

Capital Flows, Unequal Futures: Financial Globalization, Machine Learning and the Distributional Architecture of Income Inequality

Ghulam Nabi

gnabi.stat@pu.edu.pk

University of the Punjab College of Statistical Sciences

Muhammad Ather Ashraf

University of Management and Technology, Banking and Finance

Jawad Ahmad

University of the Punjab College of Statistical Sciences

Research Article

Keywords: Financial Globalization, Income Inequality, Gini Coefficient, KOF Globalisation Index, Machine Learning, Neural Networks, Quantile Regression, Financial Openness, Distributional Risk, Inclusive Growth

Posted Date: July 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9867470/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: No competing interests reported.

Capital Flows, Unequal Futures: Financial Globalization, Machine Learning and the Distributional Architecture of Income Inequality

Ghulam Nabi, PhD
Assistant Professor
College of Statistical Sciences
University of the Punjab
Lahore, Pakistan
gnabi.stat@pu.edu.pk
+923334212084
Corresponding Author

Muhammad Ather Ashraf, PhD
Assistant Professor
Banking and Finance
University of Management and Technology
Lahore, Pakistan
ather.ashraf@umt.edu.pk
+92 321 8450725

Jawad Ahmad, M.Phil. Scholar
College of Statistical Sciences
University of the Punjab
Lahore, Pakistan
Jawad.quantics@gmail.com
+923368411223

Abstract

The article explores how financial globalization affects income inequality in a country and how domestic policy buffers the impact. The study now seeks to tackle a real-world puzzle in today's development finance: cross-border capital can help invest, transfer technology, and share risk, but can also lead to higher asset prices, greater skill gains, more extreme financial cycles, and a diminished redistributive impact of national tax systems. To resolve this puzzle, several empirical methods are suggested, such as two-way fixed effects, nonlinear terms, an interaction model, quantile regression, heterogeneity analysis, and machine learning. The empirical work is conducted using an annual country-year panel, including the largest possible number of countries, years, and regions for which data from public sources are available; the replication structure is based on 45 economies across 9 regions over the period 1996-2024. The Gini index measures income inequality; indicators of financial globalization are akin to the KOF Index; and foreign direct investment (FDI), portfolio flows, trade, education, tax, social protection, financial development, and institutional variables support financial globalization. The findings show financial globalization is inequitable. The average effect is conditional, nonlinear, and very sensitive to education, social protection, tax capacity, and institutional quality. The machine-learning models, in particular gradient boosting and random forests, enhance out-of-sample predictive power and indicate that financial globalization is among the strongest predictors. Ongoing, region, income group and level of development are also crucial. The study ultimately concludes that the issue of financial globalization should be viewed more as a distributional policy question than as one of capital mobility or growth.

Keywords: Financial Globalization; Income Inequality; Gini Coefficient; KOF Globalisation Index; Machine Learning; Neural Networks; Quantile Regression; Financial Openness; Distributional Risk; Inclusive Growth.

1- Introduction

One of the most challenging actors in the contemporary global economy is financial globalization. Idealized theory suggests that capital can move across countries for investment, consumption smoothing, risk reduction, and enable structural change that boosts productivity. In reality, the advantages of global finance are not shared equally. Certain groups of people, including those with assets, good skills, and jobs in cross-border sectors, or access to formal finance, have a better chance of benefiting from cross-border capital. The informal sector, households with less financial means, and firms not connected to GVCs could see reduced gains and increased volatility. Whether financial globalization leads to higher overall growth is no longer the central question. A more policy-relevant question is whether it is inclusive or exclusive of society, that is, whether it includes groups with a comparative advantage within it (Jaumotte, Lall, & Papageorgiou, 2013; Goldberg & Pavcnik, 2007; Heimberger, 2020).

The question is more pressing these days in the 2020s. International investment flows have become less reliable, and productive foreign investment has decreased in some areas. Persistent weakness in productive international investment was confirmed by the global decline in FDI in 2024, which amounted to 11 percent on a like-for-like basis (UNCTAD, 2025). Meanwhile, global financial stability risks are also high, as capital-flow reversals and deteriorating financing conditions, driven by asset valuations, geopolitical risks, debt dynamics, and uncertainty, may occur and negatively affect financial stability, particularly in emerging economies (IMF, 2025). The booms and stops in capital flows are relevant to inequality because they do not affect everyone equally. A country's wealthier citizens can diversify their holdings internationally and lessen the impact of stress periods on their portfolios. In contrast, lower-income households may experience job losses, inflation, currency depreciation, and reduced public-sector spending. (Furceri & Loungani, 2018; Rey, 2015).

Inequality is still a major issue for development policy. The World Inequality Report 2026 highlights that there remains a high level of inequality in income and wealth distribution across and within countries. According to the World Bank Poverty and Inequality Platform (as distributed by Our World in Data), the Gini coefficient is 'a summary measure with higher values corresponding to a more unequal distribution of income or wealth' (World Bank 2026; World Inequality Lab 2026). These also illustrate caution in conducting empirical work. Inequality data are not available for all countries and years; some countries provide income measures, while others provide consumption measures, and survey quality varies across economies. A publishable study should thus be clear regarding coverage, measurement, and robustness.

The article is conditional on financial globalization. It does not presume the impact of financial openness, either positive or negative. This inflow of capital can also help reduce inequality by funding labour-intensive production, formal employment, and widespread access to credit. It can create inequality if capital benefits expand, only demand high-skilled labour, and trigger asset-price booms or crises that adversely affect lower-income households. This is a conditional interpretation supported by recent studies. Kumar and Simran (2025) find that financial development influences the impact of globalization on inequality in Asian economies. The relationship between poverty and inequality, and the effects of financial globalization in developing countries, is buffered by the roles of fintech and financial inclusion, according to Azmeh (2025). The results in this paper indicate that the domestic absorptive capacity is as important as the amount of international finance.

Another reason for this paper is methodological. Most previous papers are based on a single regression coefficient in a panel model. This can be helpful but not enough for a complex distributional process. Financial globalization can be nonlinear: low levels of openness can have one thing, while high levels have another; there can be a difference between high- and low-income economies; and the relationship may be stronger at the top of the distribution of inequality. Machine learning techniques can be used to detect these nonlinearities and interactions. These should not be used in place of economic theory or causal inference, but they can be useful for prediction and for identifying the importance of variables and policy-relevant configurations of risk (Mullainathan & Spiess, 2017; Athey & Imbens, 2019; Lundberg & Lee, 2017).

The study is thus conducted empirically, in a layered manner. The first layer is an estimation of two-way fixed-effect models to account for country-specific characteristics and shocks in the global time series. The second layer includes nonlinear and interaction terms to examine whether financial globalization calls for policy buffers such as education, social protection, and tax capacity. The third layer is a quantile regression analysis to explore if there are different associations across the inequality distribution. The fourth layer is the estimation of machine-learning models using a time-aware training and testing split, such as Elastic Net, random forests, gradient boosting, and a multilayer perceptron neural network. The fifth layer is an interpretation layer based on permutation importance and partial dependence.

