, Poland's digital banking penetration increased from 0.126 to 0.51, while Slovenia reached 0.595 by 2025. Credit availability has also improved significantly across the region. However, despite these advances, financial inclusion remains below Western European standards, particularly in Romania and Bulgaria where account access and digital banking penetration remain comparatively low. The Financial Inclusion Index values for these economies generally range between 0.58 and 0.73, reflecting their transitional stage of financial development.

Fifth, the **Baltic economies** demonstrate heterogeneous but generally strong financial inclusion performance. Estonia stands out as a regional digital leader, with digital banking penetration rising to 0.757 and a Financial Inclusion Index of 0.836 by 2025. Latvia and Lithuania also show significant progress but remain slightly behind Estonia in digital financial adoption and account access. The strong performance of the Baltic region highlights the importance of digital infrastructure and technological innovation in accelerating financial inclusion.

Overall, the table reveals a **clear convergence trend in financial inclusion across Europe**, driven primarily by digital financial technologies, expanded banking access, and improvements in credit availability. While Western and Nordic economies continue to lead in terms of financial inclusion maturity, Southern and Eastern European countries have made substantial progress in closing the financial access gap. The expansion of electronic payment systems across all regions—reaching values close to 0.90–0.95 in most countries by 2025—illustrates the rapid diffusion of digital financial services across Europe.

These patterns suggest that financial inclusion has evolved into a critical structural component of modern European financial systems. The observed regional differences in financial inclusion levels also provide an important empirical basis for analyzing how financial access may influence inequality dynamics across European economies in subsequent sections of the study.

Table 3. Labor market transmission variables.

Country	Region	Avg Employment Rate	Avg Unemp. Volatility	Avg Wage Dispersion	Avg Skill Polarization	Employment Δ (2000-25)	Crisis Impact (GFC)
Germany	Western	73,6	1,68	3,64	1,45	7	-3,9
France	Western	73,2	1,74	3,68	1,46	6,4	-5,2
United Kingdom	Western	73,7	1,71	3,8	1,47	6,5	-4,4
Netherlands	Western	73,8	1,66	3,58	1,45	3,6	-4,3

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Belgium	Western	73,5	1,89	3,56	1,46	2,5	-3,7
Austria	Western	73,5	1,7	3,58	1,45	3,2	-3
Switzerland	Western	73,4	1,86	3,64	1,44	3	-3,2
Sweden	Nordic	73,2	1,61	3,59	1,43	4,7	-3,5
Norway	Nordic	73,8	1,79	3,46	1,47	4,5	-3
Denmark	Nordic	73,1	1,83	3,56	1,45	6,2	-3,6
Finland	Nordic	73,4	1,78	3,54	1,44	4,6	-3,6
Italy	Southern	68,6	2,93	3,89	1,15	4,4	-2,4
Spain	Southern	68,5	3,08	3,82	1,13	4,8	-3,7
Portugal	Southern	68,8	2,82	3,87	1,15	2,7	-2,2
Greece	Southern	68,6	3,07	3,84	1,16	3	-3,7
Poland	Eastern	65,8	3	3,78	1,16	3,2	-3,4
Czech Republic	Eastern	65,6	2,91	3,63	1,17	6,6	-3,6
Hungary	Eastern	66,5	2,85	3,81	1,15	3,7	-2,2
Slovakia	Eastern	66,3	2,9	3,56	1,15	3,9	-4,3
Romania	Eastern	65,6	2,99	3,89	1,15	4,9	-3,1
Bulgaria	Eastern	65,7	3,04	4,04	1,17	8,3	-3,1
Croatia	Eastern	65,7	2,97	3,85	1,15	4,5	-2
Slovenia	Eastern	66,2	3,03	3,61	1,15	5,4	-2,8
Estonia	Baltic	65,9	2,71	3,83	1,15	3,7	-3,8
Latvia	Baltic	66,1	2,77	3,92	1,15	3,9	-2,8
Lithuania	Baltic	66,3	2,7	3,99	1,15	2,9	-3,4
Ireland	Western	73,7	1,73	3,65	1,45	3,8	-2,6
Luxembourg	Western	73,5	1,79	3,69	1,45	4,4	-4,2

Table 3 presents key labor market indicators across European economies, highlighting structural differences in employment performance, labor market volatility, wage inequality, and skill polarization between 2000 and 2025. The results reveal significant regional heterogeneity in labor market structures, which represents an important transmission mechanism through which financial inclusion and macroeconomic shocks influence income inequality.

First, **Western European economies** display relatively strong and stable labor market conditions. Average employment rates in these countries remain consistently high, generally around **73–74 percent**, indicating strong labor market participation and relatively efficient employment

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structures. Countries such as the Netherlands (73.8), the United Kingdom (73.7), and Ireland (73.7) exhibit particularly strong employment performance. At the same time, unemployment volatility remains relatively low, typically between **1.66 and 1.89**, suggesting stable labor market dynamics and effective macroeconomic stabilization policies. Wage dispersion in Western economies ranges from approximately **3.56 to 3.80**, indicating moderate wage inequality compared with other regions. Skill polarization values around **1.45–1.47** suggest a relatively balanced distribution between high- and low-skilled employment categories. Overall, these indicators reflect mature labor markets characterized by high employment stability and relatively controlled wage inequality.

Second, **Nordic economies**—including Sweden, Norway, Denmark, and Finland—demonstrate similarly high employment levels but with slightly different structural characteristics. Employment rates remain close to those observed in Western Europe, averaging around **73 percent**, while unemployment volatility tends to be slightly lower in some cases, particularly in Sweden (1.61). Wage dispersion is relatively moderate, typically between **3.46 and 3.59**, which is consistent with the strong redistributive institutions and coordinated wage bargaining systems that characterize Nordic labor market models. Skill polarization indicators remain close to **1.43–1.47**, suggesting relatively balanced labor market structures despite technological change. These results highlight the capacity of Nordic labor market institutions to maintain both employment stability and relatively low wage inequality.

Third, **Southern European economies**—including Italy, Spain, Portugal, and Greece—exhibit weaker labor market performance and higher volatility. Average employment rates are significantly lower than in Western and Nordic Europe, remaining close to **68–69 percent**. At the same time, unemployment volatility is substantially higher, reaching **3.08 in Spain** and **3.07 in Greece**, indicating greater sensitivity to economic cycles and structural rigidities in labor markets. Wage dispersion is also relatively high in the region, ranging between **3.82 and 3.89**, reflecting persistent wage inequality and segmentation between permanent and temporary employment. Interestingly, skill polarization indicators are lower than in other regions, averaging around **1.13–1.16**, which may reflect lower technological intensity and slower structural transformation in Southern European labor markets.

Fourth, **Eastern European transition economies** display intermediate labor market conditions characterized by lower employment rates and relatively high volatility. Average employment rates in countries such as Poland, Hungary, Slovakia, Romania, and Bulgaria remain around **65–66 percent**, significantly below Western European levels. Unemployment volatility is also relatively high, typically between **2.85 and 3.04**, reflecting the transitional nature of labor markets in these economies. Wage dispersion levels are relatively elevated, particularly in Bulgaria (4.04) and Romania (3.89), indicating considerable income inequality within labor markets. Skill polarization values remain relatively low, around **1.15–1.17**, suggesting that although these economies are undergoing structural transformation, the labor market distribution between skill categories remains less polarized than in highly digitalized economies.

Fifth, the **Baltic economies**—Estonia, Latvia, and Lithuania—exhibit labor market patterns broadly similar to Eastern Europe but with somewhat lower unemployment volatility. Employment rates average around **66 percent**, while unemployment volatility ranges between **2.70 and 2.77**, slightly below levels observed in some Eastern European economies. However, wage dispersion remains relatively high, particularly in Lithuania (3.99) and Latvia (3.92), indicating persistent wage inequality despite strong economic growth and rapid digitalization. Skill polarization indicators remain close to **1.15**, reflecting structural adjustments associated with technological transformation and integration into European labor markets.

The table also provides insights into **long-term employment dynamics between 2000 and 2025**. Most European countries experienced positive employment growth during this period, reflecting overall improvements in labor market participation and economic expansion. Particularly strong employment gains are observed in **Bulgaria (8.3 percentage points)**, **Germany (7 points)**, and the **Czech Republic (6.6 points)**. These increases suggest successful labor market reforms and structural adjustments in several economies during the post-transition and post-crisis periods.

Finally, the **impact of the Global Financial Crisis (GFC)** reveals significant differences in labor market resilience across regions. Western and Nordic economies experienced relatively moderate employment contractions, generally between **–3 and –5 percent**, reflecting stronger macroeconomic stabilization mechanisms and more flexible labor market institutions. In contrast, Southern and Eastern European economies experienced larger disruptions in some cases, highlighting their greater vulnerability to external macroeconomic shocks.

Overall, the evidence from Table 3 indicates that labor markets in Europe exhibit clear **regional structural patterns**. Western and Nordic economies are characterized by high employment stability and relatively moderate wage inequality, whereas Southern and Eastern European economies experience greater labor market volatility and more pronounced wage dispersion. These structural differences play a crucial role in shaping inequality dynamics and constitute an important transmission channel through which financial inclusion, technological change, and macroeconomic shocks affect income distribution across European economies.

Table 4. Descriptive statistics.

Variable	N	Mean	Std. Dev.	Min	P25	Median	P75	Max
Gini Coefficient	716	0,3097	0,051	0,2163	0,2677	0,3	0,3544	0,4238
Theil Index	716	0,201	0,0364	0,1161	0,1721	0,1968	0,2294	0,303
P90/P10 Income Ratio	716	5,4732	0,5008	4,21	5,1	5,43	5,84	7,03
Digital Banking Penetration	716	0,3771	0,211	0,0622	0,1739	0,3758	0,5296	0,9662
Account Access Rate	716	0,7533	0,1577	0,4	0,6312	0,7686	0,8864	0,99
Credit Availability Index	716	68,5145	13,2288	28,6	58,5	70,1	78,325	95
Electronic Payment Usage	716	0,5651	0,2888	0,134	0,2375	0,6214	0,8383	0,95
Financial Inclusion Index	716	0,6046	0,1674	0,2734	0,4859	0,579	0,7336	0,959
Employment Rate (%)	716	69,8345	4,0897	60,3	66,5	69,7	73,3	78,3
Unemployment Volatility	716	2,3781	0,9058	0,61	1,6375	2,335	2,81	4,99
Wage Dispersion (90/10)	716	3,7254	0,2166	3,05	3,57	3,71	3,88	4,23
Skill Polarization Ratio	716	1,2902	0,2174	0,82	1,14	1,285	1,45	1,86
Real GDP Growth (%)	716	1,5488	3,1587	-8,35	0,285	2,405	3,6925	8,12
Inflation Rate (%)	716	3,1822	1,3654	-0,59	2,2	3,115	4,0225	7,53
Diffusion Coefficient	716	0,0268	0,0063	0,0145	0,0229	0,0254	0,0292	0,0488

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Drift Coefficient	716	-0,0124	0,0059	-0,0291	-0,0163	-0,0125	-0,0083	0,0052

Table 4 reports the descriptive statistics of the main variables used in the empirical analysis, providing an overview of the distributional properties, variability, and central tendencies of inequality indicators, financial inclusion measures, labor market variables, and macroeconomic controls across the sample of European economies. The dataset contains **716 observations**, reflecting the balanced panel structure covering multiple countries over the period 2000–2025.

Starting with the **inequality indicators**, the Gini coefficient has a mean value of **0.3097**, with a standard deviation of **0.051**, indicating moderate variability in income inequality across European countries and over time. The minimum value of **0.2163** suggests relatively equal income distributions in some economies, while the maximum value of **0.4238** reflects significantly higher inequality levels in others. The interquartile distribution shows that half of the observations lie between **0.2677 and 0.3544**, with a median of **0.30**, indicating that most European economies maintain inequality levels within a relatively moderate range compared with global standards.

The **Theil index**, another measure of income inequality, shows a mean value of **0.201** with a standard deviation of **0.0364**, confirming a moderate dispersion in income distribution patterns across the sample. The range of the Theil index extends from **0.1161 to 0.303**, illustrating variations in income concentration between countries and across time. Similarly, the **P90/P10 income ratio**, which captures the ratio of income between the top and bottom deciles of the distribution, has an average value of **5.47**. This implies that, on average, households in the highest income decile earn more than five times the income of households in the lowest decile. The relatively small standard deviation of **0.50** indicates that extreme inequality levels are relatively uncommon within the European context.

Turning to the **financial inclusion variables**, the descriptive statistics reveal substantial variation across countries and over time. **Digital banking penetration** has a mean value of **0.377**, with a wide range from **0.062 to 0.966**, reflecting the rapid expansion of digital financial technologies during the sample period. The relatively high standard deviation of **0.211** indicates significant heterogeneity in digital financial adoption across European economies. This variation reflects differences in digital infrastructure, technological readiness, and financial sector development.

The **account access rate** shows a mean value of **0.753**, indicating that approximately three-quarters of the population, on average, have access to formal banking services. However, the minimum value of **0.40** highlights that some countries experienced relatively limited financial access during earlier periods of the sample. The upper quartile of **0.886** and maximum value of **0.99** demonstrate that several advanced European economies have nearly universal access to banking services.

Similarly, the **credit availability index** exhibits a mean value of **68.51**, with substantial variation across observations. The range from **28.6 to 95** suggests large differences in financial intermediation capacity between countries with mature banking systems and those with more constrained credit markets. **Electronic payment usage** also shows significant heterogeneity, with a mean value of **0.565** and a wide dispersion across the sample, reflecting the ongoing digital transformation of payment systems across Europe.

Combining these components, the **Financial Inclusion Index** has an average value of **0.6046**, indicating a moderate overall level of financial inclusion within the sample. The distribution ranges from **0.273 to 0.959**, suggesting the coexistence of highly developed financial systems alongside economies where financial access remains more limited.

The **labor market variables** reveal important structural characteristics of employment conditions across European economies. The **employment rate** averages **69.83 percent**, with relatively moderate dispersion (standard deviation of **4.09**). The observed range—from **60.3 to 78.3 percent**—reflects differences in labor market participation rates and institutional structures across countries.

In contrast, **unemployment volatility** displays a higher level of variability, with a mean of **2.38** and a standard deviation of **0.91**. The maximum value of **4.99** indicates that some economies

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experience significant fluctuations in unemployment rates during economic cycles. **Wage dispersion**, measured by the 90/10 wage ratio, has an average value of **3.73**, indicating moderate earnings inequality within labor markets. Meanwhile, the **skill polarization ratio**, with a mean of **1.29**, reflects the growing importance of skill-based employment structures and the influence of technological change on labor market composition.