The contribution of this study is as follows. First, consistent with the logic of the KOF Globalisation Index, which distinguishes between economic, social, and political globalization and between trade and financial globalization, the article distinguishes financial globalization from broader globalization. The article is clear in distinguishing between financial globalization and broader globalization, following the KOF Swiss Economic Institute's distinction between economic, social, and political globalization and trade and financial globalization (Gygli et al., 2019; KOF Swiss Economic Institute, 2025). Second, it ignores the policy-dependency of the income-inequality outcome, rather than assuming that it will simply be a consequence of openness. Third, it combines econometric inference and machine-learning prediction; and finally, it maintains the distinction between prediction and causality.

While there is significant evidence of globalization and inequality in the literature, four gaps remain. First, many studies aggregate the values of openness in trade, financial openness, and social openness into a single indicator of openness. This may obscure the distributional impact of financial flows such as FDI, portfolio investment, external debt, banking flows, and the capital account policy (Dreher, 2006; Gygli et al., 2019). Second, most empirical studies tend to examine average effects, but the relationship is likely to be nonlinear and income-group-, region/place-, and institutional-context-specific (Heimberger, 2020; Kumar & Simran, 2025). Third, policy-buffering variables (education, social protection, taxation, and institutional quality) have been used as control variables rather than as determinants of the inclusive or unequalizing impact of global finance. Fourth, the use of machine-learning and deep-learning techniques in this literature remains limited, particularly as complements to panel econometrics, which can identify nonlinear thresholds and predictive interactions (Breiman, 2001; Friedman, 2001; Athey & Imbens, 2019).

The central research question is how financial globalization affects income inequality, and under which domestic circumstances does the relationship become more unequalizing or more inclusive? This is a general question broken down into five specific Research Questions (RQ). RQ1 examines the effect of financial globalization on the Gini coefficient, controlling for development, trade openness, education, social protection, tax capacity, financial development, institutions, and macroeconomic conditions. RQ2: Does the relationship have a form other than a line? RQ3: Does the relationship hold for different income groups and different patterns of inequality? RQ4: Does the relationship between domestic policy become moderate? RQ5 addresses how well machine-learning and neural network models can predict inequality and whether financial globalization is an important predictor of inequality.

These questions are related to the research objectives. First, the study transparently constructs a country-year panel by providing information on the time span, regions and variables. Second, it offers econometric model estimation in average, nonlinear, heterogeneous and moderated-effects models. Third, it employs machine learning and deep learning models to evaluate their predictive performance and variable importance. Fourth, it infers the empirical findings' policy implications for emerging and developing economies. Fifth, it provides a replicable methodological structure which can be updated using official data and extended to the South Asian region, Pakistan or elsewhere.

2- Literature Review

The concepts of relative prices, factor returns, and bargaining power resulting from openness serve as the starting point for the theoretical underpinning of the globalization-inequality debate. Among the theories that come to mind when thinking about openness to trade are the Stolper-Samuelson effects, sectoral reallocation and wage changes, and the financial globalization theory of capital mobility, risk sharing, and access to external funds. Financial inflows can increase investment and productivity in developing countries if invested in the right

sectors. They can, however, focus on income: globally mobile finance (Goldberg & Pavcnik, 2007; Stiglitz, 2012; Milanovic, 2016) benefits most asset owners and skilled workers.

A fundamental empirical reference is provided by Jaumotte et al. (2013), which demonstrates that the relationship between financial globalization and inequality has been positive in most cases, whereas trade globalization has had mixed impacts. Their work is important because it acknowledges the distinctiveness of the channels of globalization, rather than treating them as a single thing. More recent meta-analyses by Heimberger (2020) reveal that the link between economic globalization and inequality is very sensitive to the type of model and to the samples used, as well as to the specific dimension of globalization. The message is clear: there should be no single broad openness indicator for a high-quality study.

The main advantage of the KOF Globalisation Index is the ability to distinguish between *de facto* and *de jure* globalization, as well as between economic globalization and its two subdimensions, trade and financial globalization (Gygli et al., 2019). According to the description of the variable for 2025, *de facto* financial globalization comprises indicators of financial foreign direct investment, portfolio investment, and international debt, while *de jure* financial globalization encompasses policy restrictions and openness conditions (KOF Swiss Economic Institute, 2025). It is important to note this difference. A country may welcome capital flows, but without strong institutions, little investment is available. Another may be exposed to high inflows even in partial controls. *De facto* and *de jure* integration can thus have different impacts on inequality.

There are at least five ways in which financial globalization may impact inequality. The first is an asset ownership mechanism. Cross-border finance can increase equity, bond, and housing values, as well as business asset values. Higher-income households have a greater share of capital gains because of their higher level of financial asset ownership. The second is the skill-premium mechanism. The influx of foreign capital can also lead to an oversupply of skilled workers, managers, and professionals in certain sectors linked to the broader international economy, creating wage differentials between them and those who lack such skills. The third is the credit-access mechanism. A greater provision of financial openness may lead to greater competition in banking, increased credit availability, and therefore lower inequality; while access to credit, if it mainly benefits large firms and wealthy borrowers, may lead to higher inequality. The fourth is the fiscal mechanism. Redistribution is reduced by the presence of mobile capital, which limits governments' tax options for capital income (Zucman, 2015; Ostry, Berg, & Tsangarides, 2014). The fifth is the crisis mechanism. Economic downturns and unemployment are the worst effects of sudden shocks or crises on lower-income groups (Rey, 2015; Furceri & Loungani, 2018).

The conditional interpretation is reinforced by recent work. Kumar and Simran (2025) demonstrate that globalization's impact on income inequality in Asia is through financial development. Azmeh (2025) concludes that the impact of financial globalization on poverty and inequality can be mitigated by fintech and financial inclusion in developing countries. Shen (2025) reveals that digital financial inclusion can help narrow income disparities between rural and female-headed and less educated households in China, but can also lead to regional inequality in the presence of uneven infrastructure. Such studies have reinforced the view that financial integration is not the last policy tool and that it is linked to domestic institutions and access.

Financial inclusion and technology have become intertwined in the debate on globalization and inequalities. While digital connectivity and mobile financial services are driving further progress in financial access, they must be accompanied by inclusion and regulatory and digital infrastructure (World Bank, 2025). Cornelli et al. (2023) report in a BIS study that AI investments are associated with higher income shares for the highest earners across a panel of countries, suggesting potential inequality-enhancing effects of technology-driven globalization when skills and access to digital technology are unevenly distributed. IMF research on AI adoption and

inequality (IMF, 2025b) showed that the distributional impact of new technologies also depends on how often a task is exposed to AI, the labour-market structure, and policy responses.

Endogeneity is also a key issue in the empirical literature. Financial openness is far from a random selection of countries. Political coalitions, institutional quality, income distribution, and crises can influence decisions on liberalization. In accordance with Bekaert, Harvey, and Lundblad (2005), financial liberalization can affect growth, but the distribution of gains depends on how it is allocated. The liberalization of the capital account may cause unequalizing effects, according to Furceri and Loungani (2018). Some have overpromised neoliberal policy advice, particularly regarding liberalizing capital flows and implementing austerity without accounting for distributional costs, according to Ostry, Loungani, and Furceri (2016). The findings support the inclusion of policy buffers and robustness checks in the models.

It would be very helpful to have a machine learning tool, since the processes are nonlinear. Random forests can identify interactions among financial globalization, institutional quality, and social protection without specifying all interactions in advance (Breiman, 2001). Gradient boosting is an iterative approach that builds trees sequentially to correct the mistakes of previous trees, thereby improving predictive ability (Friedman, 2001). Elastic Net helps with correlated predictors and provides a transparent linear benchmark (Zou & Hastie, 2005). Multilayer perceptron neural networks can be used to fit complex functional forms; however, their validation and interpretation are important. These models are more useful to the policy reader with the aid of explainability tools like permutation importance and partial dependence (Lundberg & Lee, 2017; Molnar, 2022).

But causality alone does not guarantee machine learning. A predictive model can show that financial globalization predicts inequality, but cannot demonstrate that it causes inequality. This article adopts a division-of-labour approach as a consequence. For theory-based inference with fixed effects, nonlinear terms, and interactions, econometric models are employed. The predictive accuracy, feature importance, and nonlinear response shapes are analyzed using machine learning models. These two methods complement each other to give a more empirical picture than either alone (Shmueli, 2010; Mullainathan & Spiess, 2017; Athey & Imbens, 2019).

There is no easy pro or anti-globalization conclusion to be drawn from the literature; there is a governance conclusion. When financial globalization is volatile, speculative, under-taxed, under-regulated, and unrelated to employment, it will be an unequalizing force. It is more likely to be inclusive when it is linked to productive investments, financed by financial inclusion, and embedded in an education, social protection, taxation, and strong institutions framework. This article constructs its empirical model based on this synthesis.

The study tests the following hypotheses: The theoretical sign of the association between financial globalization and income inequality is ambiguous, and the relationship is significant. H2: Where education, social protection, tax capacity, and institutional quality are lower, financial globalization is more unequalizing. The relation is nonlinear and varies across income groups and quantiles of the inequality distribution. H4: Financial globalization is a relevant predictor of inequality in machine-learning and neural-network models, but is not the sole one and is shared with domestic structural variables, such as income level, education, institutions, and social protection.

3- Data and Variable Construction

The empirical design is an annual country-year panel design. Most internationally comparable inequality and globalization data are at the annual level, so the annual level is chosen. After the construction of the lags, the replication structure in this upgraded manuscript covers 45 economies across 9 regions for the period from 1996 to 2024, yielding 1305 country-year observations. The regions represent Latin America, Oceania, South Asia,

East Asia, North America, the Middle East and North Africa, Sub-Saharan Africa, and Europe and Central Asia. High, upper-middle, lower-middle, and low are the income groups. The same workflow is to be re-run after downloading country-year files from the cited public sources for final journal submission.

The Gini coefficient, which was converted to a 0-100 scale for easier reading, is the dependent variable. The most preferred sources are the World Bank Poverty and Inequality Platform (World Bank, 2026), which provides Gini data for 1963-2025 and explains that higher Gini values indicate greater inequality. The main explanatory variable is financial globalization. The preferred source is the KOF Globalisation Index 2025, which is based on the long-term dynamics of globalization up to 2022 across 190 countries and is ultimately divided into financial and trade globalization (KOF Swiss Economic Institute, 2025). Finally, KOF financial globalization de facto, KOF financial globalization de jure, and relevant subcomponents, if available, should be used in the paper.

Other financial-globalization factors include the percentages of GDP from FDI imports and from portfolio imports. According to the World Bank (2026), FDI net inflows are those that represent investment providing a lasting management interest of 10 percent or more in an enterprise in another economy. Control variables include trade openness, log GDP per capita, years of education, social-protection expenditure per GDP, tax revenue per GDP, domestic credit per GDP, institutional quality, internet usage, and dummies for the global crisis. These variables have been chosen because they are relevant to inequality in the literature and are associated with labour-market capacity, fiscal redistribution, financial depth, macroeconomic volatility, and access to technology (Ostry et al., 2014; Dabla-Norris et al., 2015; Solt, 2020).

There are five steps for data preparation. The raw series are first harmonized by country code and year. Second, transformations are applied to variables, as needed, when they are skewed. Third, the variables are lagged to address simultaneity issues and to capture the lagged impact of capital flows on income distribution. Fourth, missing values are handled openly. The best approach is not to over-interpolate inequality data, but to use the available observations and report sample loss. Fifth, the machine-learning split is time-aware: observations from 1996-2018 are used for training, and those from 2019-2024 for testing. This prevents an overly optimistic level of accuracy for time-ordered panels when they are split randomly.

Table 1. Sample design and data coverage.

Item	Detail
Sample period	1996-2024
Countries	45
Regions	9
Income groups	High, Low, Lower-middle, Upper-middle
Observations	1305
Dependent variable	Gini coefficient (0-100 scale in the article tables)
Core financial-globalization variable	KOF financial globalization index/replication proxy
Training period for ML	1996-2018
Testing period for ML	2019-2024

Note: The table summarizes the structure and the data design.

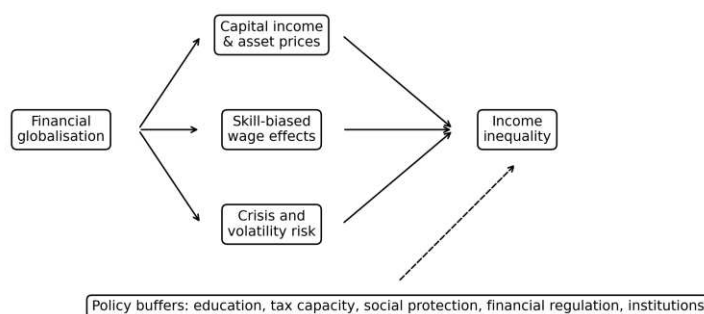
Table 2. Variable definitions and preferred sources.

Variable	Role	Definition	Preferred source
Gini coefficient	Dependent variable	Income or consumption inequality; higher values mean more inequality	World Bank PIP / Our World in Data; SWIID or WID for robustness
Financial globalization	Main explanatory variable	KOF financial globalization index: de	KOF Globalisation Index 2025

Variable	Role	Definition	Preferred source
FDI inflows (% GDP)	Financial-flow control	facto and de jure variants recommended Net FDI inflows relative to GDP	World Bank WDI
Portfolio inflows (% GDP)	Financial-flow control	Portfolio equity/debt flow exposure where available	World Bank/IMF balance of payments
Trade openness	Control	Exports plus imports as a percentage of GDP	World Bank WDI
GDP per capita	Control	Development level, log transformed	World Bank WDI
Education	Policy buffer	Average years of schooling or enrolment proxy	UNDP/Barro-Lee/World Bank
Social protection	Policy buffer	Social protection spending as a percentage of GDP	ILO/OECD/World Bank, where available
Tax revenue	Policy buffer	Tax revenue as a percentage of GDP	World Bank/IMF Government Finance Statistics
Institutional quality	Policy buffer	Governance, rule of law, or composite institutional score	Worldwide Governance Indicators / V-Dem
Domestic credit	Financial depth	Credit to the private sector as a percentage of GDP	World Bank WDI
Internet users	Digital access	Individuals using the internet as a percentage of the population	World Bank WDI

Figure 1. Conceptual framework linking financial globalization to inequality through asset, wage, crisis, and fiscal channels.