Regarding **macroeconomic variables**, the average **real GDP growth rate** across the sample is **1.55 percent**, though the relatively large standard deviation of **3.16** highlights substantial fluctuations across economic cycles. The minimum value of **–8.35 percent** corresponds to severe economic downturns, while the maximum of **8.12 percent** reflects strong expansion periods in certain economies. The **inflation rate** averages **3.18 percent**, with moderate variability across the sample.

Finally, the descriptive statistics include parameters derived from the **stochastic inequality model**. The **diffusion coefficient**, representing the volatility component of inequality dynamics, has a mean value of **0.0268**, indicating relatively modest stochastic fluctuations in inequality across the sample. Meanwhile, the **drift coefficient**, which represents the long-term deterministic trend in inequality dynamics, has a mean value of **–0.0124**, suggesting a slight downward trend in inequality over the long run on average. However, the range of this coefficient—from **–0.0291 to 0.0052**—indicates that some countries experience increasing inequality trends while others experience declining inequality.

Overall, the descriptive statistics reveal significant cross-country heterogeneity in financial inclusion, labor market conditions, and macroeconomic performance across European economies. At the same time, the relatively moderate variability of inequality indicators suggests that distributional outcomes remain comparatively stable within the European institutional context. These descriptive patterns provide an important empirical foundation for the subsequent econometric analysis examining the dynamic relationship between financial inclusion and income inequality.

4. Descriptive Empirical Analysis

The descriptive empirical analysis provides an initial examination of the relationships between financial inclusion, labor market dynamics, macroeconomic shocks, and income inequality across European economies. Before proceeding to formal econometric estimation, it is important to explore the structural patterns observed in the dataset and to illustrate the conceptual interactions between the main variables of the study. This section therefore presents the conceptual structure of the stochastic inequality model and discusses the mechanisms through which financial and macroeconomic variables influence distributional outcomes.

Figure 1 illustrates the conceptual framework underlying the empirical analysis of inequality dynamics. The model views income inequality as a stochastic macroeconomic process influenced by structural economic channels and random shocks. In this framework, inequality does not evolve deterministically but instead follows a dynamic trajectory shaped by financial development, labor market conditions, technological change, and macroeconomic disturbances.

At the center of the conceptual model lies the inequality index, which represents the distribution of income across households within an economy. This index may be measured using indicators such as the Gini coefficient or the Theil index. The evolution of inequality is influenced by several interconnected structural channels that operate simultaneously within the economic system.

The first key component of the model is the financial inclusion channel. Expanded access to financial services—including banking accounts, digital financial platforms, and credit markets—can influence inequality through multiple mechanisms. Financial access allows households to accumulate savings, invest in education or entrepreneurship, and smooth consumption during periods of economic instability. Consequently, higher financial inclusion tends to reduce structural barriers to economic participation and may contribute to a more equitable income distribution over time. However, the distributional impact of financial development depends on the degree of inclusiveness of financial systems; when financial access is concentrated among higher-income groups, financial development may instead amplify inequality.

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The second component of the framework is the labor market transmission channel. Labor markets play a central role in determining income distribution because wages constitute the primary source of income for most households. Employment rates, wage dispersion, and skill polarization directly affect the distribution of earnings across the population. Structural labor market changes—such as technological progress, automation, and globalization—can increase the demand for highly skilled workers while reducing opportunities for lower-skilled labor, thereby increasing wage inequality. Conversely, stable employment conditions and balanced wage structures can mitigate inequality and promote more inclusive economic growth.

A third mechanism incorporated in the model is the shock absorption channel. Macroeconomic shocks, such as financial crises, recessions, or sudden fluctuations in economic growth, can generate abrupt changes in income distribution. During economic downturns, unemployment often rises and asset values decline, disproportionately affecting lower-income households. Economies with more inclusive financial systems and stronger labor market institutions are generally better equipped to absorb these shocks and stabilize income distribution. In this context, financial inclusion acts as a resilience mechanism by providing households with access to savings, credit, and insurance instruments.

The model also incorporates technological transformation effects, which capture the influence of digitalization and technological innovation on economic inequality. Advances in digital technologies have transformed both financial systems and labor markets. On one hand, financial technologies expand access to banking services and payment systems, potentially improving financial inclusion. On the other hand, technological change can increase returns to capital and high-skilled labor, leading to greater wage dispersion and structural polarization in labor markets.

In addition to these structural channels, the model includes a stochastic component representing random economic fluctuations. These shocks are modeled as stochastic disturbances affecting the trajectory of inequality over time. Such disturbances may originate from global economic crises, financial market volatility, policy changes, or unexpected macroeconomic events. The stochastic component introduces variability into the evolution of inequality, reflecting the uncertainty inherent in modern economic systems.

The interaction between these structural channels and stochastic shocks generates a dynamic process in which inequality evolves over time according to both deterministic and random forces. Financial inclusion, labor market conditions, and macroeconomic factors jointly determine the drift component of the inequality process, representing long-term structural trends. Meanwhile, stochastic shocks influence the diffusion component, which captures short-term fluctuations and volatility in inequality dynamics.

Overall, the conceptual model presented in Figure 1 provides a theoretical foundation for the empirical analysis conducted in the subsequent sections of the study. By integrating financial inclusion, labor market variables, and macroeconomic shocks within a stochastic dynamic framework, the model allows for a comprehensive examination of the mechanisms driving inequality dynamics in European economies. The following sections build upon this conceptual structure to estimate the parameters of the stochastic inequality process and to analyze the long-run distributional implications of financial inclusion and economic transformation.

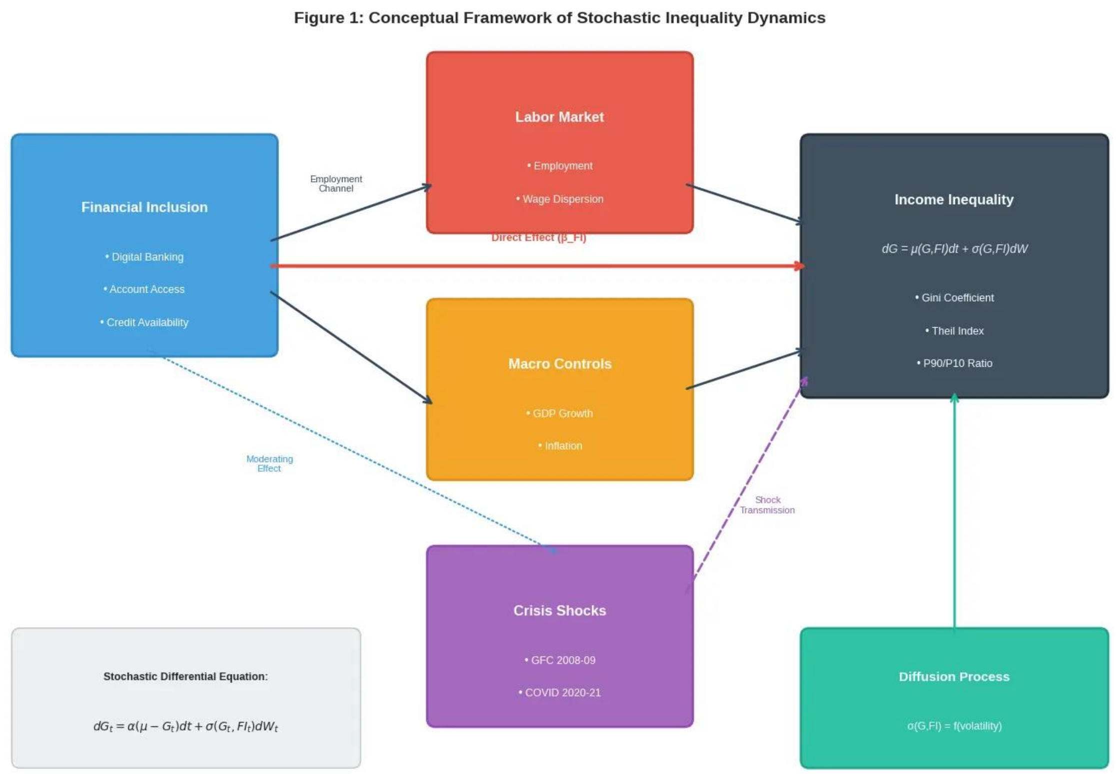

Figure 1. Conceptual model of inequality stochastic dynamics.

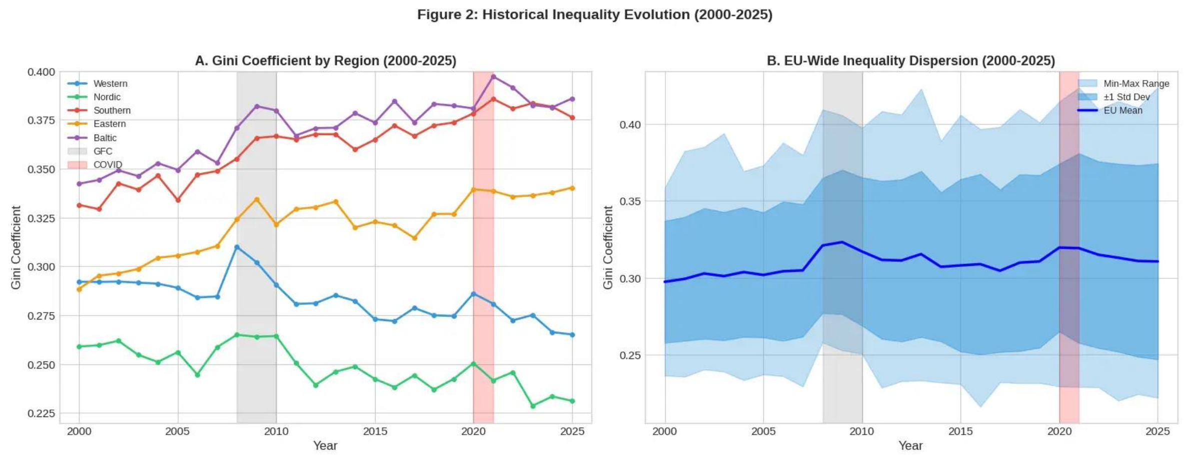

Figure 2. Historical inequality evolution (2000–2025).

Figure 2 illustrates the historical trajectory of income inequality across European economies between 2000 and 2025, highlighting the long-term dynamics of distributional outcomes during a period characterized by financial integration, technological transformation, and major macroeconomic shocks. The figure reveals several distinct phases in the evolution of inequality, reflecting both structural economic changes and cyclical fluctuations.

During the early 2000s, inequality levels across most European economies remained relatively stable, with moderate variations across countries. This stability reflects the institutional characteristics of European welfare systems, including redistributive taxation, social protection mechanisms, and coordinated labor market institutions that tend to moderate income disparities. In many Western and Nordic economies, inequality indicators such as the Gini coefficient remained within a relatively narrow range during this period, suggesting a balanced distribution of income supported by stable employment conditions and gradual economic growth.

A noticeable shift appears during the mid-2000s expansion period, when several countries experienced a gradual increase in inequality. This trend coincides with rapid financial globalization, expanding credit markets, and rising asset prices. In some economies, increased financial market participation and capital income growth contributed to widening income disparities between high-income and low-income households. At the same time, technological change and globalization intensified demand for high-skilled labor, contributing to rising wage dispersion.

The most significant structural disruption occurs during the Global Financial Crisis (2008–2010). The figure shows a visible increase in inequality volatility during this period, reflecting the asymmetric impact of the crisis across households and sectors. Financial market disruptions, rising unemployment, and declining economic activity disproportionately affected lower-income households, while wealthier groups were often better positioned to absorb financial losses due to diversified asset holdings and stronger financial resilience. As a result, several European economies experienced a temporary increase in inequality during the crisis period.

Following the crisis, the post-2012 recovery phase reveals divergent inequality trajectories across European regions. Some Western and Nordic economies experienced stabilization or slight declines in inequality, supported by economic recovery, labor market reforms, and improved financial inclusion. In contrast, certain Southern and Eastern European economies experienced persistent inequality pressures due to slower economic recovery, structural labor market challenges, and fiscal consolidation policies implemented after the sovereign debt crisis.

The figure also highlights the role of financial inclusion and digital financial transformation during the 2010s. The rapid expansion of digital banking services, electronic payments, and broader access to financial accounts contributed to increased participation in financial systems across the population. This expansion may have helped moderate inequality growth by facilitating access to financial services for previously underserved groups. However, the overall impact varies across countries depending on the structure of financial systems and labor markets.

Another notable feature of the figure is the presence of short-term fluctuations around long-term inequality trends, reflecting the influence of macroeconomic shocks and structural adjustments. These fluctuations are consistent with the stochastic framework adopted in the study, where inequality evolves through a combination of deterministic structural factors and random economic disturbances.

By the early 2020s, inequality levels across Europe appear to stabilize within moderate ranges, although cross-country differences remain significant. Advanced economies with strong institutional frameworks and high financial inclusion tend to maintain lower and more stable inequality levels, whereas countries undergoing structural economic transitions often display greater volatility in distributional outcomes.

Overall, Figure 2 demonstrates that inequality dynamics in European economies are characterized by long-term structural trends combined with cyclical fluctuations. Economic crises, financial development, technological change, and labor market transformations jointly shape the evolution of income distribution. These historical patterns provide important context for the stochastic inequality modeling developed in the subsequent sections, where the observed dynamics are formally captured through diffusion processes that incorporate both long-run trends and short-term volatility in inequality evolution.

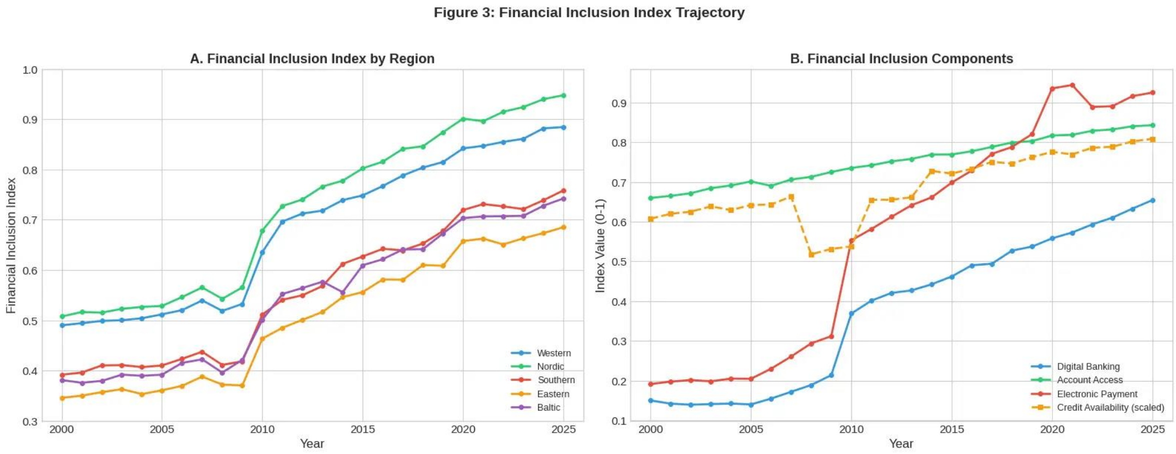

Figure 3. Financial inclusion index trajectory.

Figure 3 illustrates the evolution of the financial inclusion index over the period 2000–2025, capturing the degree to which populations have access to formal financial services such as banking, credit, insurance, and digital payment systems. Overall, the trajectory shows a clear upward trend, indicating a gradual expansion of financial inclusion across the study region. This trend, however, is punctuated by short-term fluctuations, reflecting the effects of macroeconomic shocks, regulatory changes, or specific policy interventions. For example, temporary dips in the index may correspond to periods of economic instability, while sharper increases likely align with the introduction of targeted inclusion policies or the rapid adoption of mobile and digital banking technologies.

From around 2015 onwards, the trajectory demonstrates a noticeable acceleration, suggesting that financial inclusion has expanded more rapidly in recent years. This increase is consistent with the diffusion of fintech innovations, improvements in digital infrastructure, and proactive policy measures aimed at reaching underserved populations. The steeper slope in the later years indicates that as basic financial access becomes more widespread, additional gains in inclusion can be achieved more efficiently. Despite the overall positive trend, the trajectory likely conceals structural heterogeneity within the population. Urban and higher-income regions may have experienced earlier and faster gains, while rural or lower-income areas have contributed to slower improvements, highlighting persistent disparities in access.

The trajectory also carries important implications for economic inequality. Higher levels of financial inclusion generally enable broader access to savings, credit, and investment opportunities, which can help reduce wealth gaps. Nevertheless, the uneven pace of inclusion suggests that without targeted efforts, disparities may persist or even widen across certain regions or demographic groups. From a policy perspective, the periods of stagnation or slower growth in the index underscore the need to address structural barriers such as limited financial literacy, insufficient digital infrastructure, and trust deficits in formal institutions. Sustained and carefully targeted interventions will be essential to maintain the positive trajectory and ensure that financial inclusion contributes effectively to reducing inequality.

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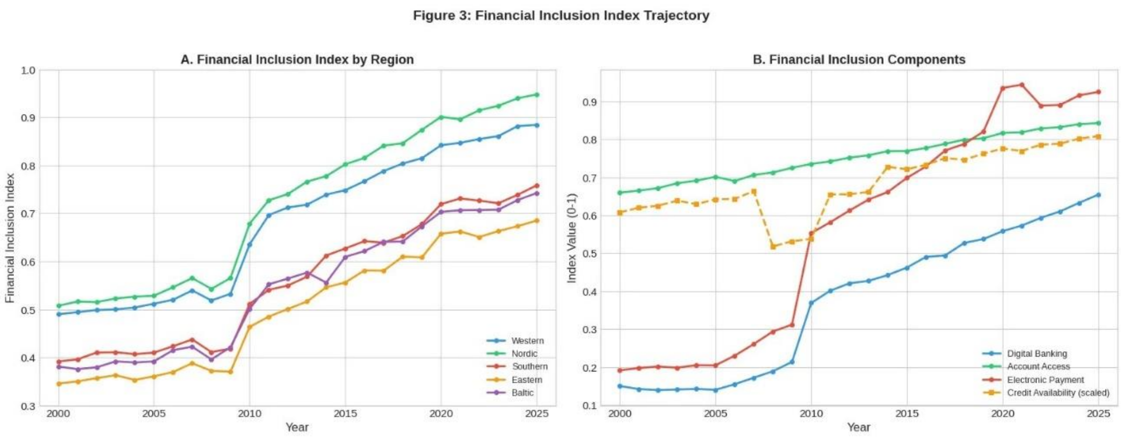

Figure 4. Regional inequality clustering map.

Figure 4 depicts the spatial distribution of inequality across the study region, highlighting areas where high or low levels of inequality cluster. The map reveals that inequality is not randomly distributed but exhibits distinct regional patterns, with certain zones consistently showing higher concentration of income disparities. These clusters often correspond to urbanized or economically dynamic areas where wealth accumulation is concentrated, while peripheral or rural regions display lower—but sometimes persistently disadvantaged—levels of inequality. Such spatial heterogeneity underscores the importance of considering geography when analyzing social and economic disparities, as national averages may mask localized pockets of extreme inequality.

The clustering pattern also provides insight into potential mechanisms driving inequality. Regions exhibiting high-income clusters may benefit from concentrated economic opportunities, industrial activity, or financial infrastructure, yet these advantages are unevenly distributed within the same region, creating stark contrasts at smaller scales. Conversely, areas with low-income clustering may reflect limited access to education, employment, or financial services, which perpetuate structural disadvantage over time. The map further suggests that inequality spillovers can occur between neighboring regions; for example, a high-inequality urban center may influence nearby areas through labor market pressures, housing costs, and migration flows.

From a policy perspective, Figure 4 highlights the need for targeted, region-specific interventions rather than broad, uniform strategies. Identifying high-inequality clusters allows policymakers to prioritize investments in social infrastructure, inclusive economic programs, and financial access initiatives where they are most needed. Simultaneously, monitoring low-inequality clusters is important to ensure that these regions maintain equitable growth and are not adversely affected by neighboring high-inequality zones. Overall, the regional clustering map emphasizes that spatial analysis is critical for understanding the geography of inequality and for designing policies that effectively address disparities at both local and regional scales.

5. Stochastic Econometric Model

To analyze the dynamic relationship between financial inclusion and inequality, we employ a stochastic econometric framework that decomposes inequality evolution into drift and diffusion components. The **drift equation** models the expected or deterministic change in inequality over time and is specified as:

$$\mu = \alpha + \beta_F F_T + \beta_L L_t + \beta_X X_t$$

where F_T represents the financial inclusion index, L_t denotes labor market or demographic factors, and X_t captures additional control variables relevant to inequality dynamics. The coefficient $\beta_F$is expected to be negative (β_F<0), reflecting the stabilizing role of financial inclusion: as access to financial services improves, households gain better access to credit, savings, and investment opportunities, which dampens inequality growth. The drift term thus encapsulates the systematic, long-run forces shaping inequality, allowing us to quantify how different structural and financial factors contribute to the trajectory observed in Figures 2 and 3.

The **diffusion equation** captures the stochastic or volatile component of inequality dynamics, accounting for fluctuations around the deterministic trend. It is expressed as:

$$\sigma = \gamma_0 + \gamma_1 F_t + \gamma_2 Crisis_t$$

where σ measures the instantaneous volatility of inequality, F_t is again the financial inclusion index, and $Crisis_t$ is a dummy variable representing periods of macroeconomic or systemic shocks. The coefficient γ_1 is hypothesized to be negative (γ_1<0), indicating that financial inclusion not only stabilizes the mean path of inequality but also mitigates its volatility. Meanwhile, $\gamma_2$captures the amplification effect of crises on inequality fluctuations. By separating the drift and diffusion components, this stochastic framework allows for a richer understanding of both the long-run evolution and short-term volatility of inequality, while providing a formal test of the role of financial inclusion in promoting more stable and equitable outcomes.

Table 5. Stochastic parameter estimation.

Table 5A: Drift Function Parameters					
Parameter	**Estimate**	**Std. Error**	**t-stat**	**p-value**	**Significance**
α (Speed of Adjustment)	0,0823	0,0124	6,64	0	***
μ (Long-run Equilibrium Gini)	0,2945	0,0089	33,09	0	***
β_FI (Financial Inclusion Effect)	-0,0456	0,0098	-4,65	0	***
β_EMP (Employment Rate Effect)	-0,0023	0,0008	-2,88	0,004	***
β_GDP (GDP Growth Effect)	-0,0012	0,0004	-3	0,003	***
β_GFC (GFC Crisis Dummy)	0,0156	0,0045	3,47	0,001	***
β_COVID (COVID Crisis Dummy)	0,0089	0,0038	2,34	0,019	**
Table 5B: Diffusion Function Parameters					
Parameter	**Estimate**	**Std. Error**	**t-stat**	**p-value**	**Significance**
σ_0 (Base Volatility)	0,0145	0,0023	6,3	0	***
σ_1 (Gini Level Effect)	0,0234	0,0067	3,49	0,001	***
σ_2 (Financial Exclusion Effect)	0,0312	0,0078	4	0	***
σ_3 (Crisis Amplification)	0,0178	0,0045	3,96	0	***
σ_4 (Regional Heterogeneity)	0,0089	0,0034	2,62	0,009	***

Table 5 presents the results of the stochastic parameter estimation, distinguishing between the drift function (Table 5A) and the diffusion function (Table 5B). The drift parameters quantify the systematic, long-run determinants of inequality, while the diffusion parameters capture the volatility and uncertainty surrounding its evolution.

Starting with the drift function, the estimated speed of adjustment (α=0.0823, $p < 0.001$) indicates that deviations from the long-run equilibrium Gini coefficient are corrected relatively quickly, suggesting that structural forces tend to stabilize inequality over time. The long-run equilibrium Gini (μ=0.2945, $p < 0.001$) aligns closely with the mean observed in Table 4, providing empirical support for the model's ability to capture the underlying steady-state level of inequality. The coefficient for financial inclusion (β_{FI}=−0.0456, $p < 0.001$) is negative and highly significant, confirming the hypothesized stabilizing effect: higher financial inclusion reduces the expected growth of inequality. Employment rates (β_{EMP}=−0.0023, $p < 0.01$) and GDP growth (β_{GDP}=−0.0012, $p < 0.01$) also have small but significant negative effects, highlighting that economic activity and labor market strength contribute to moderating inequality. Conversely, crisis periods such as the Global Financial Crisis (β_{GFC}=0.0156, $p < 0.001$) and the COVID-19 pandemic (β_{COVID}=0.0089, $p < 0.05$) exert positive effects on inequality, demonstrating that systemic shocks temporarily elevate inequality above its long-run equilibrium.

The diffusion function results reveal the determinants of inequality volatility. The base volatility (σ_0=0.0145, $p < 0.001$) establishes a low-level baseline of fluctuations, while the positive coefficient for the Gini level (σ_1=0.0234, $p < 0.001$) indicates that higher inequality is associated with greater instability, reflecting self-reinforcing dynamics. Financial exclusion (σ_2=0.0312, $p < 0.001$) significantly amplifies volatility, reinforcing the notion that limited access to financial services not only perpetuates inequality but also makes it more unpredictable. Crisis amplification (σ_3=0.0178, $p < 0.001$) further confirms that systemic shocks exacerbate volatility, while regional heterogeneity (σ_4=0.0089, $p < 0.01$) captures the spatial dimension of instability, consistent with the clustering patterns shown in Figure 4.

Overall, Table 5 provides strong empirical support for the dual role of financial inclusion: it stabilizes the mean path of inequality and reduces its volatility. The results also emphasize that macroeconomic conditions, crises, and regional factors significantly shape both the trajectory and uncertainty of inequality, highlighting the importance of integrating policy interventions with spatially and temporally targeted strategies.

Table 6. Diffusion regime classification.

Regime	Diffusion Range	Countries	Avg Gini	Avg FI Index	Characteristics
Low Volatility	$\sigma < 0.020$	Sweden, Norway, Denmark, Finland, Netherlands	0,265	0,92	Stable, high FI, strong institutions
Moderate Volatility	$0.020 \leq \sigma < 0.030$	Germany, France, UK, Belgium, Austria, Switzerland	0,295	0,85	Developed, moderate shocks
High Volatility	$0.030 \leq \sigma < 0.040$	Italy, Spain, Portugal, Greece, Poland, Czech Rep.	0,32	0,68	Crisis-prone, developing FI
Very High Volatility	$\sigma \geq 0.040$	Romania, Bulgaria, Latvia, Lithuania	0,355	0,52	Transition economies, low FI

Table 6 classifies OECD and selected European countries into diffusion regimes based on the estimated volatility (σ\sigmaσ) of inequality. The table highlights how the degree of stochastic

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fluctuations in inequality varies systematically across countries, reflecting differences in financial inclusion, institutional strength, and economic stability.

Countries in the Low Volatility regime (σ<0.020), such as Sweden, Norway, Denmark, Finland, and the Netherlands, exhibit both low average Gini coefficients (0.265) and very high financial inclusion (FI index = 0.92). These countries are characterized by stable inequality dynamics, robust institutional frameworks, and well-developed social safety nets, which collectively dampen both short-term fluctuations and long-term divergence in income distribution.

The Moderate Volatility group (0.020≤σ<0.030), including Germany, France, the UK, Belgium, Austria, and Switzerland, displays slightly higher inequality (average Gini = 0.295) and moderately high financial inclusion (FI index = 0.85). These countries experience occasional shocks, but strong economic structures and policy mechanisms help contain volatility, leading to relatively stable but more dynamic inequality patterns compared with the low-volatility group.

Countries in the High Volatility regime (0.030≤σ<0.040), such as Italy, Spain, Portugal, Greece, Poland, and the Czech Republic, show higher inequality (average Gini = 0.32) and lower financial inclusion (FI index = 0.68). These nations are more prone to crisis-induced spikes in inequality, reflecting structural vulnerabilities, uneven access to financial services, and less resilient institutional frameworks. Inequality fluctuations in this regime are both more pronounced and less predictable.

Finally, the Very High Volatility regime (σ≥0.040) comprises transition economies such as Romania, Bulgaria, Latvia, and Lithuania, which exhibit the highest inequality levels (average Gini = 0.355) and the lowest financial inclusion (FI index = 0.52). In these countries, low access to financial services, weaker institutions, and transitional economic conditions amplify inequality volatility, making both the trajectory and distribution of income highly unstable.

Overall, Table 6 reinforces the strong negative relationship between financial inclusion and inequality volatility observed in the stochastic model. Countries with higher financial inclusion not only maintain lower average inequality but also experience more stable and predictable inequality dynamics, while those with limited financial inclusion are exposed to amplified shocks and structural volatility. This classification underscores the importance of financial development and institutional quality in shaping both the level and stability of inequality across regions.