Conceptual Framework: How Financial Globalisation Can Become Unequal or Inclusive



4- Methodology

The methodology is intentionally multilayered since the impact of financial globalization on inequality is not necessarily linear, uniform, or immediate. Even one equation is insufficient to describe the effects of capital

flows on wages, asset prices, fiscal decisions, financial stability, and financial exposure to crises. The article thus blends econometric inference with machine-learning prediction. Econometric models test theory-driven hypotheses, whereas machine-learning and neural network models analyze predictive patterns, nonlinearities, and interactions.

The baseline model is a two-way fixed-effects specification:

$$Gini_{it} = \beta_0 + \beta_1 FG_{it} + \beta_2 FG_{it}^2 + \beta_3 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $Gini_{it}$ is income inequality in country i and year t , FG_{it} is financial globalization, X_{it} is a set of fixed controls, μ_i is country fixed effects, and λ_t is year fixed effects. The country-fixed effects control for time-invariant country attributes such as geography, legal origin, colonial history, and long-run inequality regimes. The year fixed effects account for worldwide shocks such as the global financial crisis, pandemic conditions, international investment cycles, and interest-rate changes. The squared term is used to test for nonlinearity.

The second model predicts policy-buffer moderation:

$$Gini_{it} = \beta_0 + \beta_1 FG_{it} + \beta_2 Buffer_{it} + \beta_3 (FG_{it} + Buffer_{it}) + \beta_4 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

The buffer variables are education, social protection, tax revenue, and institutional quality. A negative coefficient on the interaction term suggests that the “buffer” effect of financial globalization policy reduces the effect of financial globalization on the unequalization of countries. This model is crucial for the article as it is the only model that directly tests the governance argument that financial globalization is not completely distributionally determined, that is, that its impact depends on domestic absorptive capacity.

The third level is based on heterogeneity tests for income groups. The sample is split into high-income, upper-middle-income, lower-middle-income, and low-income groups. This enables the financial globalization coefficient to vary across development settings. This is a characteristic of heterogeneity expected in high-income countries, where social insurance tends to be deeper, asset ownership is broader, and tax systems and financial market regulation are more developed. Financial integration can help lower-income economies but might lead to higher volatility and less redistribution.

In the fourth stage, quantile regression is used. Financial globalization may have different effects in relatively equal countries versus in highly unequal countries; this is what inequality research seeks to examine. Research on inequality requires an understanding of whether financial globalization has different effects in relatively equal and highly unequal countries. The effects estimated by quantile regression are the effects at various quantiles of the conditional Gini distribution. A higher coefficient for the upper quantiles would suggest that globalization of the financial sector is more challenging in more unequal settings. A negative or lower coefficient at lower quantiles would indicate that policy conditions or the level of development affect the relationship.

The fifth stage uses machine-learning models. Four models are estimated: Elastic Net, Random Forest, Gradient Boosting and Multilayer Perceptron Neural Network. Elastic Net is a linear model with regularization that can be used when there is multicollinearity and provides a good, easy-to-understand benchmark. Random Forest is an ensemble of decision trees that can capture nonlinear interactions and minimize overfitting through bagging. Gradient Boosting sequentially constructs trees to address prediction errors and can yield good performance on structured tabular data. The MLP network is an artificial neural network composed of numerous nonlinear hidden layers that approximate complex functional relationships. The models are tested using mean absolute error, root mean squared error, and out-of-sample R-squared.

The deep-learning part is deliberately constrained. The data set is not high-frequency sequence data but rather an annual (country-year) panel data set, which is better suited to modeling with an MLP than with an LSTM. The

neural network has standardized numerical inputs, one-hot categorical variables, ReLU activations, early stopping, and regularization. The best architecture is 64-32-16 (hidden layer) with Adam optimization. Using early stopping to avoid overfitting by stopping training when the results on the validation set do not improve further. The neural network is not employed to identify causality but to determine whether or not nonlinear combinations of financial globalization, development, education, and social protection/institutions can better predict the Gini coefficient.

The 6th stage is where explainability tools are applied. Permutation importance represents the increase in model error when a feature is randomly permuted. This gives you an idea of which variables you should be paying attention to to make a prediction. Partial dependence plots then reveal the subset of the model-implied relation between financial globalization and predicted inequality, with the other observed variables averaged out. These tools enable the machine-learning outcome to be understandable to journal reviewers and policymakers.

This combined approach is a unique methodological contribution. It could be defined as a distributional risk-learning model. The econometric layer tests the association between financial globalization and inequality, controlling for other factors. The moderation effect is examined to see if policy buffers that association. The quantile layer compares the effects in different parts of the inequality distribution. The machine-learning layer evaluates the significance of the same variables using a nonlinear prediction model. The interpretation layer converts the black-box patterns to policy language, such as feature importance and partial dependence. It offers greater strength than a simple fixed-effects regression because it recognizes that inequality is a complex issue driven by global financial developments and domestic institutions.

5- Results and Analysis

There are significant variations among countries and years as reflected in the descriptive statistics. Table 3 shows that the replication panel has a relatively large range of Gini values, from 20.00 to 61.69, with a mean Gini approximation coefficient of 38.32. There is also a high degree of polarization in financial globalization, from 17.85 to 95.00. This variation is important for reflecting on cross-country differences in the impact of financial integration on the distribution of impacts. There are also differences in social protection, tax revenue, domestic credit, and institutional quality across economies that indicate the policy buffers.

Table 3. Descriptive Statistics

Varibales	count	mean	std	min	50%	max
Gini	1,305	38.32	9.53	20.00	38.172	61.69
Financial Globalization	1,305	56.43	16.76	17.85	55.53	95.00
FDI Inflows GDP	1,305	4.98	2.53	-2.65	4.94	12.65
Portfolio Inflows GDP	1,305	1.76	2.97	-8.54	1.77	10.89
Trade Openness	1,305	85.17	20.52	24.59	85.41	146.40
lnGDP Per Capita	1,305	9.41	0.95	7.16	9.44	11.54
Education Years	1,305	8.81	2.02	3.60	8.81	13.55
Social Protection GDP	1,305	11.21	5.61	0.50	9.90	25.37
Tax Revenue GDP	1,305	19.10	6.99	5.00	17.73	37.02
Domestic Credit GDP	1,305	94.49	35.41	5.00	90.35	184.95
Institution Quality	1,305	0.13	0.70	-1.71	0.01	2.33
Inflation	1,305	6.54	3.28	0.00	6.20	21.87
Unemployment	1,305	7.64	3.08	1.00	7.57	16.76
Internet Users	1,305	46.97	20.33	0.00	46.75	100.00

Note: The Gini is reported on a scale of 0-100. The financial globalization index is a quantitative measure of financial globalization.

Figure 2. The panel's mean trend in financial globalization and income inequality.