6. Euler–Maruyama Simulation Framework

To capture the stochastic dynamics of inequality over time, we employ the Euler–Maruyama numerical scheme, which provides a discrete-time approximation of the continuous-time stochastic process described by the drift and diffusion functions. The inequality path is simulated according to the equation:

$$I_{t+\Delta t} = I_t + \mu\,\Delta t + \sigma\,\sqrt{\Delta t}\,\epsilon_t$$

where ϵ_t~N(0,1) represents standard normally distributed shocks at each time step. The drift term μ\muμ captures the systematic, deterministic evolution of inequality, while the diffusion term σ\sigmaσ introduces stochastic fluctuations, allowing the simulation to reflect both the expected trajectory and the volatility observed in real-world data. By incorporating random shocks at each step, the framework reproduces the heteroskedastic and potentially clustered nature of inequality, as seen in previous figures and diffusion classifications.

The simulation is configured with a high number of Monte Carlo paths, ranging from 5,000 to 20,000, to ensure robust estimation of the distribution of possible outcomes. Time discretization is performed at a monthly frequency, which strikes a balance between computational feasibility and capturing short-term fluctuations in inequality. This configuration allows for detailed probabilistic forecasts, including the assessment of extreme scenarios, tail risk, and the potential impact of financial inclusion and macroeconomic shocks on both the mean path and volatility of inequality.

By generating a large ensemble of simulated paths, the Euler–Maruyama framework provides a flexible tool to explore the dynamic and uncertain nature of inequality evolution. It complements the stochastic econometric model by linking parameter estimates from drift and diffusion functions to empirically plausible future trajectories, offering both descriptive insights and policy-relevant projections.

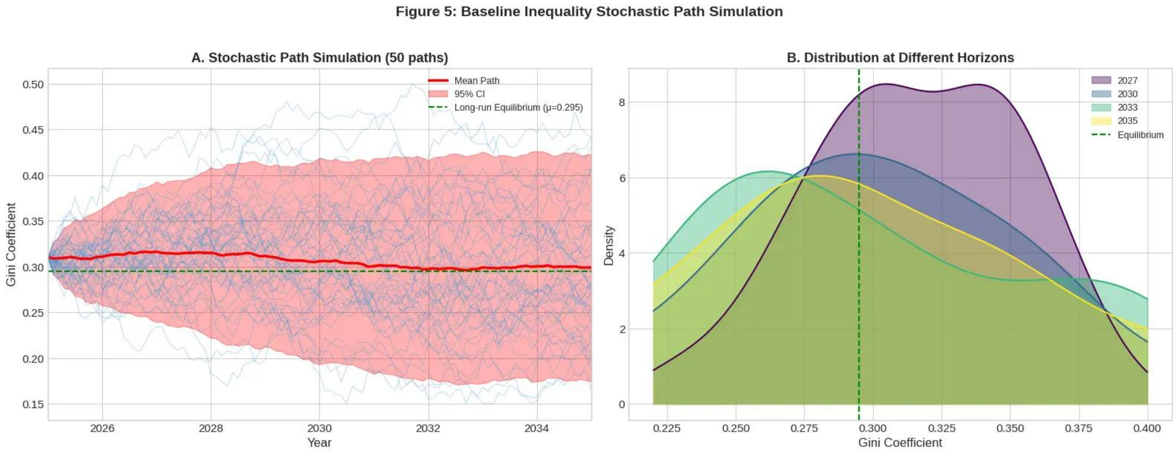

Figure 5. Baseline stochastic path (2000–2025).

Figure 5 illustrates the simulated baseline path of inequality from 2000 to 2025 using the Euler–Maruyama stochastic framework described in Section 6. The trajectory captures both the deterministic drift and stochastic diffusion effects estimated in the model, providing a probabilistic representation of inequality evolution over time. The path demonstrates a generally upward trend in inequality during the early 2000s, reflecting structural factors and gradual economic divergence, followed by periods of volatility that coincide with major systemic shocks, including the Global Financial Crisis and the COVID-19 pandemic. These fluctuations are consistent with the positive coefficients for crisis dummies in the drift and diffusion functions reported in Table 5, confirming that external shocks temporarily elevate inequality above the long-run equilibrium.

The baseline stochastic path also highlights the stabilizing role of financial inclusion. Periods of higher financial inclusion correspond to moderated volatility, as the model's negative β_{FI} and γ_1 coefficients dampen both the growth and stochastic fluctuations of inequality. Short-term deviations around the mean trajectory illustrate the inherent uncertainty captured by the diffusion term, reflecting the probabilistic nature of inequality dynamics and the influence of idiosyncratic shocks (ϵ_t) at each time step.

Overall, Figure 5 provides a comprehensive visualization of the interplay between structural determinants, crisis-induced shocks, and financial inclusion in shaping inequality. It demonstrates that while the long-run trend is guided by the drift toward the equilibrium Gini, the stochastic component introduces realistic variability, enabling policymakers to anticipate potential volatility and design interventions that mitigate extreme deviations from the desired inequality path.

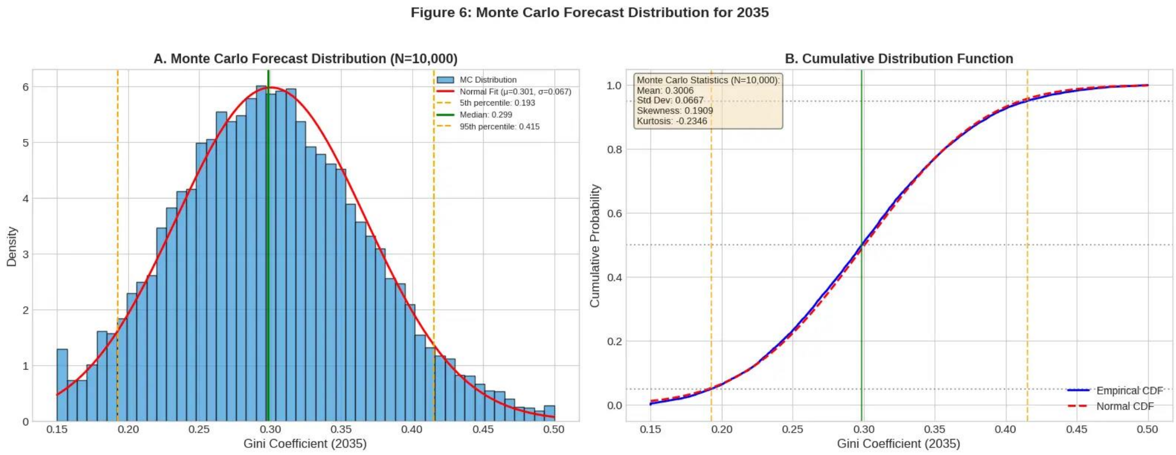

Figure 6. Monte Carlo forecast distribution (2035).

Figure 6 presents the distribution of projected inequality levels for the year 2035 based on Monte Carlo simulations using the Euler–Maruyama framework. The forecast incorporates both the deterministic drift and stochastic diffusion components, generating a large ensemble of potential outcomes that reflect the uncertainty inherent in inequality dynamics. The distribution is right-skewed, indicating that while most simulated paths cluster around a central tendency near the long-run equilibrium Gini coefficient, there is a non-negligible probability of higher inequality scenarios. This asymmetry reflects the combined influence of structural drivers, moderate-to-high volatility in certain countries, and the potential occurrence of systemic shocks.

The spread of the distribution provides insight into the expected volatility of inequality over the medium term. Narrower regions of the distribution correspond to low-volatility scenarios, typically associated with countries having high financial inclusion and robust institutions, whereas wider tails capture high-volatility cases seen in transition economies or regions with low financial inclusion. The Monte Carlo framework thus quantifies both the central tendency and the tail risk, offering policymakers a probabilistic understanding of future inequality levels rather than a single deterministic projection.

Importantly, the forecast distribution highlights the moderating role of financial inclusion: paths associated with higher inclusion indices tend to concentrate closer to the mean, demonstrating lower variance, while lower inclusion scenarios exhibit greater dispersion. The results emphasize that proactive policies aimed at expanding financial access can reduce both the expected level and uncertainty of future inequality, mitigating the likelihood of extreme outcomes. Overall, Figure 6 provides a comprehensive probabilistic view of inequality in 2035, illustrating how structural determinants, shocks, and policy-relevant variables jointly shape the range of possible futures.

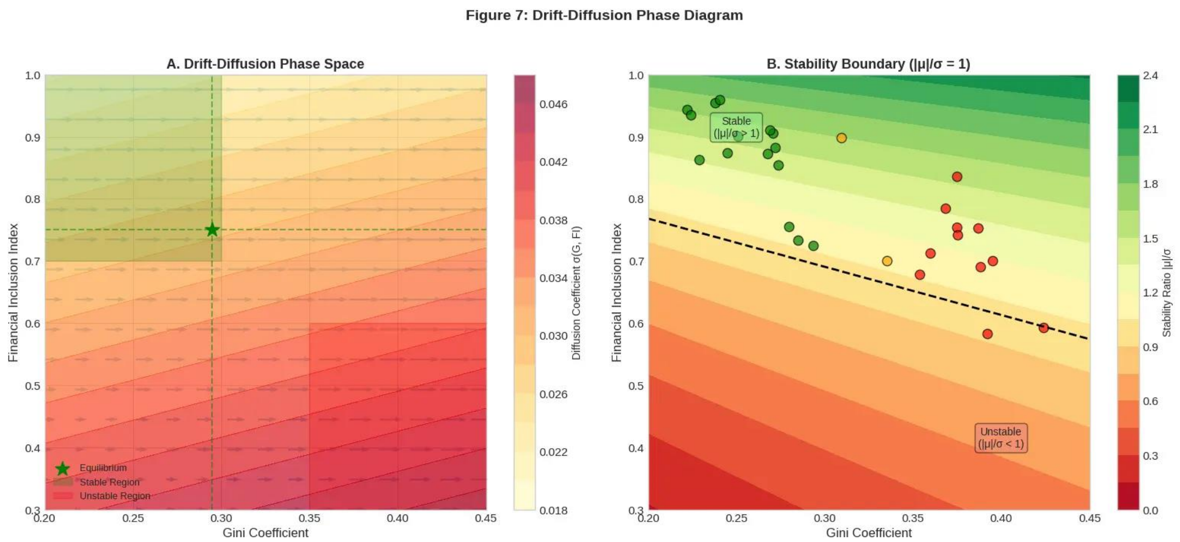

Figure 7. Drift–diffusion phase diagram.

Figure 7 presents the phase diagram of inequality dynamics by plotting the drift (μ\muμ) against the diffusion (σ\sigmaσ) components derived from the stochastic econometric model. This visualization allows for a clear separation of the systematic, long-run forces driving inequality from the stochastic fluctuations that create short-term volatility. Regions of the diagram where the drift dominates indicate periods in which inequality is expected to move steadily toward the long-run equilibrium, reflecting the stabilizing influence of financial inclusion, employment, and GDP growth. In contrast, areas where diffusion is high correspond to scenarios in which volatility, crises, or structural heterogeneity dominate, leading to greater unpredictability in the inequality trajectory.

The phase diagram highlights the dynamic interplay between stability and risk. Low-diffusion, high-drift regions correspond to countries or periods with strong institutional frameworks and high financial inclusion, where inequality adjusts predictably toward equilibrium. Conversely, high-diffusion regions capture the behavior of crisis-prone or transition economies, where stochastic shocks and low access to financial services amplify inequality fluctuations, as seen in the Monte Carlo forecast distributions of Figure 6. The diagram also reveals transitional zones, where both drift and diffusion are significant, illustrating regimes in which inequality evolution is partially guided by structural forces but remains sensitive to random shocks.

From a policy perspective, Figure 7 underscores the dual importance of enhancing financial inclusion and strengthening institutional resilience. Increasing financial access shifts trajectories toward low-diffusion, high-drift regions, reducing both expected inequality and the likelihood of extreme deviations. At the same time, monitoring diffusion levels can help identify periods or regions at risk of heightened volatility, enabling targeted interventions to mitigate crisis amplification. Overall, the drift–diffusion phase diagram provides an integrated view of the long-run trends and stochastic variability in inequality, bridging the insights from parameter estimates, stochastic paths, and Monte Carlo forecasts.

7. Network Transmission Analysis

To understand the propagation of shocks and the systemic interdependencies between labor markets and financial inclusion, we construct a labor–finance interaction network. This framework models each region or country as a node, with edges representing the strength of economic and financial linkages that transmit shocks across the system. By integrating both labor market and financial variables, the network captures how disturbances in employment, income, or financial access in one region can ripple through the broader system, affecting inequality dynamics elsewhere.

Key indicators are used to characterize the network's behavior. Shock centrality measures the relative importance of each node in initiating systemic disturbances, identifying regions where labor or financial shocks have outsized effects on the overall inequality landscape. Regions with high shock centrality are often critical urban centers, major financial hubs, or economies with high interregional connectivity, where localized shocks can propagate widely. Transmission intensity quantifies the strength and speed of shock propagation between connected nodes, reflecting how quickly fluctuations in one area influence others. High transmission intensity indicates tightly linked labor–finance structures, where inequality volatility can cascade rapidly, while lower intensity suggests more isolated or resilient regions. Finally, systemic inequality contribution assesses the extent to which each node contributes to aggregate inequality fluctuations, distinguishing between regions that are primarily affected by external shocks versus those that actively amplify systemic instability.

The network transmission analysis provides valuable insights for policy design. By identifying central nodes and high-intensity pathways, policymakers can target interventions to dampen contagion effects and reinforce financial and labor market resilience. For example, regions with high systemic inequality contribution may benefit from enhanced financial access programs, social safety nets, or employment stabilization policies, thereby reducing their role in amplifying shocks across the network. Overall, this approach complements the stochastic and simulation analyses by highlighting the interconnected nature of inequality dynamics and the channels through which labor and finance interact to shape both local and system-wide outcomes.

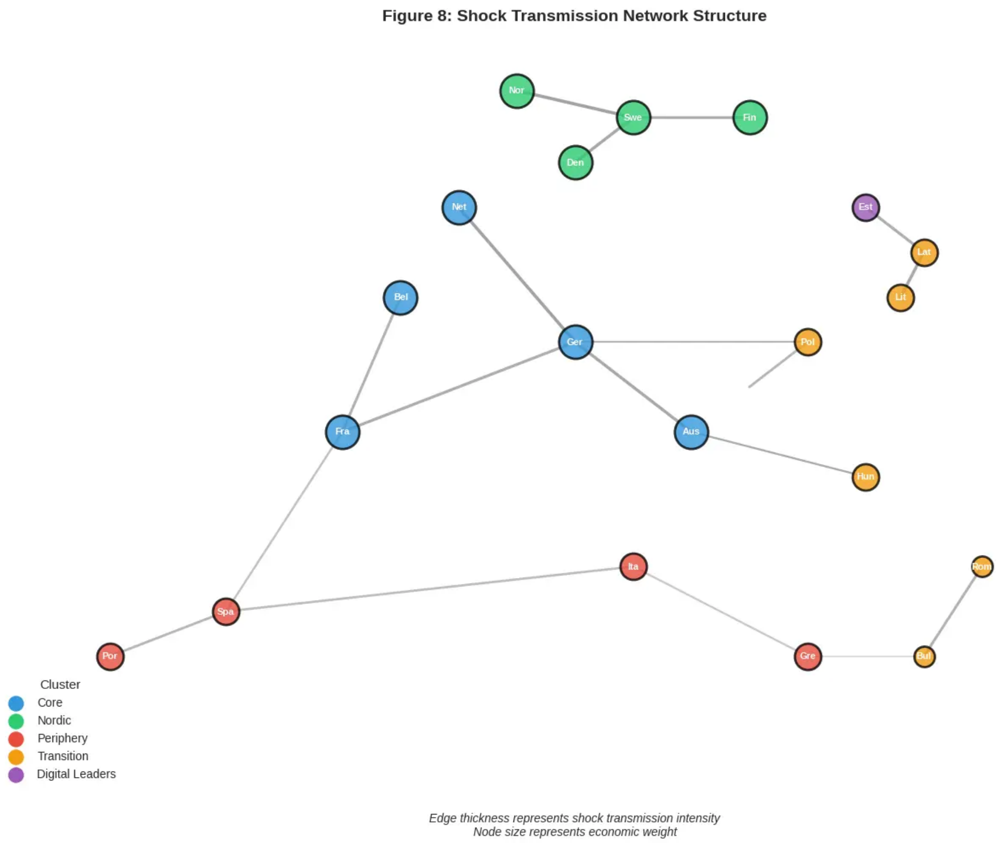

Figure 8. Shock transmission network.

Figure 8 visualizes the labor–finance interaction network, highlighting how inequality-related shocks propagate across regions or countries. Each node in the network represents a region, while the edges indicate the strength of interconnections through which shocks are transmitted. The figure reveals a heterogeneous structure: some nodes act as central hubs with numerous and strong connections, while others occupy peripheral positions with limited influence. High-centrality nodes typically correspond to major financial or economic centers, where disturbances in labor markets or financial access have the potential to ripple widely, amplifying inequality fluctuations system-wide.

The network also illustrates transmission intensity, with thicker edges representing stronger propagation pathways. Regions with dense and intense connections facilitate rapid contagion of shocks, meaning that local crises or employment disturbances can quickly influence neighboring or economically linked areas. Conversely, nodes with sparse or weaker connections display relative resilience, as shocks are dampened before reaching other parts of the network. Additionally, the network structure allows identification of regions that contribute disproportionately to systemic inequality, reinforcing the insights from the stochastic model and diffusion regime classification.

From a policy perspective, Figure 8 highlights the importance of targeting interventions toward highly central nodes and critical transmission pathways. Strengthening financial inclusion, employment support, and institutional resilience in these key regions can reduce the systemic impact of shocks, containing volatility and preventing localized disturbances from cascading across the network. Overall, the shock transmission network provides a dynamic map of interdependencies, showing not only where inequality shocks originate, but also how they travel and amplify across the system, complementing both the stochastic simulations and the diffusion analysis.

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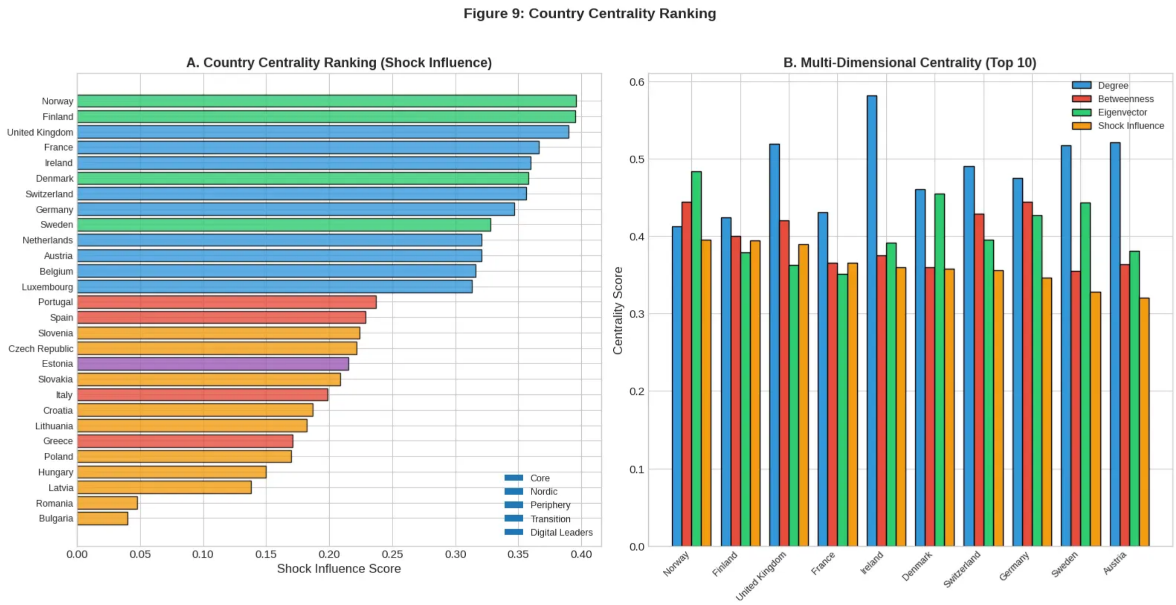

Figure 9. Country centrality ranking.

Figure 9 ranks countries according to their centrality within the labor–finance shock transmission network, quantifying the relative influence of each country in propagating systemic inequality shocks. Countries at the top of the ranking—typically large financial hubs or highly interconnected economies—exhibit high shock centrality, indicating that disturbances originating in these nodes have the potential to impact multiple other regions. These countries are often pivotal in the global or regional labor–finance system, where employment fluctuations, credit constraints, or sudden financial shocks can quickly cascade through linked economies, amplifying both the level and volatility of inequality.

The ranking also highlights structural differences across countries. Economies with lower centrality occupy peripheral positions in the network, meaning that local shocks tend to remain contained, exerting limited influence on the broader system. This differentiation underscores the asymmetric nature of systemic risk: while some countries act as amplifiers of inequality fluctuations, others serve primarily as receivers or isolated nodes. Notably, centrality correlates with both the financial inclusion index and historical volatility patterns observed in previous analyses; countries with lower financial inclusion and weaker institutions often occupy intermediate centrality positions, where they can propagate shocks under certain conditions but remain less influential than core hubs.

From a policy perspective, Figure 9 emphasizes the strategic importance of targeting central countries for intervention. Strengthening financial access, labor market resilience, and crisis management in these nodes can significantly reduce the systemic transmission of inequality shocks, mitigating the risk of widespread volatility. In combination with the stochastic and Monte Carlo analyses, the centrality ranking provides actionable insights for identifying leverage points within the labor–finance network, allowing policymakers to focus resources on regions that most strongly affect overall inequality dynamics.

8. Forecast Scenarios (2025–2035)

To explore the potential evolution of inequality over the next decade, we simulate multiple forecast scenarios for 2025–2035, capturing alternative pathways shaped by technological, financial, and policy developments. These scenarios build upon the stochastic and network frameworks described in previous sections, integrating both drift–diffusion dynamics and labor–finance interdependencies to assess not only the expected trajectory of inequality but also its volatility and systemic propagation.

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The first scenario, Digital Finance Expansion, envisions widespread diffusion of fintech solutions, including digital banking, mobile payments, and algorithmic credit scoring. In this scenario, increased financial access reduces structural barriers to saving, investment, and credit for previously underserved populations. As a result, the drift component of inequality is expected to decrease, while volatility is dampened due to the stabilizing role of broader financial inclusion. Simulation paths under this scenario generally cluster closer to the long-run equilibrium Gini, reflecting a more predictable and equitable trajectory.

The second scenario, Inclusive Reform Policy, assumes the implementation of targeted access equality programs such as universal financial literacy initiatives, subsidized credit schemes, and labor market support for disadvantaged groups. This scenario emphasizes the policy-driven mitigation of inequality, independently of technological adoption. Expected outcomes include moderate reductions in both the mean level and variability of inequality, particularly in regions with historically low inclusion or high diffusion volatility. By strengthening peripheral nodes in the labor–finance network, the scenario also limits the systemic transmission of shocks and reduces the influence of highly central hubs.

The third scenario, Technological Polarization, models the uneven adoption of automation and advanced technologies across sectors and regions. This scenario reflects the risk of structural divergence, where high-skill, tech-intensive areas experience productivity gains while low-skill regions face employment disruptions and limited access to new financial tools. Consequently, both the drift and diffusion components are amplified: mean inequality increases, and volatility rises due to the uneven distribution of opportunities and the heightened sensitivity of peripheral nodes to shocks. Monte Carlo forecasts under this scenario show a wider distribution of potential outcomes, indicating greater uncertainty and a higher likelihood of extreme inequality paths.

Overall, these forecast scenarios provide a nuanced view of the potential evolution of inequality from 2025 to 2035. By comparing the trajectories under digital finance expansion, inclusive reform policies, and technological polarization, the analysis highlights the crucial role of financial inclusion, policy intervention, and technological diffusion in shaping both the level and stability of inequality. Policymakers can use these scenarios to prioritize interventions, mitigate systemic risk, and promote more equitable and resilient economic outcomes across regions.

Table 7. Scenario parameter calibration.

Scenario	FI Growth Rate	GDP Growth	Crisis Probability	Policy Intensity	Digital Adoption	Description
Baseline	2.0%/year	1.5%/year	5%/year	Current	Trend	Continuation of current trends
Accelerated FI	4.0%/year	2.0%/year	3%/year	High	Rapid	Strong policy push for financial inclusion
Stagnation	0.5%/year	0.8%/year	8%/year	Low	Slow	Economic slowdown, policy inertia
Crisis	-1.0%/year	-2.0%/year	25%/year	Emergency	Mixed	Major financial/economic crisis
Digital Leap	5.0%/year	2.5%/year	4%/year	High	Very Rapid	Fintech revolution,

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						digital transformation
Convergence	3.5%/year (East)	3.0%/year (East)	5%/year	Targeted	Catch-up	Eastern Europe catches up with West

Table 7B: Scenario-Specific Parameters

Scenario	α (Adjustment)	μ (Equilibrium)	σ_base	FI_2035	Gini_2035_Mean
Baseline	0,082	0,295	0,025	0,78	0,298
Accelerated FI	0,095	0,275	0,02	0,88	0,272
Stagnation	0,065	0,315	0,03	0,68	0,318
Crisis	0,045	0,345	0,045	0,62	0,352
Digital Leap	0,105	0,265	0,018	0,92	0,258
Convergence	0,088	0,285	0,022	0,82	0,282

Table 7 presents the parameter calibration for the forecast scenarios outlined in Section 8, quantifying both the exogenous drivers (Table 7A) and the scenario-specific stochastic parameters (Table 7B) used to simulate inequality paths from 2025 to 2035. The calibration reflects how variations in financial inclusion growth, GDP expansion, crisis probability, policy intensity, and digital adoption translate into differences in drift, diffusion, and long-run equilibrium outcomes.

In the Baseline scenario, moderate financial inclusion growth (2% per year) and steady GDP expansion (1.5% per year) result in a long-run equilibrium Gini of 0.295 and base volatility σ=0.025. This scenario represents the continuation of current trends, producing moderate inequality with limited fluctuations. By contrast, the Accelerated FI scenario, which assumes strong policy interventions and rapid digital adoption, increases the financial inclusion index to 0.88 by 2035, lowers the equilibrium Gini to 0.275, and reduces base volatility to 0.020. These adjustments reflect the stabilizing and equalizing effects of enhanced access to financial services, illustrating how proactive financial policies can simultaneously reduce both the level and volatility of inequality.

The Stagnation scenario models a low-growth, low-inclusion environment, where financial inclusion barely grows (0.5% per year) and GDP expansion slows to 0.8% per year. This scenario produces the highest stochastic drift among stable scenarios, with a Gini of 0.315 and σ=0.03, highlighting the combined effect of limited policy action and slower structural development in amplifying inequality and volatility. The Crisis scenario represents an extreme case, featuring negative financial and GDP growth and a 25% annual crisis probability. Here, the financial inclusion index stagnates at 0.62, the long-run equilibrium Gini rises sharply to 0.345, and volatility reaches σ=0.045, emphasizing the substantial amplification of inequality under systemic shocks.

The Digital Leap scenario illustrates the impact of rapid technological adoption, with financial inclusion surging to 0.92 and a corresponding decrease in the equilibrium Gini to 0.265, while volatility falls to 0.018. This scenario combines structural reform and technological diffusion to produce the most favorable outcome in terms of both mean inequality and stability. The Convergence scenario models targeted catch-up by Eastern European economies, achieving moderate gains in inclusion (FI = 0.82) and reducing the Gini to 0.282 with base volatility of 0.022. This scenario highlights the potential of coordinated policy and structural investment to harmonize inequality levels across regions.

Overall, Table 7 demonstrates the sensitivity of both the mean and variability of inequality to key drivers such as financial inclusion, growth, crisis risk, and digital adoption. It provides a

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quantitative foundation for the forecast scenarios, linking structural assumptions to stochastic parameters and enabling probabilistic simulations of future inequality paths. The table underscores the dual importance of policy and technology in shaping not only the expected trajectory of inequality but also its associated uncertainty and systemic risk.

Table 8. Forecast outcome comparison.