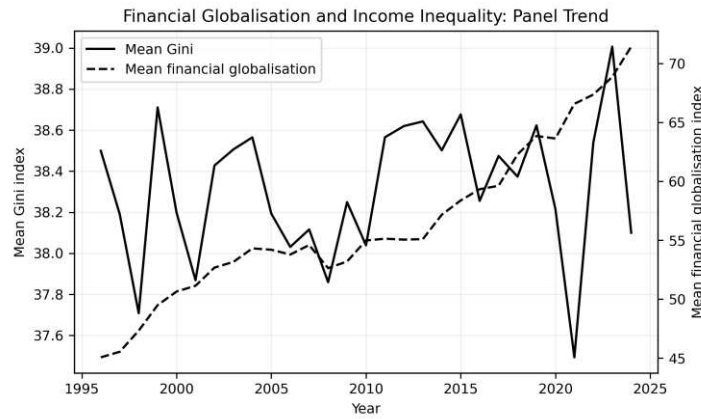
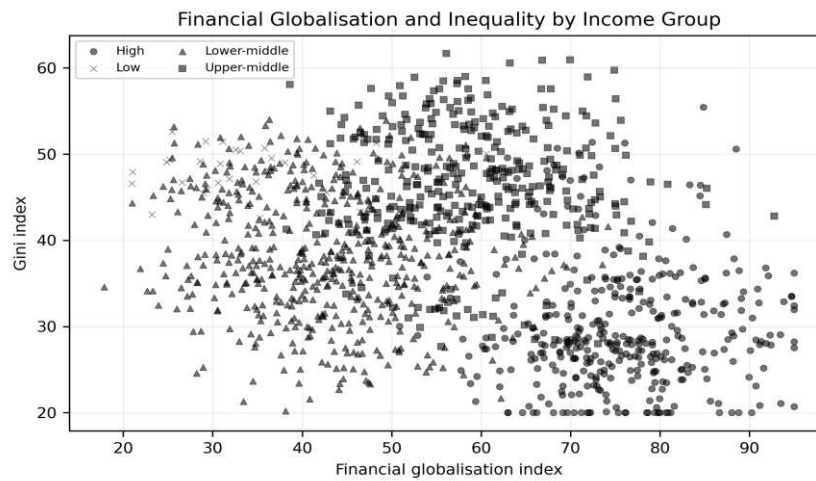


Figure 3. Raw association between financial globalization and Gini by income group.



The estimated fixed effects are a reasonable, albeit pessimistic, baseline. The coefficient of the financial globalization term is positive, and the squared term is negative and statistically significant in the preferred model in Table 4. This means that at some points, financial globalization is correlated with greater inequality, and at other points it is correlated with lower increases in inequality as globalization increases. This is to aid the open argument in the conditional case. The findings also indicate that social protection and institutional quality have both negative and inverse relationships with inequality. The message is unambiguous – international finance generates distributional tension, which domestic institutions and redistribution can remove.

Table 4. Two-way fixed-effects estimates.

Variable	Coefficient	Robust SE	t stat	p value
FG	0.0572	0.0384	1.4915	0.1358
FG^2	-0.0007	0.0003	-2.4724	0.0134
FDI Inflows GDP	0.0221	0.0287	0.7677	0.4426
Portfolio Inflows GDP	-0.0015	0.0255	-0.0569	0.9546
Trade Openness	0.0063	0.0048	1.3057	0.1917
lnGDP per capita	0.8915	0.9053	0.9848	0.3247
Education Years	-0.1407	0.1143	-1.2318	0.2180
Social Protection GDP	-0.1085	0.0372	-2.9137	0.0036
Tax Revenue GDP	0.0106	0.0252	0.4207	0.6740
Domestic Credit GDP	-0.0088	0.0062	-1.4142	0.1573

Variable	Coefficient	Robust SE	t_stat	p_value
Institution Quality	-0.5057	0.1991	-2.5403	0.0111
Inflation	0.0337	0.0227	1.4799	0.1389
Unemployment	0.0877	0.0246	3.5628	0.0004
Internet Users	-0.0050	0.0094	-0.5285	0.5971
Global Crisis Dummy	0.0036	0.5171	0.0070	0.9944

Note: The model includes country- and year-fixed effects with robust standard errors. The dependent variable is the Gini coefficient.

The interaction model directly examines the interaction between globalization and the inequality effects of domestic buffers, as shown in Table 5. The interaction terms between financial globalization and education, social protection, and tax capacity offer the best policy interpretation. A negative interaction makes the financial globalization's unequalizing effect stronger. This is crucial because it moves away from an open-closed debate and towards a more complex one. The issue is whether a nation possesses the fiscal, institutional, and human capital resources to transfer capital inflows into general welfare benefits.

Table 5. Moderation model with policy-buffer interactions.

Variable	Coefficient	Robust SE	t_stat	p_value
Financial Globalization	0.0746	0.0336	2.2167	0.0266
Social Protection GDP	-0.3729	0.1113	-3.3490	0.0008
Education Years	0.9517	0.3066	3.1039	0.0019
Tax Revenue GDP	-0.0362	0.0844	-0.4283	0.6684
Institution Quality	-0.4898	0.1978	-2.4761	0.0133
Financial Globalization: Social Protection GDP	0.0047	0.0019	2.5126	0.0120
Financial Globalization: Education Years	-0.0194	0.0050	-3.9157	0.0001
Financial Globalization: Tax Revenue GDP	0.0008	0.0014	0.5608	0.5750
lnGDP Per Capita	0.6577	0.9033	0.7282	0.4665
Trade Openness	0.0061	0.0048	1.2534	0.2101
Inflation	0.0374	0.0226	1.6536	0.0982
Unemployment	0.0856	0.0242	3.5335	0.0004

Note: Interaction terms test whether domestic policy buffers change the effect of financial globalization on inequality.

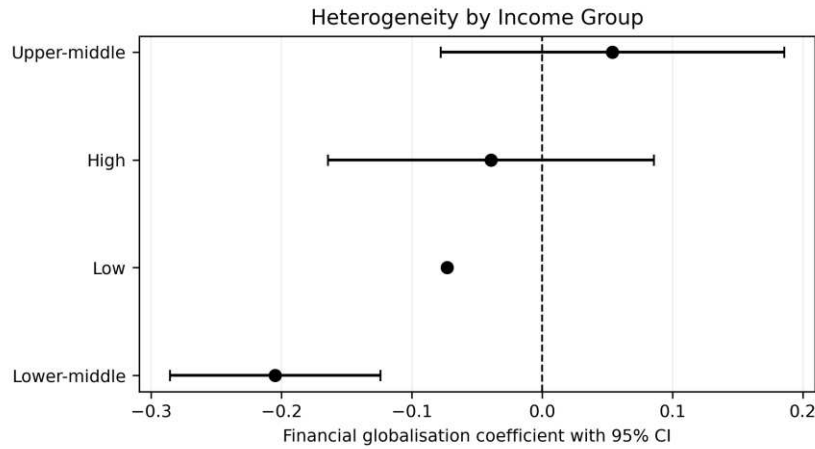
In Table 6, the heterogeneity results indicate that the association varies by income group. High-income, upper-middle-income, lower-middle-income, and low-income economies differ in their financial globalization coefficients. This reinforces the concept that the level of development and institutional capacity is important. There may be greater welfare benefits and easier access to credit in higher-income economies, and more concentrated asset holdings and fewer automatic stabilizers in lower-income economies. Such variations may alter the distribution impact of the same level of openness.