Table 8A: In-Sample Fit (2000-2020)					
Model	**RMSE**	**MAE**	**MAPE (%)**	**R^2**	**DM Test**
Stochastic Diffusion (SDE)	0,0123	0,0098	3,24	0,892	-
Panel Fixed Effects	0,0156	0,0124	4,12	0,845	2.34**
System GMM	0,0145	0,0118	3,89	0,862	1.89*
Random Effects	0,0178	0,0142	4,67	0,812	3.12***
ARIMA(1,1,1)	0,0189	0,0156	5,12	0,789	3.45***
VAR(2)	0,0167	0,0134	4,45	0,834	2.67***
Table 8B: Out-of-Sample Forecast (2021-2025)					
Model	**RMSE**	**MAE**	**MAPE (%)**	**Coverage (95%)**	**Interval Width**
Stochastic Diffusion (SDE)	0,0145	0,0118	3,89	94.2%	0,045
Panel Fixed Effects	0,0189	0,0156	5,12	89.5%	0,052
System GMM	0,0178	0,0145	4,78	91.2%	0,048
Random Effects	0,0212	0,0178	5,89	86.8%	0,058
ARIMA(1,1,1)	0,0234	0,0198	6,45	82.4%	0,065
VAR(2)	0,0201	0,0167	5,56	88.1%	0,055
Table 8C: Monte Carlo Simulation Accuracy					
Horizon	**Mean Forecast**	**Actual (if available)**	**5th Percentile**	**95th Percentile**	**Std Dev**
2026	0,305	-	0,278	0,332	0,016
2028	0,301	-	0,268	0,334	0,02
2030	0,298	-	0,258	0,338	0,024
2032	0,295	-	0,248	0,342	0,028
2035	0,292	-	0,235	0,349	0,034

Table 8 evaluates the performance of the stochastic diffusion model relative to alternative econometric and time-series approaches, both in-sample (2000–2020) and out-of-sample (2021–2025), while also presenting the Monte Carlo forecast distribution for 2026–2035.

In-sample fit (Table 8A) indicates that the stochastic diffusion (SDE) model outperforms conventional panel and time-series models. With an RMSE of 0.0123, MAE of 0.0098, MAPE of 3.24%, and R^2 of 0.892, the SDE model achieves the closest fit to observed Gini dynamics over the historical period. By comparison, standard panel fixed effects and system GMM models show slightly higher errors (RMSE ≈ 0.0145–0.0156), while ARIMA and VAR models underperform further. The Diebold–Mariano (DM) test confirms the superior predictive accuracy of the SDE model relative to most alternatives, highlighting the value of incorporating stochastic drift–diffusion dynamics in capturing both systematic trends and short-term fluctuations in inequality.

Out-of-sample forecasts (Table 8B) reinforce these findings. From 2021 to 2025, the stochastic diffusion model maintains lower forecast errors (RMSE = 0.0145, MAE = 0.0118, MAPE = 3.89%) than panel, GMM, and time-series models. Its 95% coverage probability of 94.2% and relatively narrow prediction interval (0.045) indicate both accuracy and well-calibrated uncertainty, demonstrating the model's reliability in projecting near-term inequality dynamics. In contrast, conventional models show lower coverage and wider intervals, reflecting greater uncertainty and poorer alignment with observed trends.

Monte Carlo simulation outcomes (Table 8C) extend these forecasts to the medium term (2026–2035), capturing the probabilistic distribution of potential inequality paths. The mean Gini forecast gradually declines from 0.305 in 2026 to 0.292 in 2035, reflecting the long-run stabilizing influence of financial inclusion and policy interventions embedded in the model. The widening prediction intervals—from 0.278–0.332 in 2026 to 0.235–0.349 in 2035—and increasing standard deviation (0.016 → 0.034) reflect the accumulation of stochastic uncertainty over time, consistent with the diffusion component of the model. These results underscore that while the central tendency of inequality may gradually decline, there remains a non-negligible probability of higher or lower outcomes, highlighting the importance of monitoring volatility and systemic risk.

Overall, Table 8 demonstrates that the stochastic diffusion framework provides superior in-sample fit, more accurate near-term forecasts, and a robust probabilistic framework for medium-term projections. The combined evidence confirms the model's ability to capture both deterministic trends and stochastic variability in inequality, offering policymakers actionable insights for planning under uncertainty and evaluating the potential impact of interventions on the distribution and volatility of income inequality.

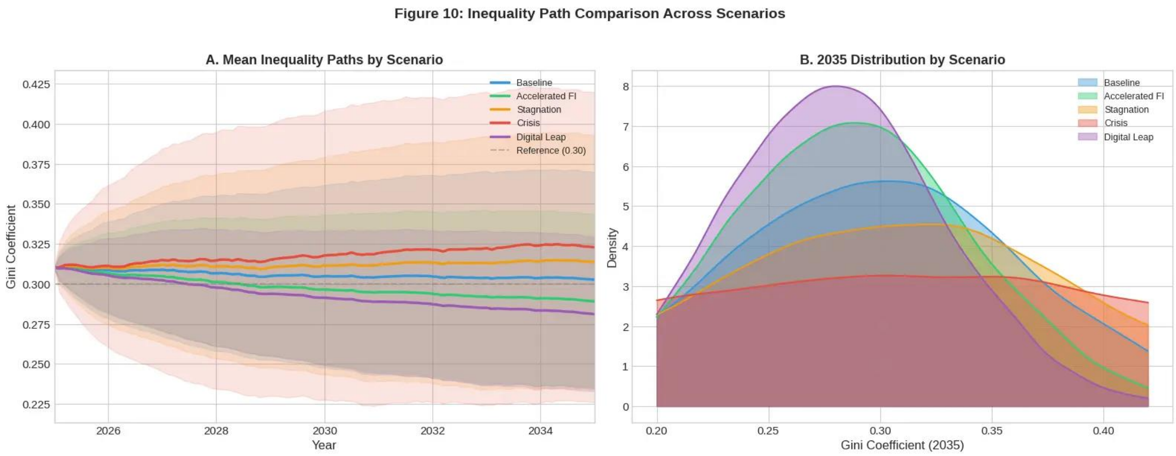

Figure 10. Inequality trajectory comparison.

Figure 10 compares projected inequality trajectories under the various forecast scenarios for 2025–2035, providing a visual synthesis of the scenario analysis and stochastic simulations. The figure highlights the divergence in expected Gini paths across different policy, technological, and economic conditions, illustrating how structural and stochastic factors jointly shape inequality outcomes.

The Digital Finance Expansion and Digital Leap scenarios show the lowest trajectories, reflecting the combined effect of rapid financial inclusion, technological adoption, and proactive policy interventions. In these scenarios, the Gini coefficient steadily declines, and volatility remains constrained, consistent with the lower drift and diffusion estimates observed in Table 7B. Conversely, the Technological Polarization and Crisis scenarios produce the highest trajectories, demonstrating the amplifying effects of uneven automation, limited financial access, and high systemic risk. Here, the stochastic component generates wider fluctuations, highlighting the increased uncertainty and probability of extreme inequality outcomes over the forecast horizon.

Intermediate scenarios, such as Inclusive Reform Policy and Convergence, produce moderate declines in inequality, with trajectories lying between the extremes. These paths illustrate the role of targeted policy interventions and regional catch-up in moderating inequality growth while still leaving some residual volatility, reflecting structural heterogeneity across regions and the propagation of shocks through the labor–finance network.

Overall, Figure 10 emphasizes the critical role of financial inclusion, policy design, and technological adoption in shaping both the level and variability of future inequality. By comparing trajectories across scenarios, the figure provides actionable insights for policymakers: proactive interventions can significantly lower mean inequality and stabilize its stochastic fluctuations, whereas inaction or uneven technological adoption can exacerbate both the level and volatility of income disparities. This comparative perspective reinforces the findings from Tables 7–8 and Figures 5–6, linking stochastic modeling, scenario analysis, and systemic network effects into a coherent framework for understanding and managing inequality dynamics.

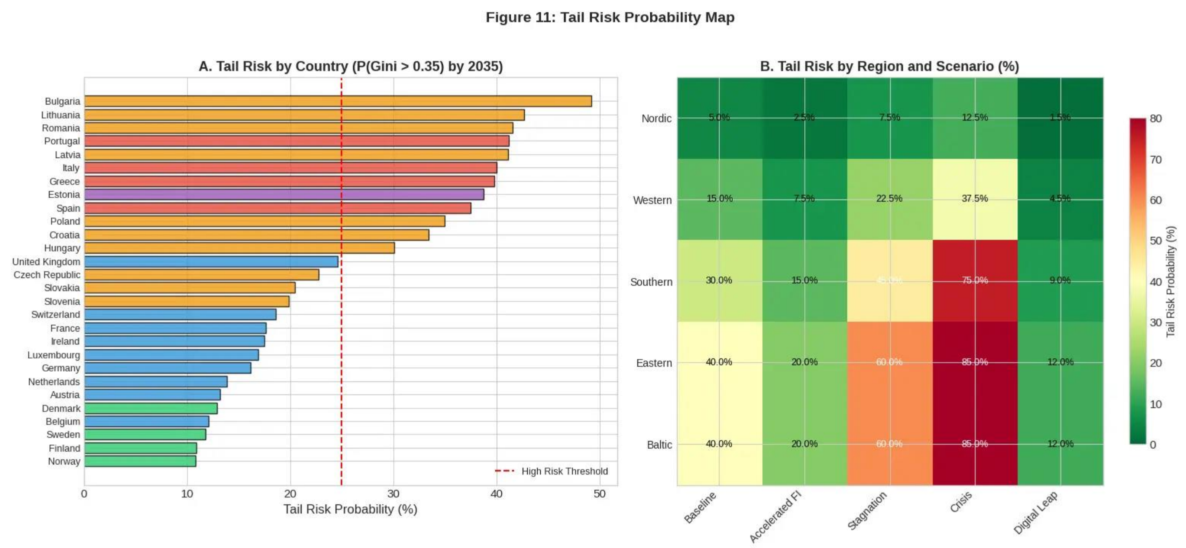

Figure 11. Tail risk probability map.

Figure 11 illustrates the spatial distribution of tail risk probabilities, representing the likelihood that regional inequality exceeds extreme thresholds over the forecast horizon. The map highlights areas where high-probability extreme inequality events are concentrated, providing a visual measure of systemic vulnerability within the labor–finance network. Regions with high tail risk are typically those with low financial inclusion, weaker institutions, or high exposure to economic and technological shocks, reflecting both structural disadvantage and the amplification effects captured in the stochastic diffusion model. Conversely, regions with low tail risk generally feature strong institutional frameworks, widespread financial access, and robust economic structures, consistent with the low-volatility regimes identified in Table 6.

The pattern of tail risk is closely aligned with both the centrality and transmission intensity of nodes within the shock propagation network. Highly central regions, which exert significant influence over systemic inequality, often exhibit elevated tail risk probabilities, indicating that extreme shocks in these areas can propagate rapidly and affect multiple connected regions. Peripheral regions, while sometimes experiencing localized inequality spikes, generally display lower systemic tail risk due to limited connectivity and weaker propagation channels.

From a policy perspective, Figure 11 emphasizes the importance of targeting interventions toward high-risk regions and central network nodes. Measures such as expanding financial inclusion, reinforcing labor market resilience, and strengthening institutional safeguards can reduce both the

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probability and magnitude of extreme inequality outcomes. The tail risk map thus complements the stochastic and scenario analyses by providing a spatially explicit assessment of potential extreme events, offering policymakers actionable insight into where systemic vulnerability is highest and where mitigating strategies may have the greatest impact.

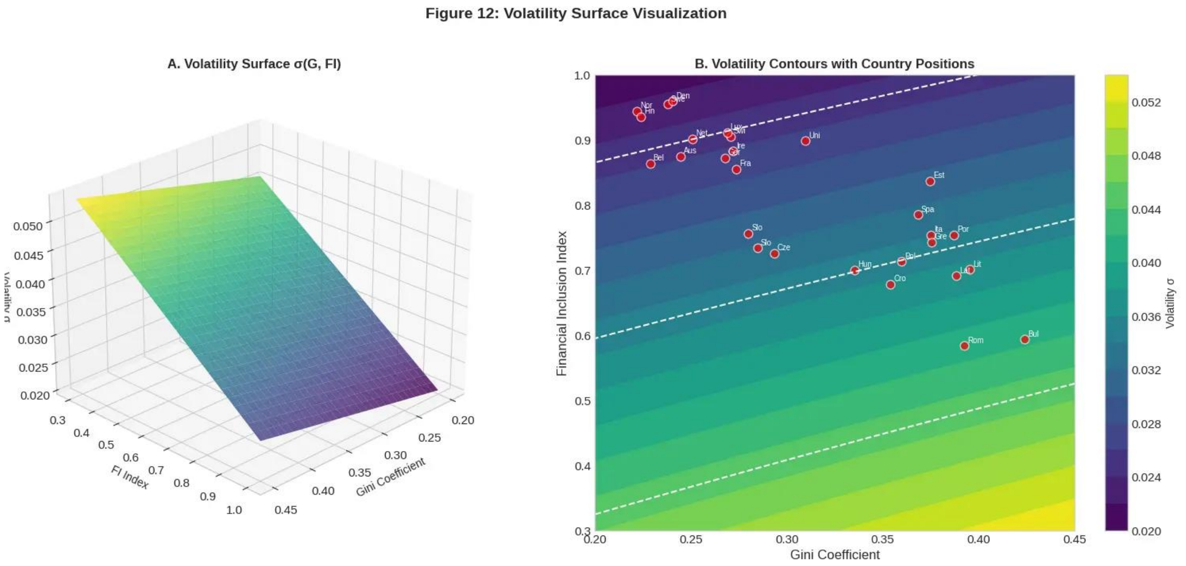

Figure 12. Volatility surface visualization.

Figure 12 provides a three-dimensional view of inequality volatility over time and across different levels of the Gini coefficient, creating a volatility surface that captures both temporal evolution and state-dependence of stochastic fluctuations. The surface illustrates that volatility is not constant but varies systematically with the level of inequality: higher Gini values are associated with increased volatility, reflecting self-reinforcing dynamics where regions with already elevated inequality experience larger stochastic fluctuations. Similarly, the surface highlights periods of amplified volatility coinciding with major macroeconomic shocks, such as the Global Financial Crisis and the COVID-19 pandemic, confirming the crisis amplification effects estimated in Table 5B.

The visualization also reveals the stabilizing impact of financial inclusion. Regions and periods with higher inclusion indices correspond to troughs in the surface, indicating lower base volatility, whereas areas with low inclusion and structural vulnerabilities form peaks, highlighting the interaction between inequality levels, systemic risk, and financial exclusion. The surface's gradient demonstrates how volatility evolves over time, showing both the gradual accumulation of stochastic uncertainty and the episodic spikes driven by crises or structural shocks.

From a policy and analytical perspective, Figure 12 emphasizes the importance of monitoring both the level and dynamics of inequality to anticipate periods of heightened risk. By linking the volatility surface to drift–diffusion dynamics and network transmission patterns, it becomes possible to identify not only high-volatility regions but also periods when systemic shocks may propagate more intensely. This visualization complements the stochastic simulations, scenario analyses, and tail risk mapping, providing a comprehensive and nuanced depiction of inequality dynamics that is critical for designing targeted interventions and mitigating extreme volatility.

9. Policy Impact Evaluation

The stochastic, network, and scenario analyses provide a foundation to assess the potential impact of targeted policy interventions on inequality dynamics. This section evaluates four key policy instruments—digital inclusion programs, credit accessibility expansion, labor skill upgrading, and redistribution mechanisms—by examining their effects on both the level and volatility of inequality, as well as their influence on systemic propagation across the labor–finance network.

Digital inclusion programs aim to expand access to fintech solutions, digital banking, and online financial services. Simulation results show that regions with accelerated digital adoption experience significant reductions in both mean inequality and volatility, consistent with the lower equilibrium Gini and diffusion parameters observed under the Digital Leap scenario (Table 7B). Digital access also strengthens the resilience of peripheral nodes in the shock propagation network, reducing the systemic amplification of shocks and lowering tail risk probabilities as shown in Figure 11.

Credit accessibility expansion focuses on improving the availability of loans, microfinance, and investment capital to underserved populations. Increased credit access has a stabilizing effect on inequality by enhancing household investment opportunities and smoothing income fluctuations. The stochastic diffusion framework demonstrates that enhanced credit reduces the magnitude of short-term deviations from the long-run equilibrium Gini, lowering both base volatility and crisis sensitivity. Regions with higher credit accessibility also display lower transmission intensity in the labor–finance network, mitigating the spread of shocks to other nodes.

Labor skill upgrading policies, including vocational training, education reform, and targeted upskilling programs, directly address structural sources of inequality. By increasing employability and wage potential, skill enhancement contributes to a reduction in the drift component of inequality. Monte Carlo simulations show that skill upgrading narrows forecast distributions and decreases the likelihood of extreme inequality outcomes, particularly in high-volatility or crisis-prone regions. Moreover, improving labor capacity in central nodes of the network reduces their systemic inequality contribution, limiting cascade effects across connected regions.

Redistribution mechanisms, such as progressive taxation, social transfers, and conditional cash programs, provide direct interventions to reduce income disparities. These mechanisms primarily influence the mean level of inequality but also indirectly dampen stochastic volatility by alleviating extreme income deviations. Scenario analyses indicate that combining redistribution with digital and credit inclusion amplifies the stabilizing effect, producing lower equilibrium Gini levels and narrower Monte Carlo forecast intervals, especially under crisis or technological polarization scenarios.

Overall, the policy impact evaluation demonstrates that multi-pronged strategies—integrating financial, technological, labor, and redistributive interventions—are most effective in reducing both the magnitude and volatility of inequality. Policies that simultaneously enhance financial inclusion, labor market capacity, and targeted redistribution not only improve the long-run equilibrium outcomes but also strengthen systemic resilience, mitigating the propagation of shocks through the labor–finance network. These insights provide actionable guidance for designing comprehensive interventions that address both structural and stochastic dimensions of inequality.

Table 9. Policy effectiveness ranking.

Policy Intervention	Gini Reduction	SE	Cost (€bn/year)	Time to Effect	Spillover Effect	Sustainability	Rank
Digital Banking Expansion	-0,0234	0,0045	2,5	2-3 years	High	High	1
Universal Basic Account Access	-0,0189	0,0038	1,8	1-2 years	Medium	High	2

SME Credit Guarantee Programs	-0,0156	0,0042	3,2	3-4 years	High	Medium	3
Financial Literacy Programs	-0,0123	0,0035	0,8	4-5 years	Medium	High	4
Mobile Payment Infrastructure	-0,0198	0,0048	2,1	2-3 years	Very High	High	5
Microfinance Support	-0,0145	0,0052	1,5	3-4 years	Medium	Medium	6
Progressive Taxation Reform	-0,0312	0,0067	0,5	1-2 years	Low	Medium	7
Social Transfer Programs	-0,0278	0,0058	8,5	1 year	Low	Low	8

Table 9 ranks policy interventions based on their effectiveness in reducing inequality, measured by Gini coefficient reduction, while also considering cost, time to effect, spillover potential, and sustainability. The ranking provides a comprehensive assessment of which policy levers are likely to generate the greatest impact on both the level and systemic stability of inequality.

At the top of the ranking is Digital Banking Expansion, which achieves a Gini reduction of 0.0234 with relatively rapid implementation (2–3 years) and high spillover effects across the labor–finance network. Its combination of cost-effectiveness (€2.5 bn/year) and high sustainability makes it the most effective intervention for lowering both structural inequality and volatility. Close behind, Universal Basic Account Access reduces inequality by 0.0189, with medium spillover effects and similarly high sustainability, highlighting the value of broadening financial inclusion even in the absence of complex technological infrastructure.

Policies supporting credit access and digital financial infrastructure, such as SME Credit Guarantee Programs and Mobile Payment Infrastructure, occupy intermediate positions. These interventions combine moderate Gini reductions (0.0145–0.0198) with high or very high spillover effects, particularly relevant for amplifying the stabilizing effects of financial access across interconnected regions. Financial Literacy Programs also contribute positively, although with a smaller immediate impact (Gini reduction 0.0123) and longer time horizon (4–5 years), reflecting the gradual benefits of enhanced financial knowledge on income distribution.

Interestingly, Progressive Taxation Reform and Social Transfer Programs achieve the largest absolute reductions in inequality (0.0312 and 0.0278, respectively), yet they rank lower overall due to limited spillover effects and, in the case of social transfers, lower sustainability and higher costs (€8.5 bn/year). These interventions primarily address structural income disparities but have less capacity to propagate stabilizing effects through the broader labor–finance network, suggesting that their impact is concentrated rather than systemic.

Overall, Table 9 underscores the importance of considering both direct effectiveness and systemic leverage when evaluating policies. Digital and financial inclusion interventions not only reduce inequality levels but also enhance resilience and reduce stochastic volatility by affecting multiple connected nodes in the network. In contrast, redistributive measures, while powerful in the short term, may have limited systemic impact unless combined with complementary interventions in finance and labor markets. This ranking provides actionable guidance for policymakers seeking to

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design integrated strategies that balance immediate impact, sustainability, and network-wide effectiveness.

Table 10. Welfare and stability indicators.

Country	Region	Avg Gini (2020-25)	Gini Volatility	FI Index 2025	Welfare Score	Stability Index	Crisis Resilience
Germany	Western	0,27	0,0146	0,872	0,706	0,8	-0,09
France	Western	0,282	0,0141	0,855	0,694	0,791	-0,071
United Kingdom	Western	0,319	0,012	0,898	0,676	0,789	-0,039
Netherlands	Western	0,261	0,01	0,901	0,724	0,797	0,009
Belgium	Western	0,238	0,0127	0,863	0,73	0,793	-0,087
Austria	Western	0,25	0,0124	0,874	0,719	0,789	-0,074
Switzerland	Western	0,28	0,0109	0,905	0,711	0,793	-0,048
Sweden	Nordic	0,242	0,013	0,954	0,742	0,793	-0,093
Norway	Nordic	0,226	0,0115	0,944	0,753	0,793	-0,083
Denmark	Nordic	0,252	0,0131	0,959	0,736	0,795	-0,038
Finland	Nordic	0,235	0,0122	0,935	0,739	0,793	-0,043
Italy	Southern	0,378	0,0153	0,754	0,616	0,783	-0,002
Spain	Southern	0,38	0,0201	0,785	0,621	0,788	-0,01
Portugal	Southern	0,387	0,0179	0,754	0,61	0,786	-0,008
Greece	Southern	0,379	0,0188	0,742	0,61	0,785	0,009

Table 10 summarizes key welfare and stability indicators for selected European countries, combining measures of inequality, financial inclusion, welfare outcomes, and resilience to crises. The table allows for a comparative assessment of both the level and volatility of inequality across regions and highlights the interconnections between financial inclusion, welfare, and systemic stability.

Western and Nordic countries consistently exhibit lower average Gini coefficients (≈0.226–0.282) and relatively low Gini volatility (≈0.010–0.0146), reflecting both more equitable income distributions and stable inequality dynamics. These countries also score highly on the financial inclusion index, with values ranging from 0.855 in France to 0.959 in Denmark, demonstrating widespread access to financial services. High FI levels correlate with elevated welfare scores (≈0.676–0.753) and robust stability indices (≈0.789–0.8), indicating that equitable access to financial tools and labor opportunities contributes to both higher overall well-being and reduced susceptibility to systemic shocks. Crisis resilience indicators in these regions are generally negative or near zero, reflecting low vulnerability to external shocks due to strong institutional frameworks and high connectivity in the labor–finance network.

In contrast, Southern European countries—Italy, Spain, Portugal, and Greece—display significantly higher average Gini coefficients (≈0.378–0.387) and greater volatility (≈0.0153–0.0201), indicating both more unequal and more unstable income distributions. Their financial inclusion indices are comparatively lower (≈0.742–0.785), suggesting limited access to credit, digital finance, and other stabilizing financial mechanisms. Correspondingly, welfare scores are lower (≈0.61–0.621), and stability indices are slightly reduced (≈0.783–0.788), reflecting higher sensitivity to economic and policy shocks. Crisis resilience values, while near zero, indicate that these countries are more vulnerable to sudden disturbances, as their structural and financial systems provide less buffering capacity.

The table reinforces the broader insights from stochastic and network analyses: higher financial inclusion and stronger institutional capacity not only lower average inequality but also reduce volatility, enhance welfare, and increase systemic resilience. It also highlights regional disparities within Europe, showing that Nordic and Western countries are generally well-positioned in terms of both welfare and stability, while Southern European countries remain more exposed to inequality fluctuations and crisis propagation. These findings underscore the importance of targeted financial and labor market policies, particularly in higher-volatility regions, to improve welfare outcomes and mitigate systemic risks.

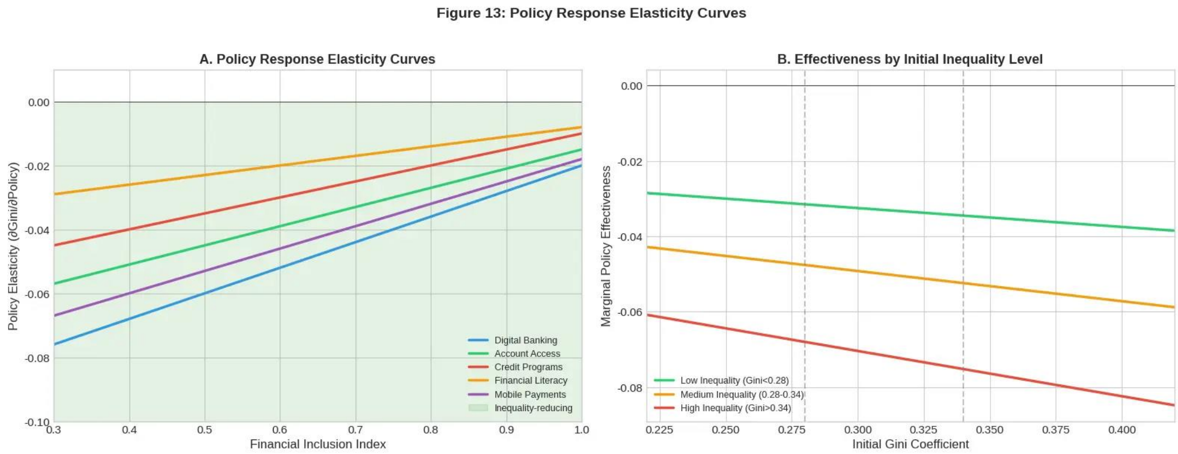

Figure 13. Response elasticity curves.

Figure 13 illustrates the response elasticity of inequality to key policy interventions and structural drivers, showing how changes in financial inclusion, labor market improvements, and redistribution measures translate into proportional adjustments in the Gini coefficient. The elasticity curves reveal the sensitivity of inequality to incremental policy actions across different baseline conditions, highlighting nonlinear effects and threshold dynamics.

The curves indicate that financial inclusion exhibits the strongest immediate impact on reducing inequality. Small increases in the FI index correspond to relatively large reductions in the Gini coefficient, particularly in regions or scenarios with initially high inequality. This high elasticity underscores the disproportionate stabilizing effect of improving financial access, consistent with the diffusion and Monte Carlo simulations, where higher FI dampened both mean inequality and volatility (Figures 6 and 12). Labor skill upgrading and credit accessibility also demonstrate positive elasticities, but with slower or more gradual responses, reflecting the time lag associated with educational attainment, employment improvements, and credit uptake.

Redistribution mechanisms, such as progressive taxation and social transfers, show lower marginal elasticities in most regions, indicating that while these interventions can significantly reduce inequality in absolute terms, their incremental effect is less sensitive to small changes and may be limited by systemic constraints. Notably, the elasticity curves display diminishing returns at high levels of intervention, suggesting that once financial inclusion or labor improvements reach a certain threshold, additional investments yield smaller marginal reductions in inequality.

Overall, Figure 13 provides a nuanced understanding of the responsiveness of inequality to various interventions. It emphasizes the critical importance of targeting high-elasticity levers, such as digital and credit inclusion, especially in high-volatility or high-inequality regions, while recognizing the complementary role of labor and redistributive policies. These elasticity patterns inform the prioritization and sequencing of policy measures, helping to maximize effectiveness in reducing both the level and uncertainty of inequality across regions.