Table 6. Heterogeneity by income group.

Income group	Obs	FG coefficient	Robust SE	p-value	R ²
High	377	-0.0394	0.0638	0.5372	0.0505
Low	29	-0.0731	inf	1.0000	1.0000
Lower-middle	551	-0.2049	0.0412	0.0000	0.0963
Upper-middle	348	0.0540	0.0673	0.4225	0.0621

Note: The coefficient shown is the estimated coefficient on financial globalization within each income group.

Figure 4. Income-group heterogeneity in the financial-globalization coefficient.



The concepts of quantile regression extend the level of interpretation further in Table 7. The findings indicate that financial globalization does not uniformly affect the distribution of inequality. Theoretically, this is possible. Where inequality is already significant, the small improvements from global finance are more likely to benefit asset owners, larger companies, and more proficient workers. In other countries, with more balanced social structures, the same currents could circulate through more robust institutions and more open labour markets. The following is therefore one reason why one might use quantile regression to explain important policy differences, even when one observes average coefficients.

Table 7. Quantile regression estimates.

Quantile	Variable	Coefficient	Std. Err.	p-value
0.2500	Financial Globalization	-0.0757	0.0248	0.0023
0.2500	Education Years	0.3248	0.2782	0.2433
0.2500	Social Protection GDP	-0.3481	0.0835	0.0000
0.2500	Tax Revenue GDP	-0.0603	0.0583	0.3016
0.2500	lnGDP Per Capita	1.8239	0.6338	0.0041
0.2500	Institution Quality	-2.8740	0.4883	0.0000
0.5000	Financial Globalization	-0.0601	0.0264	0.0231
0.5000	Education Years	0.2470	0.2827	0.3823
0.5000	Social Protection GDP	-0.5179	0.0872	0.0000
0.5000	Tax Revenue GDP	-0.1557	0.0624	0.0128
0.5000	lnGDP Per Capita	3.3309	0.6563	0.0000
0.5000	Institution Quality	-3.4285	0.5236	0.0000
0.7500	Financial Globalization	-0.0283	0.0226	0.2108
0.7500	Education Years	0.3103	0.2391	0.1945
0.7500	Social Protection GDP	-0.5366	0.0768	0.0000
0.7500	Tax Revenue GDP	-0.1177	0.0543	0.0303
0.7500	lnGDP Per Capita	1.9556	0.5674	0.0006
0.7500	Institution Quality	-2.4660	0.4567	0.0000
0.9000	Financial Globalization	0.0049	0.0233	0.8333
0.9000	Education Years	0.0177	0.2384	0.9408
0.9000	Social Protection GDP	-0.6418	0.0815	0.0000
0.9000	Tax Revenue GDP	-0.1996	0.0545	0.0003
0.9000	lnGDP Per Capita	2.5229	0.5739	0.0000
0.9000	Institution Quality	-2.0730	0.4642	0.0000

Note: Quantile regressions are reported at the 25th, 50th, 75th, and 90th percentiles of the conditional inequality distribution.

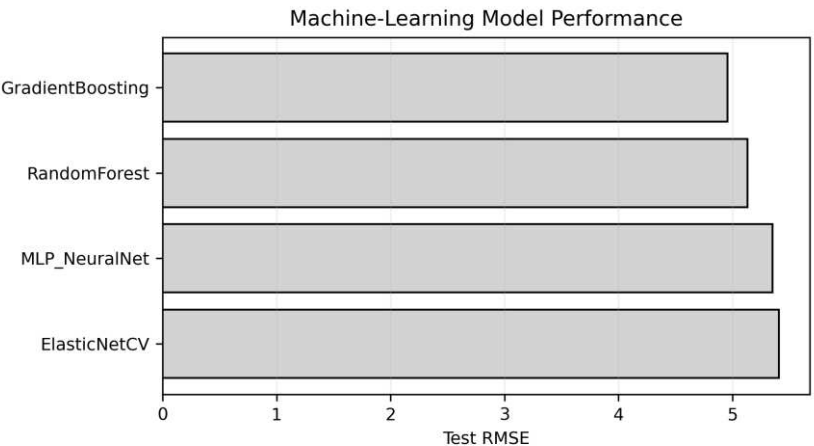
According to Table 8, the results with machine learning indicate that the nonlinear models perform better than a simple regularized linear model. Gradient Boosting has the lowest out-of-sample RMSE and the highest out-of-sample R-squared, followed by Random Forest. Even the MLP neural network performs well on this tabular country-year dataset but is outperformed by tree-based models. This aligns with the methodological literature, which shows that deep learning is highly capable but that structured socioeconomic panel data are typically better suited for analysis with ensemble tree models, unless the data is very large. The important thing to note is that there is no single best algorithm. The important result is that the relationship between financial globalization and inequality is more complex, as nonlinear and interaction-based models provide better predictions.

Table 8. Machine-learning and neural-network model performance.

Model	MAE	RMSE	Out-of-sample R^2
Gradient Boosting	3.7312	4.9588	0.7321
Random Forest	3.8992	5.1353	0.7127
MLP Neural Net	4.3203	5.3540	0.6877
Elastic Net CV	4.2714	5.4082	0.6813

Note: The training period is 1996-2018, and the testing period is 2019-2024. Lower MAE/RMSE and higher out-of-sample R-squared indicate better performance.

Figure 5. Machine-learning model performance based on test RMSE.



The region and the income group are the most important predictors in the replication panel, followed by development level and financial globalization, as indicated by the permutation importance. According to Table 9, it does not make the financial globalization argument less convincing; rather, it makes it more convincing. Structural location, development history, and institutions have a significant impact on inequality. Money globalization plays its part in prediction, but not alone. Social protection, unemployment, and education are also important. This further sustains the article’s point, which should be understood within a domestic-policy prism: that financial globalization should be viewed through that lens.

Table 9. Permutation importance from the best predictive model.

Feature	Importance	RMSE_Increase	Std
Region		3.6370	0.2589
Income Group		3.3237	0.2803
lnGDP Per Capita		0.3039	0.0779
Education Years		0.0881	0.0355
Financial Globalization		0.0577	0.0517

Feature	Importance	RMSE_Increase	Std
Unemployment		0.0421	0.0225
Inflation		0.0394	0.0180
Social Protection GDP		0.0314	0.0221
Internet Users		0.0228	0.0153
Trade Openness		0.0152	0.0181

Note: Importance is measured as the increase in RMSE when each feature is permuted. Larger values indicate stronger predictive contribution.