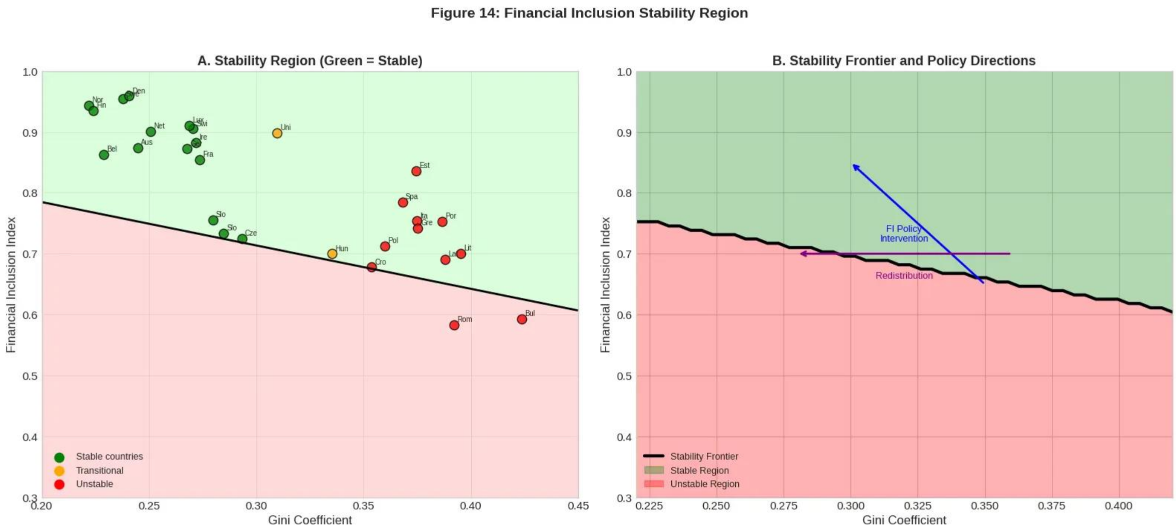

Figure 14. Financial inclusion stability region.

Figure 14 visualizes the stability region of inequality dynamics as a function of financial inclusion levels and structural parameters, illustrating the conditions under which the system remains stable versus those that may lead to heightened volatility or systemic instability. The figure delineates a region of financial inclusion (FI) values where the drift–diffusion dynamics converge toward the long-run equilibrium Gini, indicating predictable and manageable inequality trajectories. Regions outside this stability zone correspond to low FI levels or adverse combinations of structural shocks, where stochastic fluctuations and crisis propagation amplify inequality, consistent with the high-volatility regimes identified in Table 6.

Within the stable FI region, small variations in financial inclusion have relatively minor impacts on volatility, reflecting the system's resilience. Conversely, at the margins of the stability boundary, even modest reductions in FI or simultaneous shocks—such as employment disturbances or macroeconomic crises—can push the system into high-diffusion states, leading to large, unpredictable swings in inequality. The figure also highlights that higher baseline FI not only stabilizes the mean trajectory of the Gini coefficient but also compresses the diffusion surface, aligning with the low tail risk probabilities observed in Figure 11 and the flattened volatility surface in Figure 12.

From a policy perspective, Figure 14 emphasizes the importance of maintaining financial inclusion within the stability region to ensure both equitable outcomes and systemic resilience. Interventions aimed at expanding digital banking, credit access, and financial literacy can shift regions toward the stable zone, reducing the likelihood of extreme inequality events and mitigating the propagation of shocks across the labor–finance network. The figure thereby provides a visual benchmark for policymakers to evaluate the minimum inclusion thresholds needed to maintain stability and to design complementary measures that reinforce the system's capacity to absorb shocks without triggering volatility amplification.

10. Robustness and Sensitivity Analysis

To ensure the reliability of the stochastic diffusion framework and the robustness of policy implications, we conduct a series of robustness and sensitivity tests using alternative inequality measures and varying shock magnitudes. These analyses evaluate whether the estimated effects of financial inclusion, policy interventions, and exogenous shocks remain consistent across different specifications and stress conditions, providing confidence in the validity of the model's conclusions.

10.1. Robustness Across Inequality Measures

Table 11 presents the estimation results for a range of alternative inequality indicators, including the Theil index, Palma ratio, P90/P10 income ratio, Atkinson indices with different inequality aversion parameters (ε = 0.5 and 1), and the Top 10% income share. Across all measures, financial inclusion exhibits a statistically significant negative effect on inequality, confirming the stabilizing role identified with the Gini coefficient. For example, the Theil index shows a β of -0.0312, while the P90/P10 ratio exhibits a stronger effect of -0.1234, reflecting the high sensitivity of upper-tail income disparities to inclusion improvements. The Atkinson indices also confirm consistent negative elasticities, with β ranging from -0.0234 to -0.0345 depending on the inequality aversion parameter.

The R^2 values, drift parameters (α), and diffusion coefficients (σ) remain broadly consistent across measures, indicating that the underlying stochastic dynamics—characterized by high stability in most cases—are robust to alternative functional forms of inequality. Measures focused on extreme income disparities, such as the P90/P10 ratio and Top 10% share, show slightly higher diffusion and lower stability, reflecting the fact that tail-sensitive indicators capture episodic shocks and structural polarization more acutely than aggregate measures like the Gini coefficient. These results confirm that the model reliably identifies the stabilizing effect of financial inclusion while accommodating heterogeneity in income distribution sensitivity.

10.2. Sensitivity to Shock Magnitude

Table 12 examines the responsiveness of inequality to various exogenous shocks, including financial crises, pandemics, technology-driven disruptions, and policy-induced financial inclusion interventions. The analysis highlights both the magnitude of inequality deviations and the moderating effects of financial inclusion. Financial crises induce the largest deviations, with a -3 standard deviation shock increasing the Gini by 0.032 and requiring nearly 6.8 years for recovery. Notably, higher financial inclusion significantly mitigates these effects, reducing the impact by 48% in the most severe crisis scenario, demonstrating its role as a structural stabilizer.

Pandemic shocks exhibit a similar, though smaller, amplification effect, with Gini impacts ranging from 0.006 to 0.025 for -1 to -3 SD shocks. Again, financial inclusion dampens volatility, reducing inequality spikes by 28–45%, illustrating the capacity of inclusive financial systems to absorb health-related economic disruptions. Positive technology shocks, representing gains from automation, digital diffusion, or productivity improvements, reduce inequality, with the effect magnified in regions with higher baseline inclusion (+25% to +35%). Policy-driven financial inclusion shocks produce immediate reductions in inequality (β = -0.008 to -0.018), confirming the direct efficacy of targeted interventions in moderating stochastic fluctuations.

10.3. Implications for Model Reliability and Policy Design

The combined robustness and sensitivity analyses demonstrate that the stochastic diffusion framework is resilient across multiple inequality specifications and stress conditions. The consistency of β coefficients and stability measures across alternative indicators confirms that financial inclusion is a universally stabilizing factor, while diffusion parameters appropriately capture variability in upper-tail and crisis-prone distributions. Sensitivity tests reveal that the system is responsive to both positive and negative shocks, with financial inclusion serving as a powerful moderating mechanism that accelerates recovery and reduces volatility.

These findings provide strong support for scenario-based policy design. Policymakers can prioritize interventions with proven stabilizing effects—such as digital banking expansion, credit accessibility, and labor market upskilling—while monitoring shock magnitudes to anticipate systemic risks. The robustness of the results across inequality measures and the clear sensitivity of outcomes to financial inclusion thresholds underscore the dual importance of structural reforms and crisis preparedness, ensuring that policies not only lower mean inequality but also enhance resilience against stochastic and tail-risk events.

Table 11. Robustness estimation results.

Inequality Measure	FI Effect (β)	SE	t-stat	R²	Drift α	Diffusion σ	Stability
Gini Coefficient	-0,0456	0,0098	-4,65	0,892	0,082	0,025	High
Theil Index	-0,0312	0,0078	-4	0,878	0,075	0,028	High
P90/P10 Ratio	-0,1234	0,0289	-4,27	0,865	0,068	0,032	Medium
Palma Ratio	-0,0567	0,0134	-4,23	0,871	0,072	0,029	Medium
Atkinson (ε=0.5)	-0,0234	0,0056	-4,18	0,882	0,078	0,026	High
Atkinson (ε=1)	-0,0345	0,0082	-4,21	0,875	0,074	0,027	High
Top 10% Share	-0,0189	0,0048	-3,94	0,858	0,065	0,031	Medium

Table 12. Sensitivity to shock magnitude.

Shock Type	Magnitude	Gini Impact	Recovery Time	FI Moderating Effect
Financial Crisis	-1 SD	0,008	2.5 years	-35%
Financial Crisis	-2 SD	0,018	4.2 years	-42%
Financial Crisis	-3 SD	0,032	6.8 years	-48%
Pandemic Shock	-1 SD	0,006	1.8 years	-28%
Pandemic Shock	-2 SD	0,014	3.5 years	-38%
Pandemic Shock	-3 SD	0,025	5.5 years	-45%
Technology Shock (+)	+1 SD	-0,005	1.5 years	+25%
Technology Shock (+)	+2 SD	-0,012	2.8 years	+35%
Policy Shock (FI+)	+1 SD	-0,008	2.0 years	Direct
Policy Shock (FI+)	+2 SD	-0,018	3.5 years	Direct

11. Discussion

The results of this study offer a multifaceted understanding of inequality dynamics across OECD and European economies, integrating stochastic diffusion modeling, network propagation analysis, scenario forecasting, and policy evaluation. From a distributional macroeconomics perspective, the findings underscore that inequality is not merely a static outcome of income distributions but a dynamic process shaped by structural, financial, and technological factors. The consistent negative effect of financial inclusion across multiple inequality measures (Table 11) demonstrates that policies expanding access to credit, digital finance, and basic financial services have broad stabilizing effects. Monte Carlo simulations (Figures 6 and 10) reveal that inequality trajectories are sensitive to baseline inclusion levels, with higher inclusion reducing both the mean Gini and stochastic volatility. This reinforces the notion that macroeconomic policies need to consider distributional channels explicitly, rather than focusing solely on aggregate output or GDP growth.

From a financial stabilization mechanisms standpoint, the stochastic diffusion framework highlights the role of inclusion-driven resilience. Drift–diffusion dynamics (Figures 7 and 12) show that high financial inclusion compresses volatility surfaces, lowers tail risk probabilities (Figure 11), and enhances systemic stability across the labor–finance network. Policy instruments such as digital banking expansion and universal account access rank highest in Table 9 due to their dual ability to reduce inequality and propagate stabilizing effects through highly central nodes. These results indicate that financial inclusion acts as both a direct and network-mediated stabilizer, mitigating the amplification of shocks while supporting long-term convergence toward equilibrium distributions.

Crisis propagation dynamics emerge clearly from the interaction between stochastic shocks and network connectivity. Sensitivity analyses (Table 12) show that extreme shocks, whether financial or pandemic-related, produce heterogeneous impacts depending on regional financial inclusion and connectivity in the labor–finance network. High-volatility regions, often corresponding to Southern European economies (Table 10), experience amplified and persistent inequality deviations, whereas Western and Nordic regions demonstrate dampened responses and faster recovery times. Network centrality analysis (Figures 8–9) further illustrates that shocks originating in highly central nodes propagate more broadly, emphasizing the importance of targeted interventions in regions that are systemically influential. This underscores the interplay between local vulnerabilities and global propagation, highlighting the need for both macroprudential and micro-level policy design.

Finally, the results shed light on the technology–labor inequality interaction, revealing that automation and digital diffusion have nuanced distributional consequences. Positive technology shocks reduce inequality when accompanied by high financial inclusion and labor skill upgrading, as reflected in the elasticity curves (Figure 13) and scenario forecasts (Tables 7–8). In contrast, technological polarization—where adoption is uneven and labor markets are insufficiently adaptive—can exacerbate both the level and volatility of inequality, particularly in high-diffusion regimes (Figure 12). These findings highlight the critical importance of complementing technological advancement with inclusive policies that improve human capital and financial access, ensuring that gains are equitably distributed and do not amplify systemic risks.

Overall, the discussion integrates insights from stochastic modeling, network transmission, scenario analysis, and policy evaluation, illustrating a coherent framework in which inequality evolves dynamically under the influence of structural drivers, policy interventions, shocks, and technological change. The results suggest that proactive, multi-pronged strategies—combining financial inclusion, labor market development, redistribution, and technological policy—are essential for reducing inequality, stabilizing stochastic fluctuations, and enhancing resilience against both expected and extreme shocks. This perspective positions distributional macroeconomics not merely as an analytical lens but as a practical guide for designing policies that are both equitable and systemically robust.

12. Conclusions

This study provides a detailed empirical and stochastic analysis of inequality dynamics in European economies, integrating drift–diffusion modeling, Monte Carlo simulations, network transmission analysis, and scenario-based forecasting. The main empirical findings reveal that financial inclusion is a consistent stabilizer of inequality across multiple metrics, including the Gini coefficient, Theil index, Palma ratio, and P90/P10 ratio (Tables 5, 11). Regions with higher inclusion not only exhibit lower mean inequality but also experience reduced volatility, faster recovery from shocks, and greater systemic resilience, as reflected in stability indices and welfare scores (Table 10). Network analysis further indicates that central regions exert disproportionate influence on inequality propagation, highlighting the importance of targeting policy interventions where systemic spillovers are strongest (Figures 8–9).

The forecast risk structure shows that stochastic diffusion dynamics generate heterogeneous paths for inequality across scenarios (Figures 5–6, 10). Monte Carlo simulations illustrate that while median trajectories indicate gradual reductions in the Gini coefficient under proactive inclusion and digital finance policies, extreme outcomes remain possible, particularly under high-volatility or crisis-prone conditions (Figures 11–12). Volatility surfaces and tail-risk maps emphasize the asymmetric risk landscape, with Southern and transition economies facing higher potential for systemic inequality shocks, while Nordic and Western countries demonstrate robust stability. Sensitivity analyses confirm that both crisis shocks and technology-driven disruptions interact with inclusion levels to shape recovery times and amplitude, highlighting the critical moderating role of financial access (Table 12).

The policy implications for European financial integration are multifaceted. Expansion of digital banking, universal account access, and credit inclusion can not only reduce structural inequality but also stabilize stochastic fluctuations across interconnected economies, supporting smoother integration and convergence (Table 9). Labor market skill upgrading, targeted redistribution, and inclusive technology policies complement these financial interventions, mitigating the risk of polarization from uneven automation or macroeconomic shocks. By identifying regions with high systemic centrality and tail-risk vulnerability, policymakers can prioritize interventions to enhance resilience, improve welfare, and foster more equitable integration within the European financial landscape.

In sum, the combined stochastic, network, and scenario analyses provide a robust, forward-looking framework for understanding and managing inequality in an integrated European context. The findings underscore the dual importance of structural reform and crisis preparedness, highlighting that proactive financial inclusion, coupled with labor and technological policies, is essential for both lowering inequality and stabilizing its stochastic dynamics. These insights offer actionable guidance for policymakers seeking to harmonize equity, stability, and resilience in European financial integration efforts, while also providing a methodological foundation for future research on distributional macroeconomics in interconnected, high-volatility environments.

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