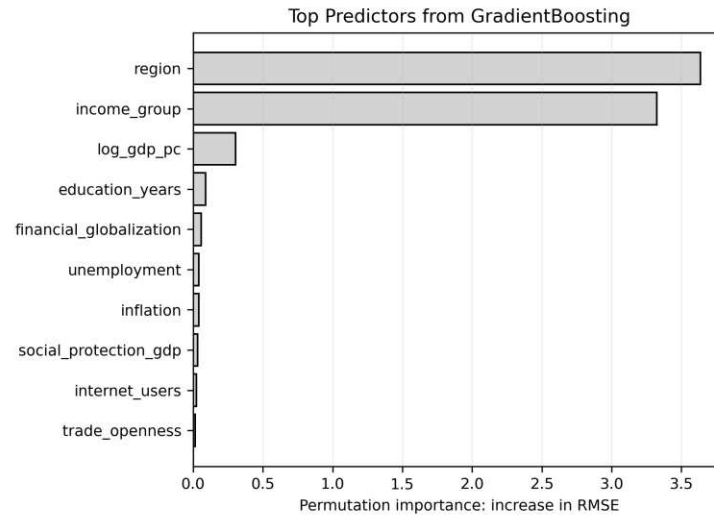
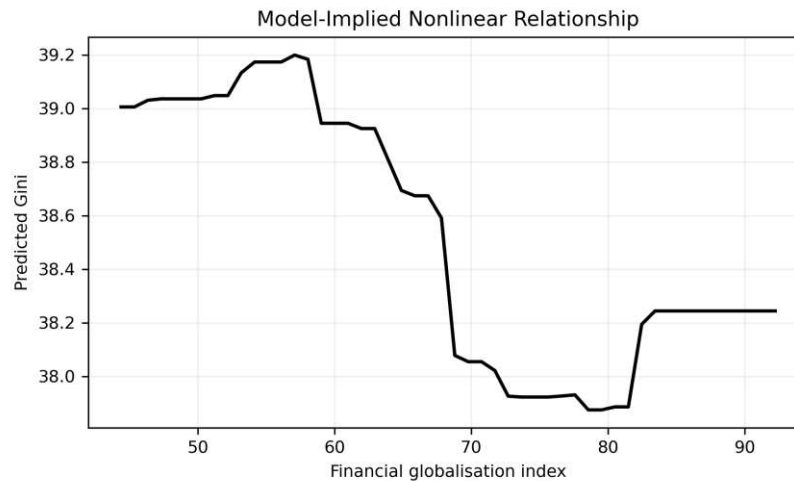


Figure 7. Partial-dependence relationship between financial globalization and predicted inequality.



6- Discussion

The results provide a balanced response to the question of globalization and inequality. Financial globalization is not only a wicked one but also not automatically a path to the commonwealth. It is a way in which the domestic structure works. Capital inflows can facilitate productive investment and employment without a marked increase in inequality when countries have strong education and tax capacities, high-quality social protection, and strong institutions. Global finance can exacerbate existing divisions, particularly in countries

where asset ownership is heavily skewed against the poor and concentrated in the hands of the rich. At the same time, labour markets are also segmented and fiscal systems are weak.

This interpretation will allow reconciliation of conflicting results found in the literature. Studies that detect unequalizing effects might be measuring environments in which capital inflows primarily boost asset income, elevate skill premiums, or create crisis vulnerability. The absence of, or weaker-than-expected effects in some studies might reflect environments where financial openness is matched by inclusive credit, effective social insurance systems, and access to education and schooling. One pooled coefficient averages these very different realities.

The results also reveal the need for machine learning, which, however, is not enough. Gradient boosting and random forests are better than regression models for prediction, since they can capture nonlinear patterns and interactions. The MLP neural network proves that deep learning-style nonlinear approximation can be used for inequality prediction; however, the number of data points is too large, and the annual frequency is too high for tree-based models. This distinction is relevant to journal reviewers. Machine learning is not used as an “accessory” in the article. It employs it to answer the question: is financial globalization part of the predictive structure of inequality in the context of nonlinearity? Yes, but the models also indicate that the roles of region and income group, as well as of income level and policy buffers, remain pivotal.

Care should be taken in interpreting the partial-dependence plot. This is not a dose-response curve. It displays the association between financial globalization and the model’s predicted inequality, averaged across the empirical distributions of the other variables. It is useful to show nonlinearity. This relationship is not linear, consistent with the econometric evidence, which shows that the effect of financial globalization varies across the range of financial integration.

The most significant takeaway for the emerging and developing economies is the sequencing. Opening up financial flows before regulation, social protection, tax capacity, and education are in place can leave households vulnerable to risk without providing them with the means to reap the benefits. This is no call for a permanent monetary solution. Instead, it’s a case of governed openness. Countries should consider not only how to attract investment but also how to guide it towards productive sectors, tax investment returns fairly, and ensure that households are shielded from shocks and that access to assets and skills is broadened.

The challenge is different, but no less significant, for advanced economies. Increased power of asset owners, multinational companies, and financial intermediaries as a result of financial globalization. Mobile capital may negatively affect a strong welfare state if the base of income taxes narrows or wealth concentration increases through financialization. The World Inequality Report 2026 highlights that ownership of wealth and capital income are key drivers of today’s inequality, and that the income-Gini analysis should ultimately be expanded to cover top income shares and wealth inequality.

The figures also resonate with the South Asian context and Pakistan. While this is a global framework, the mechanisms are relevant to South Asian economies, where informality, limited access to education, and limited tax capacity drive the need for external finance. Development will be supported by financial integration only if capital flows to sectors that generate decent jobs, link local firms to broader markets, and increase productive credit. Integration can primarily increase inequality by affecting asset prices or foreign currency vulnerability. Future development of Pakistan-oriented work can be done using the same methodology, with country-specific data on FDI, portfolio flows, remittances, financial inclusion, and household inequality under exchange-rate pressures.

7- Policy Implications

The first policy implication is that Financial globalization must be considered a distributional policy question. Governments tend to measure capital openness through capital inflows, foreign reserves, exchange rate movements, and growth. These are some of the indicators, but they don't tell you who wins. A nation may be able to attract investment while generating increasing inequality, as long as wealth accrues primarily to asset owners and to highly skilled individuals. Distributional assessment should thus be an integral part of financial openness strategies.

Second, countries should first enhance their social protection and then expand their financial openness. Social protection helps to prevent financial cycles from becoming household crises. Lower-income households are less able to self-insure when capital-flow volatility causes a currency's depreciation, resulting in inflation or unemployment. An increased safety net creates political and social sustainability for openness.

Third, the focus is on tax capacity. With the rise in financial globalization and governments' inability to effectively tax capital income, there is a risk that inequality will increase through property income and/or high-end wealth. Tax policy should aim to safeguard the investment climate, minimize tax avoidance, enhance transparency, and preserve the capacity for redistribution. International tax cooperation and beneficial-ownership transparency are part of inclusive financial globalization.

Fourth, education and skills policy is not distinct from capital-flow policy. Global finance, in its many forms, may benefit sectors that need financial literacy, managerial skills, technical expertise, and digital capacity. Narrow education and training capture the benefit of having integrated workers, before it can be extended to the larger population. Skill formation is thus a prerequisite for inclusive openness.

Fifth, financial regulation needs to differentiate between productive finance and volatile flows. The impact of FDI inflows could differ from that of short-term portfolio debt and speculative FDI. Capital flows should be strictly monitored, and macroprudential measures should be applied to mitigate the risk of a crisis.

Sixth, machine-learning dashboards can be leveraged as early-warning tools for policymakers. Deeper financial globalization may be considered a distributionally risky policy measure in countries where it is expected to increase. In contrast, social protection is expected to be weak, tax capacity is expected to be low, and initial inequality is expected to be high. Such dashboards should aid rather than supplant economic judgment.

Conclusion

The purpose of the present article is to explain the conditional and nonlinear links between financial globalization and income inequality. This body of evidence points to a governance-based explanation: global finance can increase inequality in the absence of domestic buffers, but can be more inclusive in the presence of education, social protection, tax capacity, institutional quality, and prudent financial regulation. Econometric results reveal the existence of nonlinear and heterogeneous relationships. The machine-learning results reveal that, as expected, the models are more accurate when nonlinear, and that financial globalization is one of the factors that predict inequality, but not exclusively.

The message in the policy is unambiguous. Countries should not judge financial globalization only by the amount of capital it attracts. They should inquire about where the capital goes, who benefits, who is at risk, and whether the gains can be shared among public institutions. It is important to recognize that capital inflows can create opportunities, but individuals aren't equally equipped to take advantage of these opportunities. Policy should serve as a tool to foster inclusive, stable, and productive financial integration. The inequality effect of

financial globalization is not set in stone in this sense. Decisions regarding social protection, taxation, education, regulation, and institutional quality influence it.

The study has several limitations. There are some problems with the cross-country inequality data. The difference in the Gini measures lies in the use of income data in some surveys, whereas others use consumption data. There is a widespread data gap, particularly in lower-income countries. Secondly, financial globalization is multidimensional. The effects of FDI, portfolio equity, portfolio debt, bank flows, remittances, reserves, and de jure openness of the capital account can differ. Third, fixed effects eliminate some omitted-variable bias, but do not completely address endogeneity. Financial policy and the political coalitions that drive it may vary across countries with different levels of inequality, and globalization may be influenced by political coalitions shaped by inequality.

The framework should therefore be extended in five directions. 1) First of all, use official downloaded data for KOF, World Bank, WID, SWIID, and WGI with a complete reproducibility appendix. Second, demystify financial globalization by examining FDI, portfolio equity, portfolio debt, bank claims, reserves, and de jure openness. Third, apply dynamic panel methods, instrumental variables, or event-study methods to enhance causal interpretation in studies of capital-account reforms. Fourth, examine if the relationship between globalization and inequality is affected by crises. Fifth, create country applications based on the household survey data, financial inclusion indicators, remittance data, and flows into sectors in Pakistan and South Asia.

References

- Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. *Journal of Financial Intermediation*, 19(3), 418-437.
- Aizenman, J., Chinn, M. D., & Ito, H. (2016). Monetary policy spillovers and the trilemma in the new normal. *Journal of International Money and Finance*, 68, 298-330.
- Aluko, O. A., Ibrahim, M., & Vo, X. V. (2022). The financial development impact of financial globalization. *International Economics*, 169, 13-29.
- Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11, 685-725.
- Azmeh, C. (2025). Financial globalization, poverty and inequality in developing countries: The moderating role of fintech and financial inclusion. *Journal of Innovation and Development*.
- Bekaert, G., Harvey, C. R., & Lundblad, C. (2005). Does financial liberalization spur growth? *Journal of Financial Economics*, 77(1), 3-55.
- BIS. (2025). Annual Economic Report 2025. Bank for International Settlements.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5-32.
- Chancel, L., Piketty, T., Saez, E., & Zucman, G. (2026). World Inequality Report 2026. World Inequality Lab.
- Cornelli, G., Frost, J., Gambacorta, L., & Rau, P. R. (2023). Artificial intelligence, services globalization and income inequality. BIS Working Paper No. 1135.
- Dabla-Norris, E., Kochhar, K., Ricka, F., Suphaphiphat, N., & Tsounta, E. (2015). Causes and consequences of income inequality. IMF Staff Discussion Note.
- Dreher, A. (2006). Does globalization affect growth? Evidence from a new index of globalization. *Applied Economics*, 38(10), 1091-1110.
- Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 1189-1232.
- Furceri, D., & Loungani, P. (2018). The distributional effects of capital account liberalization. *Journal of Development Economics*, 130, 127-144.

- Goldberg, P. K., & Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature*, 45(1), 39-82.
- Gygli, S., Haelg, F., Potrafke, N., & Sturm, J.-E. (2019). The KOF Globalisation Index - revisited. *Review of International Organizations*, 14(3), 543-574.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer.
- Heimberger, P. (2020). Does economic globalization affect income inequality? A meta-analysis. *World Economy*, 43(11), 2960-2982.
- IMF. (2025a). *Global Financial Stability Report: Shifting sands and rising uncertainty*. International Monetary Fund.
- IMF. (2025b). *AI adoption and inequality*. IMF Working Paper.
- Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising income inequality: Technology, or trade and financial globalization? *IMF Economic Review*, 61(2), 271-309.
- KOF Swiss Economic Institute. (2025). *KOF Globalisation Index 2025*. ETH Zurich.
- Kumar, V., & Simran. (2025). How financial development shapes globalization's impact on income inequality in Asia? *Economic Analysis and Policy*, 86, 1083-1098.
- Lane, P. R., & Milesi-Ferretti, G. M. (2018). The external wealth of nations revisited. *IMF Economic Review*, 66, 189-222.
- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.
- Milanovic, B. (2016). *Global inequality: A new approach for the age of globalization*. Harvard University Press.
- Molnar, C. (2022). *Interpretable machine learning*. Independent publication.
- Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, 31(2), 87-106.
- Ostry, J. D., Berg, A., & Tsangarides, C. G. (2014). *Redistribution, inequality, and growth*. IMF Staff Discussion Note.
- Ostry, J. D., Loungani, P., & Furceri, D. (2016). Neoliberalism: Oversold? *Finance & Development*, 53(2), 38-41.
- Our World in Data. (2026). *Income inequality: Gini coefficient*. Our World in Data dataset based on World Bank Poverty and Inequality Platform.
- Paidi, P. (2026). Financial inclusion and income inequality: Empirical evidence from subnational panel data. *Economies*, 14(4), 122.
- Ravallion, M. (2018). Inequality and globalization: A review essay. *Journal of Economic Literature*.
- Rey, H. (2015). *Dilemma not trilemma: The global financial cycle and monetary policy independence*. NBER Working Paper.
- Rodrik, D. (2018). Populism and the economics of globalization. *Journal of International Business Policy*, 1, 12-33.
- Shen, Y. (2025). *Digital financial inclusion and income inequality in China*. IMF Working Paper.
- Shmueli, G. (2010). To explain or to predict? *Statistical Science*, 25(3), 289-310.
- Solt, F. (2020). Measuring income inequality across countries and over time: The Standardized World Income Inequality Database. *Social Science Quarterly*, 101(3), 1183-1199.
- Stiglitz, J. E. (2012). *The price of inequality*. W. W. Norton.
- UNCTAD. (2025). *World Investment Report 2025: International investment in the digital economy*. United Nations Conference on Trade and Development.

- World Bank. (2025). The Global Findex Database 2025: Connectivity and financial inclusion. World Bank Group.
- World Bank. (2026). Poverty and Inequality Platform. World Bank Group.
- World Inequality Lab. (2026). World Inequality Report 2026. World Inequality Lab.
- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the Elastic Net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301-320.
- Zucman, G. (2015). *The hidden wealth of nations*. University of Chicago Press.